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Designing for Success

Exploring the interplay between achievement goals and progress visualisation preferences in a learning analytics dashboard

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Abstract

Student-facing learning analytics dashboards process and visualise learning traces to enable informed decision-making and goal-setting. Previous work contributes to understanding how to use feedback reference frames in designing these dashboards to cater to students with a mastery or performance achievement goal orientation. This study aimed to build upon this work by also investigating the interaction between feedback reference frames and an achievement goal orientation's valance, i.e., approach or avoidance, and emphasising the need for progress indicators that are individualised to one's achievement goal orientation. To this end, we created and evaluated four alternative dashboard designs of an existing learning analytics dashboard to cater to each achievement goal orientation in the framework by Elliot and McGregor. Results show limited significant effects in the evaluation scores by performance-approach and mastery-approach-oriented students to an upward social feedback reference frame and an absolute achievement feedback reference frame, respectively. No effects were found for the achievement goals of negative valance. Considering methodological limitations and sample size, the findings indicate that while the conceptual distinction between approach and avoidance achievement goals is solid, understanding its implications in the design of learning analytics dashboards may prove difficult. It is important to understand and address these nuances in order to accommodate every learner effectively.

Keywords: learning analytics, dashboard, feedback reference frames, achievement goals, visualisation

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Chapter 1

Introduction

Learning analytics dashboards (LADs) process and display aggregated data-driven reports about student learning progress to support students and teachers in making informed decisions and setting goals [1, 2, 3]. For student use, in particular, LADs aim to foster self-regulated learning (SRL) skills by visualising their learning behaviour and status [2, 4, 5]. Such dashboards have been studied and applied to support various phases of SRL, including forethought (e.g., goal-setting and planning), performance, and reflection [3, 6].

While research on learning analytics dashboards often uses self-regulated learning as the go-to educational framework to inform its design decisions, it rarely proves to support SRL [5, 6], and uses appropriate measures to evaluate the design [3]. It is, therefore, vital that LADs are designed with their educational objectives in mind and are subsequently evaluated along metrics that match these objectives. In that aspect, previous research indicates that forethought and performance phases of SRL are particularly underrepresented as target outcomes of LADs [3].

The current research aims to bridge this gap between design intentions and outcomes by evaluating visualisations that employ different feedback reference frames to cater to student goals. Goal-setting, as part of the forethought phase of self-regulated learning, is a complex task that provides context for making sense of subsequent tasks, directs planning, strategy choice, and flexible task management, and provides standards for monitoring and evaluating performance [7]. One's goals can have different intentions or purposes [8]. As hypothesised and demonstrated (e.g., [8, 9]), goal intentions, referred to as "achievement goals", can be described along two axes: they can be performance and mastery-oriented (definition), and within this definition, one can approach success or avoid failure (valance). Students with a mastery goal orientation seek to improve their knowledge, skill, and competence compared to their previous performance, while students with a performance goal orientation seek to outperform others [8].

Within a LAD, different feedback reference frames can be used to reflect the different goal orientations of students. Aguilar [10] found that, for university students, self-focused visualisations were more reflective of mastery goal orientations, whereas comparative visualisations yielded interpretations reflective of performance goal orientations. In another study, Gallagher et al. [11] found that, in a corporate context, workspace learners spent more time actively engaging with the learner data when receiving task-focused visualisations, while learners that received comparative visualisation spent more time reviewing the dashboard.

These findings suggest that one's goal orientation, preferences, and behaviour in a LAD may indeed be linked. While previous work made significant contributions on how to design for mastery and performance achievement goal orientations, additional research could further uncover the interplay between LAD design elements and achievement goal orientations, including elements that cater to approach or avoidance goals. Therefore, the current research aims to understand how one's preferences in progress visualisations in a LAD and their achievement goal orientation scores are linked.

1.1. Background and context

The research is rooted in the context of technology-enhanced learning (TEL), an interdisciplinary field combining knowledge from psychology, educational sciences, and computer and information science to replicate, supplement, or transform teaching or learning using technology [12]. In particular, the research positions itself around the concepts of learning analytics and dashboards, blended learning, self-regulated learning, and motivation in learning.

Learning analytics is particularly valuable for developing self-regulated learning skills within blended learning environments by employing performance data to stimulate awareness, reflection, and sensemaking [1]. Multiple approaches to using this data exist, such as open learner models, early warning systems, and dashboards [4, 13]. This research will focus on learning analytics dashboards (LADs) - data-driven decision-making tools that encourage learner's awareness, reflection, and sense-making [1] via different data visualisations such as bar and line plots, pie charts, and scatter plots, as well as more novel techniques such as glyphs or interaction matrices [14].

These visualisations and indicators intend to enable learners to make informed decisions about their learning process and motivate them [5, 10]. However, research does not agree on the best approach to motivate students. While visualisations with comparative information are shown to increase the time a student spends in a LAD [11] and is indicated by students as more motivating [10], research also argues that this comparative information may foster competition, rather than an increase in knowledge [5], and progress information may yield better quality learning [11].

A possibly fruitful approach to catering to all students might be to adapt the learning progress visualisations to students' (possibly changing) goal-setting preferences. Other studies report successfully implementing visualisations designed around goal orientation constructs (e.g., [10, 15, 16], although the responses to their evaluation seem to vary. For example, a 2022 study by Barba et al. [17] showed that students were reluctant to compare their performance with peers, while a 2020 study by Russell et al. [18] showed that performance feedback was not associated with students dropping out of a course. Exploring the interplay between achievement goals and different progress visualisations in a learning analytics dashboard may yield interesting insights into how students make sense of learning analytics and goal orientation in their learning.

To this end, we developed and implemented four alternative designs of the StudyLens dashboard (`https://studylens.science.uu.nl/web`), a learning analytics dashboard being developed by the Software Technologies for Learning and Teaching (STLT) research group within the Information and Computing Sciences department of Utrecht University (see also: [19, 20]). The four alternative designs were inspired by previous research on achievement goal orientations within LADs and were, while not labelled as such, intended to cater to each of the four orientations as described in the model of Elliot and McGregor [9]: performance-approach, performance-avoidance, mastery-approach, and mastery-avoidance. With different feedback reference frames to indicate the student's progress, the designs nudged towards goals corresponding to the achievement goal orientations. Chapter 3 describes these designs in more detail.

1.2. Problem statement

While a substantial body of research exists on how to support self-regulated learning using LADs, previous work still needs insight into how to specifically design and employ feedback reference frames to cater to achievement goals of different valance, i.e., approach and avoidance. Answering this question may hold valuable insights into how to better cater LADs to different kinds of students and optimize their learning by exploiting their achievement goal orientation.

1.3. Objectives and research question

In order to attain these insights, three main objectives frame this research. First, the aim is to design, implement, and further explore alternative interfaces of StudyLens that are individualised to one's goal orientation. The second aim is to explore how achievement goal orientations influence one's evaluation of the designs. Lastly, this research aims to distil prescriptive design knowledge on supporting self-regulated learning using progress indicators in a learning analytics dashboard in which the feedback reference frames are individualised to an individual goal orientation. These objectives are captured in the following research question guiding this research: *How does the achievement goal orientation of a student affect their preferences in progress visualisations in a learning analytics dashboard?*

In order to address this question, 54 undergraduate students provided their achievement goal scores and evaluated the four alternative dashboard designs. Relations between the responses were explored using statistical hypothesis testing, comparing the median evaluation scores of student groups categorised by their course activity and achievement goal scores. Using this approach, we aimed to uncover the effect of achievement goal orientation and course activity on the preference of feedback reference frame. Chapter 5 outlines this approach in detail.

1.4. Contributions

The contributions of this study are twofold. First, this study aims to solidify the previous findings that a social feedback reference frame caters to performance-oriented students, and a progress or achievement feedback reference frame caters to mastery-oriented students. The results may discover implications for providing students with different visualisations and feedback reference frames based on their goal orientation. For practitioners, this may stress the importance of using or avoiding certain visualisations or offering students the choice. Additionally, we aim to find elements of LAD design that can be used to cater to achievement goals of different valance.

1.5. Structure of the thesis

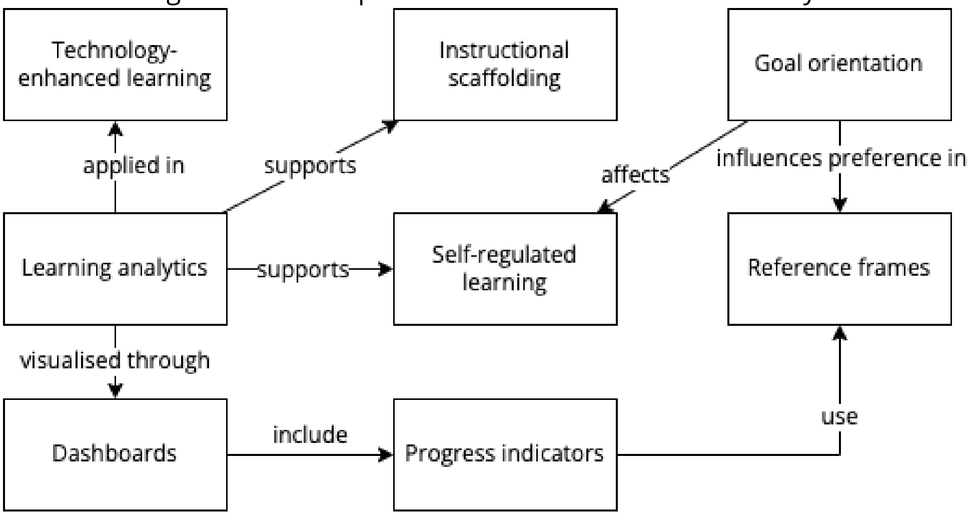
The upcoming chapter provides an overview of the core concepts used to come to these contributions and discusses the main theories, models, and previous findings surrounding these concepts. Next, chapter 3 describes the contributions to the StudyLens dashboard that were made in the context of this thesis. Chapter 4 outlines and discusses the contributions of the experimental setup that was initially planned for this thesis but could not proceed due to participant attrition. Chapter 5 describes the main experiment that was ultimately conducted for this thesis, including sources, materials, and procedures, and the results that followed from these methods. Finally, chapter 6 summarises the results, discusses its implications and draws conclusions, including recommendations for future research.

Chapter 2

Literature Overview

The following chapter provides an overview of the literature available on the field of study. The conceptual framework includes eight concepts, as shown in Figure 2.1. The following sections provide a theoretical overview of the presented framework.

Figure 2.1: Conceptual framework of the current study.



2.1. Technology-enhanced learning

While many interpretations and definitions exist, the term 'technology-enhanced learning' (TEL), sometimes referred to as 'e-learning', 'learning technology', or 'computer-based learning' [21], is commonly described as the application of information technologies to support and enhance learning and teaching [12]. Such technologies can take many forms: from applications used in formal learning, such as interactive videos, serious games, and mobile learning platforms, to applications primarily used in informal learning, such as general-use communication technologies [22]. Research on TEL recognises learning as a *design science*. Within this reasoning, learning technologies are understood to be *designed artefacts* that emerged from accumulated research into how human learning functions and how to improve the effectiveness of technologies supporting it [23]. But while the aim of TEL is agreed upon to be to improve learning and teaching processes and outcomes, the reported effects of TEL on teaching and learning appear to be mixed [24]. One possible explanation for this could be that many interventions seem to focus on how to replicate and supplement existing learning and teaching practices using technology rather than on how to *transform* these practices [12, 25]. Despite this ongoing discussion regarding the effectiveness of TEL, what is generally accepted is that TEL is another promising way to provide instructional scaffolding.

2.2. Instructional scaffolding

Technology in education can be applied to support scaffolding; that is, external support (usually in the form of a more knowledgeable other) in the learning process in order for the student to achieve a task that would be beyond their abilities when unassisted [26, 27]. The ultimate goal of scaffolding is that this support will gradually decline to the point that the student can achieve said task independently [28]. As a result, scaffolding happens within the *zone of proximal development*, which is the distance between one's unassisted performance and one's performance with the help of a more capable other [29, 30]. Literature differentiates between four kinds of scaffolding: conceptual, procedural, strategic, and metacognitive (e.g., [31, 32, 33]).

Conceptual scaffolding refers to students' support in defining and refining the concepts to be studied [31]. It helps students to decide what to consider in their learning, define how concepts are connected, and prioritise [32]. Conceptual scaffolds can be provided, but can also be student-generated with the guidance of the more knowledgeable other by providing instructions on how to create them.

Next, procedural scaffolding supports students in using the tools they use in their learning, such as supporting technology or learning resources [31, 32]. The aim of procedural scaffolding, at least originally, is to reduce the cognitive load associated with the use of learning tools and resources [31] until such processes become intuitive. In this aspect, the notion of procedural scaffolding is reminiscent of the cognitive load theory [34, 35] and its concept of extraneous cognitive load - that is, cognitive load determined not by learning itself, but by "how the information is presented and what the learner is required to do by the instructional procedure" [35].

Strategic scaffolding refers to the support to seek alternative approaches to learning and problem-solving. Hannafin et al. [31] describe three types of strategic scaffolding: 1) prompting possible approaches to the problem at hand or asking probe questions about how to approach the problem, 2) alerting the student to available resources and tools they may need in their learning task and guide them in using them, and 3) aiding reflection on the chosen strategies by prompting students to test their understanding of the task. The aim is to support students in selecting the correct information, evaluating resources, and integrating new knowledge with the knowledge they already possess.

Lastly, metacognitive scaffolding supports students in structuring their thinking and learning. It aims to help identify what the student already knows and in what areas their knowledge is deficient [32]. Metacognitive scaffolding may be provided through reflection reminders, suggesting learning milestones, and progress monitoring [31, 33]. It is during this metacognitive scaffolding that learning analytics can prove particularly valuable supporting tools.

2.3. Learning analytics

Learning analytics holds the potential to provide adaptive and personalised scaffolds to students in order to improve their learning. While many definitions of learning analytics exist, many use it to describe "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [36, 37]. Essentially, learning analytics (LA) functions as a decision-making tool, enabling educators to improve education and identify students-at-risk, and enabling students to gain insight and reflect on their learning [38].

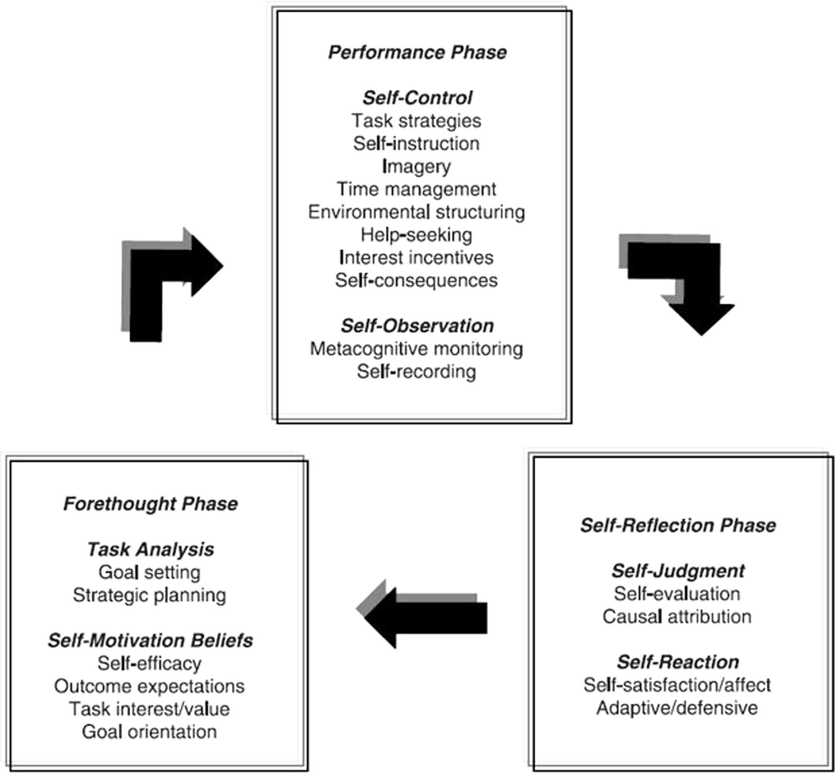
Learning analytics is a relatively new area of study, with its first dedicated conference, the 1st International Conference on Learning Analytics and Knowledge (LAK), held in 2011. It is a multidisciplinary field involving contributions from learning sciences, statistics, machine learning and AI, computer and information science, sociology, and psychology, amongst others [39]. It emerged from and is a subset of academic analytics but has a different focus: whereas academic analytics are most commonly used by institutional bodies, learning analytics, and the insights that may be generated from it, are most commonly used by educators and students [38, 40]. Many applications of learning analytics exist: monitoring, prediction, adaptation, personalisation, and decision-making support, to name a few (e.g., [41, 40, 42]).

However, while the interest in learning analytics has grown substantially over the years [37, 43, 42], it has also been criticised for its alleged lack of grounding in learning science, and limited evidence that it improves teaching and (self-regulated) learning (e.g., [5, 44, 45, 6, 46]). For example, while many studies use self-regulated learning (SRL) as the core theory to inform their design [5], they only used learning analytics to measure the students' SRL skills, not to support students in it [6].

2.4. Self-regulated learning

Self-regulated learning (SRL) refers to the process through which students proactively and intentionally plan, monitor, and evaluate their learning activities to achieve their goals effectively. Many models exist that encapsulate this process, such as Zimmermann's [47], Winne and Hadwin's [48] or Pintrich's model [8]. This study uses Zimmerman's cyclical model due to its widespread use and hypothesised better applicability to cases in higher education [49]. According to Zimmerman [47], the process of self-regulated learning involves three key phases: forethought, performance, and reflection (see Figure 2.2). Students set goals, plan strategies, and activate prior knowledge during the forethought phase. In the performance phase, students manage their efforts to complete a task by focusing on their physical and motivational efforts in completing the task (self-control) and tracking their performance in doing so (self-observation). Finally, during the reflection phase, students evaluate their learning and adjust their plan if needed.

Figure 2.2: Zimmerman's cyclical phase model of self-regulation. Adapted from [50].



Self-regulated learning is a critical skill for academic and personal success, as it allows individuals to take control of their learning process [51]. Effective self-regulated learners are intrinsically motivated, aware of their strengths, limitations, and current knowledge, and guided by their personal goals [47, 51]. They actively participate in the learning process and construct their own meanings, goals, and strategies from both their own and provided information [8]. Past research shows that these learners tend to have higher academic achievement and greater self-efficacy. Zimmerman and Martinez-Pons, for example, found that highly self-regulated students scored higher on a standardised achievement test than students that were less self-regulated [52]. Pintrich and De Groot [53] found that self-regulation skills were positively correlated to academic performance and achievement.

2.5. Goal orientation and self-regulated learning

Self-regulatory skills are often connected with one's achievement goal orientation. More specifically, existing work refers to self-regulatory skills as a mediating construct between goal orientation and achievement outcomes [54].

Goal orientation refers to attitudes towards a task (in the context of education: learning) and motivations for engaging in it. Elliot and McGregor [9] describe four goal orientations. They position these in a framework of two dimensions: definition and valance. First, definition. According to Elliot and McGregor and previous work on achievement goals (see [55] for an overview), a student can be mastery or performance-oriented. A mastery-oriented student is focused on self-improvement and compares their performance to their past performance [56]. On the other hand, a performance-oriented student focuses more on normative standards (e.g., grades) and outperforming others on these standards [9, 57]. The valance dimension of the framework indicates how a student judges their performance. Students with an approach goal orientation strive to approach success, while students with an avoidance goal orientation strive to avoid failure [9]. Following these dimensions, a mastery-approach student wants to learn and understand everything there is to learn about the topic. On the other hand, a mastery-avoidant student is driven by the worry that they may be unable to understand the matter. Likewise, a performance-approach student strives to gain a good grade and outperform others. In contrast, a performance-avoidant student is driven by the possibility of obtaining a bad grade or performing worse than others.

A substantial body of research suggests that students' goal orientation influences their self-regulatory skills. Introduced by Pintrich [8] as an integral part of his SRL model, other researchers soon tested and adopted goal orientations as a part of the self-regulated learning process. Multiple studies report a relation between a mastery goal (or learner goal) orientation and self-regulatory skills [58, 59, 60, 57], and using deep learning strategies more often [61, 62, 50]. On the other hand, performance goals (or ability goals) have been associated with extrinsic regulation strategies [61], as well as negative affect, helplessness, and poorer subsequent performance after setbacks [62]. However, the literature on the effect of performance goals on self-regulated learning is inconclusive. Other studies report no clear link between performance goals and self-regulatory strategies [63, 8], or actually a positive effect on self-regulatory strategy use for performance-approach students [60]. In conclusion, while the effect of performance-oriented goals remains debated, it is clear that students' goal orientation can, at least to some extent, affect their self-regulatory skills. Adapting to and accommodating various goal orientations within learning environments, such as learning analytics dashboards, may yield benefits to student learning outcomes.

2.6. Learning analytics dashboards

Student-facing learning analytics dashboard (LAD) applications harness the data and insights from learning analytics to support processes vital to self-regulated learning, such as awareness, reflection, and sensemaking [1, 2, 14]. While these dashboards historically were mainly developed for teachers to inform decisions about students and teaching practices [1, 2], student-facing applications have gained more and more attention [2, 64, 65]. Like instructor-facing dashboards, student-facing dashboards "provide graphical representations of the current and historical state of a learner [...] to enable flexible decision making" [1], i.e., help them in their learning. These visualisations can take many forms, such as graphs, timelines, or bubble charts [14].

As the interest in student-facing LADs rose, so did the critical assessments of their implementations [66]. Multiple works have criticised existing applications for their lack of grounding in learning theory [6, 65, 67]. For example, while Festinger's Theory of Social Comparison [68] is often used in existing dashboard designs to inform the use of performance comparison between students, the didactic benefit of such techniques is debated [5, 11]. Furthermore, students were found to be rarely consulted in the design of dashboards and instead rely on a one-size-fits-all design [66]. These limitations call for adaptive and student-centred dashboards deeply grounded in educational theory.

An interesting effort in this respect is that of Jivet et al. [66]. In their work, they developed twelve visual indicators and implemented them in a learning analytics dashboard for MOOCs where students could select what progress indicators (i.e., learning data) they would like to see. Half of these indicators were performance-oriented, and the other half were learning (i.e., mastery) oriented. They found that while specific self-regulatory skills predicted specific indicator choices, goal orientation had no predictive power in indicator selection. Using more fine-grained goal classifications was suggested for a better understanding of the influence of learner goals in self-regulated learning.

2.7. Progress indicators

Learning analytics dashboards use various data visualisation techniques to convey information about student progress. Visualisations or indicators in LADs aim to communicate information about learning activity using graphical representations to aid in perception, understanding, and decision-making [69]. Communicating predictions, student performance, or information about student self-regulation seems to be the most prevalent uses of indicators in LADs [70].

Historically, visualisations in dashboards are often based on traditional statistical techniques [1] and embrace the view of a dashboard as a single-page application [71, 72]. Even now, most learning analytics dashboards use graphs and plots (e.g., scatter or bubble plots), while more advanced or novel techniques are rarely used [14]. Furthermore, there seems to be a discrepancy between the sophistication of the visualisations and the connection with educational theory [14]. These findings suggest that the field of learning analytics needs to be further integrated with its supporting disciplines, i.e., information visualisation and learning science.

2.8. Feedback reference frames

Progress indicators guide a student towards a set or chosen goal. So-called *reference frames* allow students to interpret and evaluate their progress towards these goals [73, 16]. Literature distinguishes three kinds of feedback reference frames to which students can measure their success: course expectations (absolute, progress), the student's prior activity (achievement), and the activity of other students (social) [64, 5, 16]. Jivet et al. [5] describe how, next to the object of evaluation (an absolute standard, a prior self, or the other), these feedback reference frames also differ when the object of evaluation happens. A social reference frame, they argue, focuses on comparison with the present. On the other hand, an achievement feedback reference frame focuses on comparing with a past self, and an absolute or progress reference frame focuses on comparing with a future self.

Research on the effect of these feedback reference frames is mixed. Student-facing LADs commonly employ a social reference frame to contextualise the student's performance, often motivated by theories such as social comparison theory and achievement goal theory [5]. Existing work reports various positive effects of these social reference frames, including an increase in student motivation and performance [74], and effective help-seeking strategies [75, 11]. However, multiple studies argue for careful consideration in employing social reference frames, as social reference frames may foster competition in learners rather than knowledge gain [5], while progress reference frames may help in gaining a deeper understanding of the learning material [11]. These findings suggest that each feedback reference frame has its caveats and reinforce the idea that feedback reference frames should be individualised and adaptable to the student [66].

Chapter 3

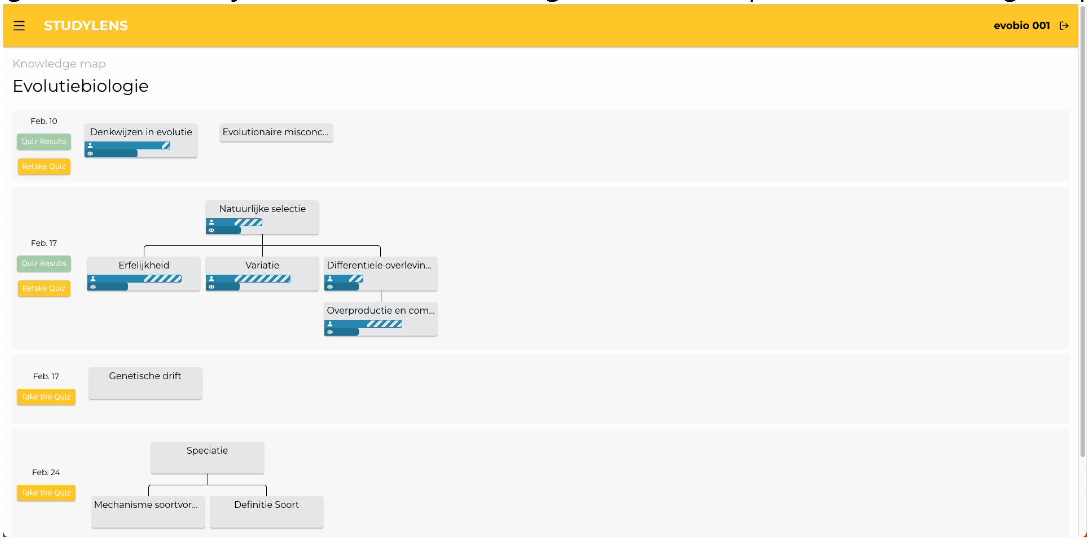
Contributions to StudyLens

To explore how feedback reference frames can be used to adapt progress visualisations to the individual student, the current study extended the existing StudyLens dashboard (`https://studylens.science.uu.nl/web`). We introduced four distinct progress visualisations, each designed to cater to a different achievement goal orientation and utilising a different feedback reference frame. This chapter outlines the technological and design contributions resulting from this process.

3.1. About StudyLens

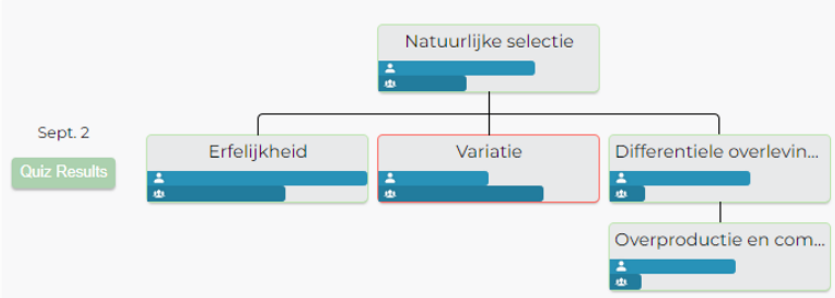
StudyLens visualises learning traces of students in a main component called the "knowledge map". The knowledge map consists of (possibly interconnected) nodes representing concepts and misconceptions associated with a course. These nodes are contextualised in a weekly schedule, with a formative test displayed for each week.

Figure 3.1: The StudyLens dashboard, showing its central component, the knowledge map.



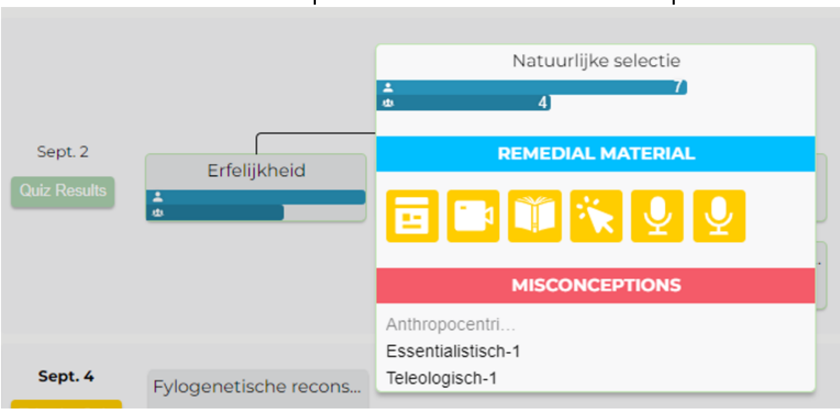
Students can take these formative tests, related to one or more concepts and misconceptions, by pressing the "Take quiz" button (displayed on the left). Upon completion, the scores on the concerning concepts are updated and displayed. By default, the changes made in the current study aside, these scores are compared to the average of their peers (Figure 3.2).

Figure 3.2: Completion bars per concept, including social comparison bars.



Students can improve upon the knowledge of a concept or misconception by completing associated learning tasks (Figure 3.3), which will progress the progress bar from the formative test. These learning tasks can take many forms: factsheets, videos, text, and interactive content and exercises are among the possibilities. Completion scores are stacked on top of the initial quiz score; when the student completes all the remedial material, their score will be 100%.

Figure 3.3: Students can complete remedial material to improve their score.

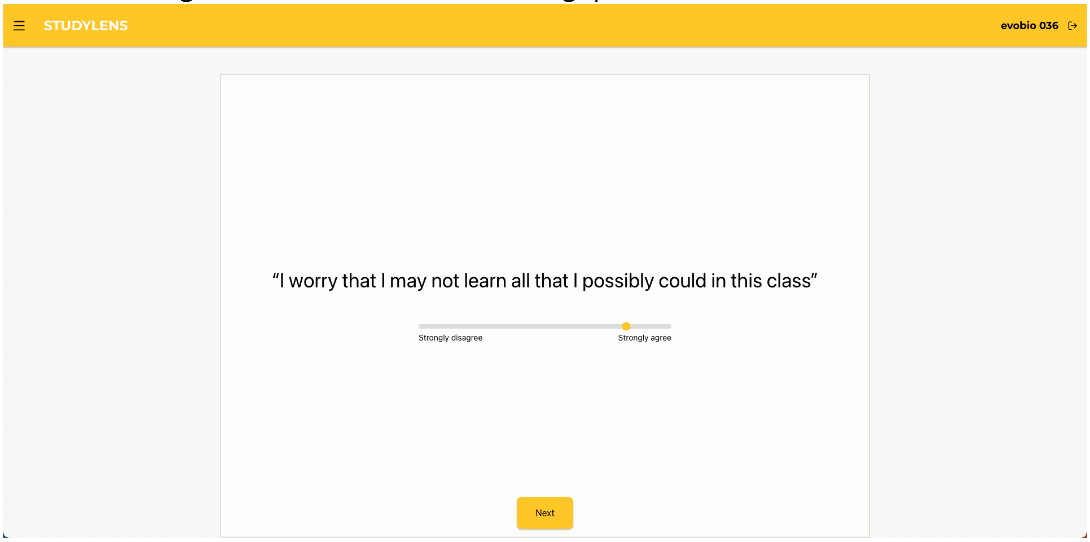


3.2. The onboarding

The onboarding was shown when a student in the experiment group for this study first accessed the dashboard. It featured an explanation of the StudyLens dashboard and the included individualisations and a simple inventory of the probable goal orientation of the student. It used only four questions from the original Achievement Goal Questionnaire to keep it brief. As the quiz was purely meant to inform and did not ultimately decide the achievement goal orientation for the student, it did not have to be entirely accurate. For each subscale, the item with the highest factor loading in the original paper by Elliot and McGregor [9] was chosen, resulting in the following items:

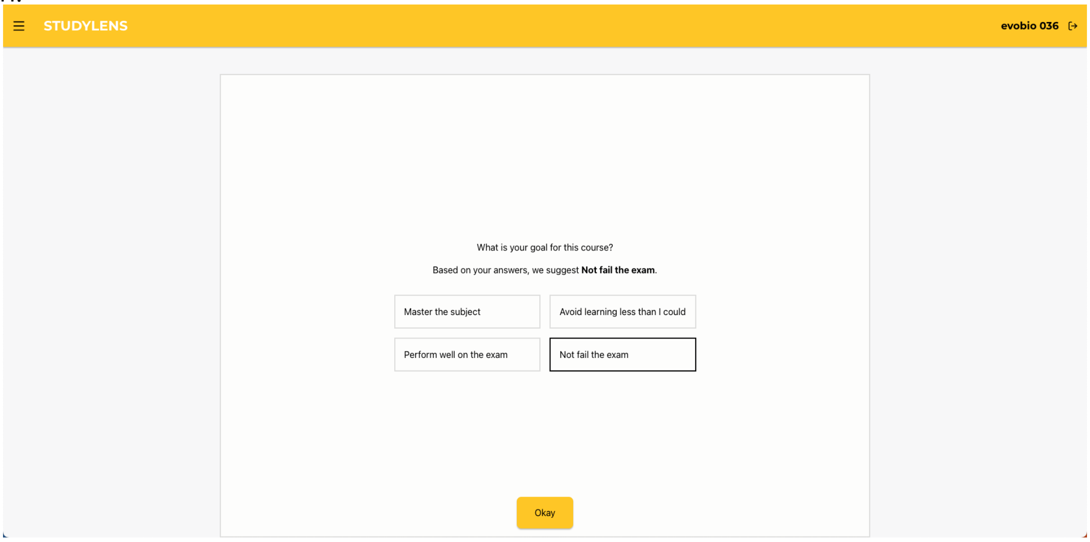
- It is important for me to do better than other students.
- I worry that I may not learn all that I possibly could in this class.
- I just want to avoid doing poorly in this class.
- I want to learn as much as possible from this class.

Figure 3.4: One of the onboarding questions in the dashboard.



At the end of the onboarding quiz, students could self-select their achievement goal orientation (Figure 3.5). The orientation that was suggested to the student based on their answers to the previous questions was highlighted with a black border. For determining the suggested orientation, we summed the score of each question for its corresponding dimensions. For example, if a student answered 2 on "It is important for me to do better than other students.", both the performance and approach scores would be increased by 2. The system would suggest the achievement goal orientation that matched the highest definition and valance scores of the student. For instance, if a student has the following values: mastery 8; performance 7; approach 5; avoidance 10; the system would suggest the mastery-avoidance achievement goal orientation. If no single achievement goal orientation could be suggested, the system would not suggest one.

Figure 3.5: At the end of the onboarding, students could self-select their achievement goal orientation.



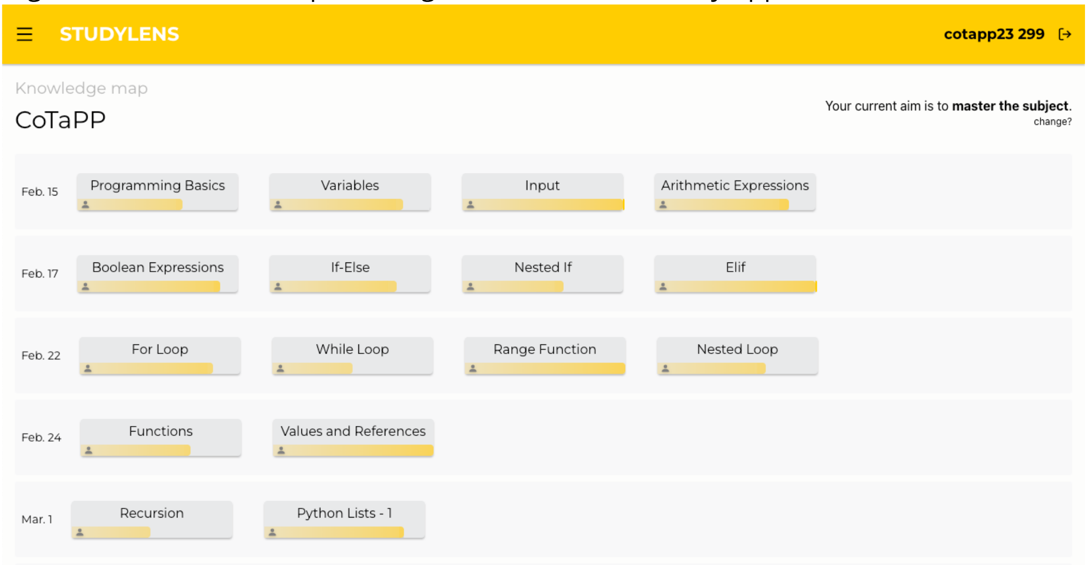
3.3. The dashboard designs

With the information from the onboarding quiz, the dashboard showed individualised progress visualisations to the students. Four dashboard designs were developed, each tailored to one of the achievement goal orientations conceptualised by Elliot and McGregor [9]. The designs were inspired and, to an extent, bounded by the current design of the StudyLens dashboard, as the initial plan of this study was to evaluate the designs with a course that used StudyLens, and thus, the designs had to be implemented within the current dashboard.

3.3.1. Mastery-approach (Dashboard Alpha)

Dashboard Alpha (Figure 3.6) was designed to cater to mastery-approach-oriented students. It uses an absolute achievement feedback reference frame, visualised with a single-colour progress bar that started pale and linearly increased its tint as the student progressed. The rationale behind this design is that a student who wants to approach mastery aims to improve constantly, regardless of how that progress compares to others.

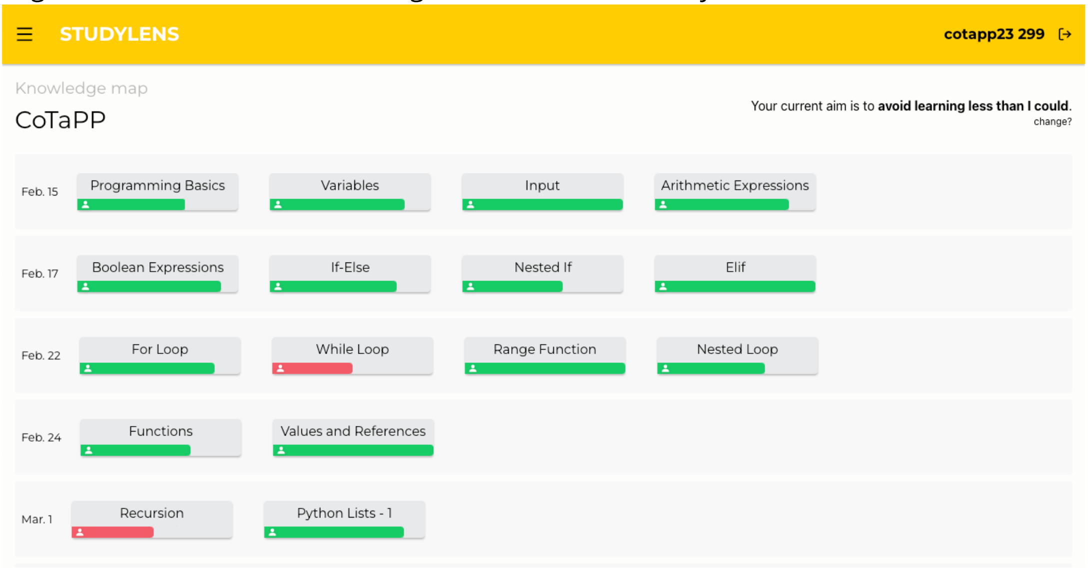
Figure 3.6: Dashboard Alpha, designed to cater to mastery-approach-oriented students.



3.3.2. Mastery-avoidance (Dashboard Beta)

Dashboard Beta (Figure 3.7) was designed to cater to mastery-avoidance-oriented students. It shows a normative achievement feedback reference frame, which evaluates progress through a pass/fail dichotomy. Concepts with progress below 60% are shown in red, and those with progress above 60% are shown in green. The rationale behind this design is that a mastery-avoidant student would want to avoid misunderstanding the material, which, in university settings, is normalised as a score less than 60%. The design nudges students from staying behind on concepts using culturally loaded evaluation colours.

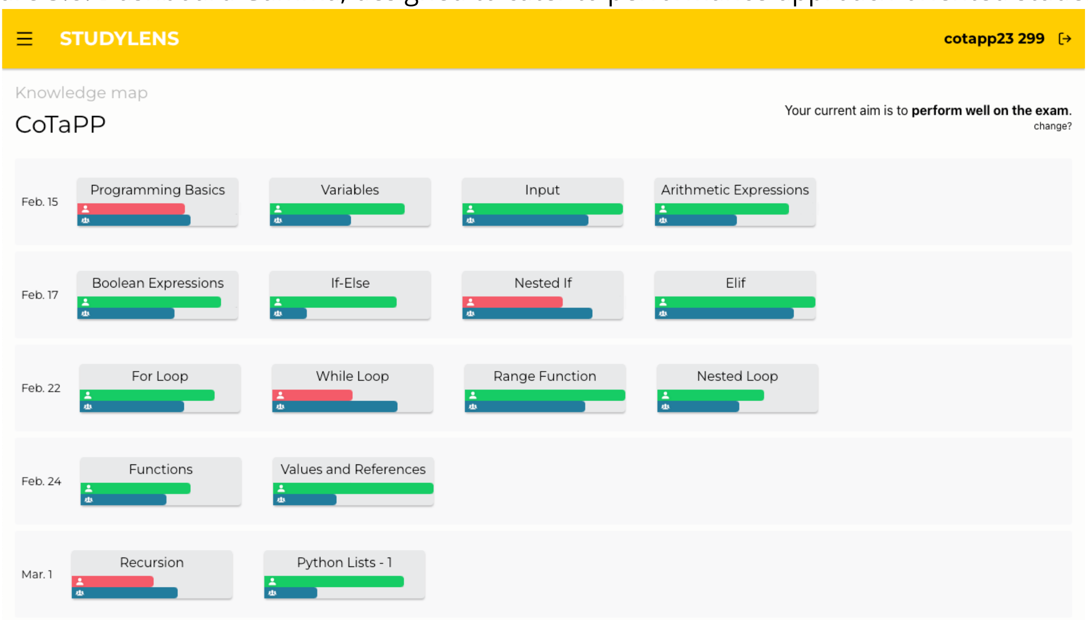
Figure 3.7: Dashboard Beta, designed to cater to mastery-avoidance-oriented students.



3.3.3. *Performance-approach (Dashboard Gamma)*

Dashboard Gamma (Figure 3.8) was designed to cater to performance-approach-oriented students. It utilises an upward social feedback reference frame by showing the students their progress relative to the average progress of the top fifty per cent of students in the course. The rationale behind this design is that a student who aims to outperform others, i.e., a performance-approach-oriented student, would aim to perform better than most of their peers. The design nudges them towards this goal using a comparative progress bar and evaluation colours that enable quick sensemaking.

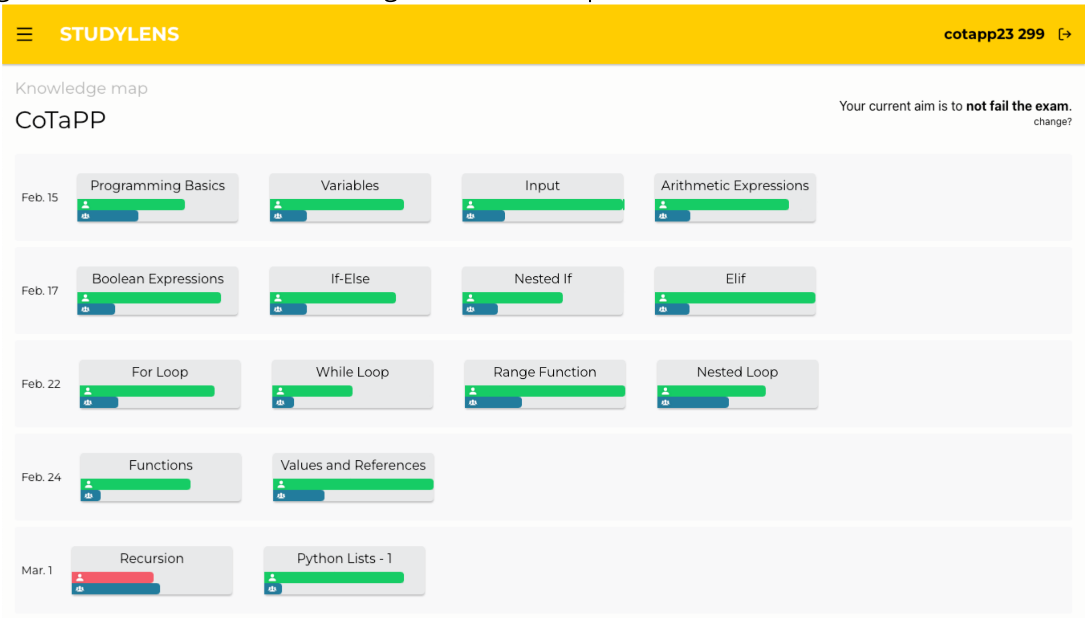
Figure 3.8: Dashboard Gamma, designed to cater to performance-approach-oriented students.



3.3.4. Performance-avoidance (Dashboard Delta)

Lastly, Dashboard Delta (Figure 3.9) was designed to cater to performance-avoidance-oriented students. It uses a downward social feedback reference frame by showing the students their progress compared to the average progress of the bottom fifty per cent of students in the course. The design is similar to that of Dashboard Gamma, but instead of nudging the student to outperform others, it nudges the student not to do worse than others. Here, too, the evaluation colours enables quick sensemaking.

Figure 3.9: Dashboard Delta, designed to cater to performance-avoidance-oriented students.



Chapter 4

The in Vivo Experiment

Whilst the current study further defined the relation between students' achievement goal orientations and visualisation preferences, it did not provide detailed insight into how these visualisations shape interaction with a learning analytics dashboard. As stated in the introduction, previous work has successfully designed and implemented visualisations designed around goal orientation constructs (e.g., [10, 15, 16, 17, 18]). As one's achievement goal orientation cannot be considered static (e.g., [76, 77]) and the impact of different kinds of feedback varies per student [2], a logical next step is to make feedback visualisations adaptable to the student. For this, a different experiment was originally planned to be conducted as part of this thesis. This experiment was to be conducted in a real world setting – a course – and would span the entirety of the third term of the academic year 2022-2023. It followed a different design, had different outcome measures, and aimed to answer the following question: *How does the achievement goal orientation of a student affect their use of progress visualisations in a learning analytics dashboard?*

Unfortunately, the experiment resulted in insufficient data due to participant attrition. The remainder of this chapter elaborates on the experiment's outlined methodology and provides a short reflection on the process.

4.1. Study approach

The study was addressed as a mixed-method, mostly observational study. Following the designs outlined in the previous chapter, an extension of StudyLens was realised that individualises progress visualisations to the goal orientation preferences of students. This extension was to be evaluated for the entirety of a term in an undergraduate course on Evolutionary Biology taught at Utrecht University, in which around 35 students were enrolled. Within this course, actively completing activities in StudyLens was optional, although results of formative tests would show up in StudyLens nonetheless.

The study measured the goal orientation changes of students and their learning behaviour and outcomes. The influence of the goal orientation adaptations and changing behaviour (independent variables) on students' learning behaviour and learning outcomes (dependent variables) were to be analysed using quantitative analyses after the end of the term. While the study followed an inductive approach to keep an open view, we established three additional questions to guide the analysis of the gathered data:

1. How do students with different goal orientations interact with the learning analytics dashboard?
2. How does the interaction of students who switch their goal orientation compare to students who do not?
3. How does the realised goal support mechanism affect learning outcomes, engagement, and motivation?

4.2. Participants

The participants in this study included around 35 undergraduate students enrolled in an introductory course on Evolutionary Biology at the Undergraduate School of Science of Utrecht University, The Netherlands. While no demographics were collected, it can be assumed that these participants were in the age range of 18 to 25.

Students were invited to participate by their course instructor on February 6, 2023, at the start of the course. Participation involved actively using the dashboard throughout the course, filling in an evaluating questionnaire at the end of the course, and optionally providing detailed feedback in an interview. Participants were self-selected and did not receive an incentive for their participation.

During March 2023, it became evident that students were not using the dashboard actively enough to obtain meaningful insights using the outlined study design. In the end, we collected four consent forms, and activity logs indicated that nine students were actively using StudyLens in the course.

4.3. Materials

The primary outcome measure in this study was the participant interaction and switching behaviour with the different dashboard versions. We wanted to explore how this data related to the secondary outcome measures: students' achievement goal orientation, personality, and social comparison orientation.

4.3.1. Interaction logs

Interaction logs were administered via an API call to the StudyLens backend, and stored in the backend in a standardised, yet flexible way. Table 4.1 provides a specification of the data that was included within these logs.

Name	***Type***	***Required***	***Example***
courseid	String	Yes	`evobio-1-2023`
userid	String	Yes	`evobio02`
verb	String	Yes	`STARTED`
activityid	Integer	Yes	`61`
sessionid	String	Yes	`43fd828731048cda3`
extrajson	String	No	`{"clicked_concept_id": 23}`

Table 4.1: Specification of the data in the log entries collected within StudyLens.

Table 4.2 provides a specification of the kinds of activities that were logged within the system.

Specification	***Verb***	***Included details***
Logging into the system	`LOGIN`	—
Logging out of the system	`LOGOUT`	—
Changing the achievement goal orientation	`CHANGED`	course, goal orientation
Loading a course	`LOADED`	path
Opening a learning activity	`OPENED`	activity, course, session
Closing a learning activtity	`CLOSED`	activity, course
Completing a learning activity	`COMPLETED`	activity, course
Hovering over a learning concept	`INTERACTED`	course, in knowledge map, learning goal, learning concept
Clicking on a learning concept	`INTERACTED`	course, in knowledge map, learning goal, learning concept
Playing a video	`INTERACTED`	activity, course current video time
Pausing a video	`INTERACTED`	activity, course, current video time
Stop watching a video	`INTERACTED`	activity, course, current video time
Starting a formative quiz	`STARTED`	activity, course
Answering a question in a formative quiz	`ANSWERED`	activity, course, time, included answer options
Submitting a formative quiz	`SUBMITTED`	activity, course, session, start time, end time, answers

Table 4.2: Specification of the types of log entries collected within StudyLens.

4.3.2. Achievement goal orientations

The original Achievement Goal Questionnaire (AGQ; [9]) was selected to measure students' achievement goal orientation. The 2001 questionnaire consists of 12 Likert scale questions, with four items each for the subscales performance-approach, performance-avoidance, mastery-approach, and mastery-avoidance. Each item is answered on a five-point Likert scale, from "strongly disagree" to "strongly agree", with a neutral option included.

4.3.3. Personality inventory

The Big 5 10-item personality inventory (TIPI; [78]) was selected to measure students' personality traits. The 2003 questionnaire consists of 10 Likert scale questions, with two items each for the subscales extraversion, agreeableness, conscientiousness, emotional stability, and openness to experiences. Each item is answered on a seven-point Likert scale, from "strongly disagree" to "strongly agree", with a neutral option included.

4.3.4. Social comparison orientation

The Iowa-Netherlands Comparison Orientation Measure (INCOM; [79] was selected to measure students' individual differences in social comparison orientation. The 1999 questionnaire consists of 11 Likert scale questions that measure one's ability to compare to others and one's opinion on doing so. Each item is answered on a five-point Likert scale, from "strongly disagree" to "strongly agree", with a neutral option included.

4.4. Reflections

As the study described in this chapter had to be abandoned because of attrition, it is advisable to take measures to avoid attrition in a possible redo or follow-up of the study. First, the participant briefing happened via a third party - the course instructor. Doing the participant briefing ourselves in a future study may prove beneficial. This way, we have more control over our instructions, and students clearly know who to contact with questions or comments. Furthermore, attrition could be reduced by rewarding (active) participation with an incentive. Depending on what can be agreed with the course instructor and available resources, students can be incentivised to participate with extra credits or a reward, such as a coupon. Lastly, we can reduce the impact of attrition by getting more courses to participate, therefore reaching out to more students.

Chapter 5

The Main Experiment

As the original setup of this thesis resulted in insufficient insights due to participant attrition, an alternative study design was outlined and executed. The following chapter describes this experiment in detail. As described in the introduction, it aimed to answer the following question: *How does the achievement goal orientation of a student affect their preferences in progress visualisations in a learning analytics dashboard?*

5.1. Methods

This study measured students' goal orientation and their responses to the four alternative progress visualisation designs. Using quantitative methods, we analysed the influence of the goal orientation and previous activity with StudyLens (independent variables) on students' responses to the alternative designs (dependent variables). Three research questions guided the analysis of the data:

1. What are students' preferences for progress visualisations in a learning analytics dashboard?
2. How does the performance group of a student, i.e., how active they were in the dashboard, influence their preferences for progress visualisations?
3. How does the achievement goal orientation of a student influence their preferences for progress visualisations?

The following sections describe the participants, materials, and procedures used to answer these questions.

5.1.1. Participants

The participants in this study included 165 students following an introductory course on Computational Thinking and Python Programming (CoTaPP) at the Faculty of Science of Utrecht University, The Netherlands. The course included students of both graduate and undergraduate programs, combining students enrolled in three similar bachelor's, pre-master's, and master's courses. While no demographics were collected, it can be assumed that these participants were in the age range of 18 to 25.

Students were invited to participate on April 5, 2023, at the end of the course. The course instructor, whom we informed beforehand about the study, reserved the last half hour of the lecture for students to complete the survey. Participants were self-selected and did not receive an incentive for their participation. As part of the course they were enrolled in, they had prior experience with the StudyLens dashboard, which may have provided context or expectations regarding the alternative designs.

5.1.2. Materials

The primary outcome measure in this study was the participant response to four alternative dashboard designs designed to tailor to specific goal orientations. We explored how these responses related to the secondary outcome measure, the achievement goal orientation of students, that is, in the context of education, the reasons for learning (e.g., [9, 55]).

5.1.2.1. Dashboard designs

The same dashboard designs of the in vivo experiment (see chapter 3) were used in the current experiment setup. In order to make the designs and the data shown in them more meaningful, students were shown designs that showed a performance evaluation that matched their performance in the course.

5.1.2.2. Achievement goal orientations

The original Achievement Goal Questionnaire (AGQ; [9]) was used to measure students' achievement goal orientation. The 2001 questionnaire consists of 12 Likert scale questions, with four items each for the subscales performance-approach (α = .88), performance-avoidance (α = .81), mastery-approach (α = .81), and mastery-avoidance (α = .78). Participants answered each item on a five-point Likert scale, from "strongly disagree" to "strongly agree", with a neutral option included. All subscales were found to be sufficiently internally consistent.

5.1.3. Impressions of the dashboard variants

A second questionnaire was created to measure the responses to the alternative dashboard variants. The questionnaire consisted of six items for each of the four variants. The items were designed to encapsulate various processes of the forethought phase of self-regulated learning (see Table 5.1), as conceptualized by Zimmerman and Campillo [80]. Answers were on a four-point Likert scale, from "strongly disagree" to "strongly agree". Because we anticipated the dashboard designs that included social comparison mechanisms to be divisive, we omitted the middle option to prevent participants from unwillingly admitting to a socially undesirable attitude [81]. The items were internally consistent (α = .87).

Item	***Process***	***Type***
The information presented on this dashboard is easy to understand.	Task analysis	Scale
This dashboard would help me decide what I should study next.	Strategic planning	
This dashboard would help me understand how to achieve my learning goals.	Goal setting	
This dashboard would help me do better in this course.	Self-efficacy	
This dashboard would make me feel motivated.	Self-motivational belief	
This dashboard would give me a clear idea about how I'm doing in the course.	Outcome expectations	
When you looked at the dashboard above, which topic do you think you should study next?	Task analysis	Open

Table 5.1: Items of the questionnaire to measure responses to the dashboard variants

5.1.4. Procedure

Students were invited to participate by their instructor during the last 30 minutes of their class. Participation involved filling out a survey that was administered via Microsoft Forms. The survey consisted of the Achievement Goal Questionnaire (AGQ), the Iowa–Netherlands Comparison Orientation Measure (INCOM), 12 items about the student's experience with StudyLens, the seven evaluation items for each dashboard variant (28 items in total), and a final item in which participants were asked to rank the dashboard variants in order of preference. The survey consisted of a total of 60 items.

After collection of the data, hypothesis testing was performed. The Likert scale items were treated as non-normal ordinal data and were tested using the non-parametric Kruskal-Wallis *H* test and post hoc Dunn's test. The tests aimed to evaluate whether there was a difference in the measure of interest between the evaluated groups. The null hypothesis presumed that the medians of the evaluated groups were equal.

We first aimed to determine if the overall sample preferred a particular dashboard variant. If this would be the case, it would indicate limitations in the experiment design. An outspoken preference or aversion towards a particular design may hint at the designs being of varying quality or another bias not accounted for in this study. In order to test this, the first alternative hypothesis read:

> H_1: *At least one dashboard variant is evaluated differently from the others.*

Next, we looked at the differences in preferences between students classified by the amount of interaction they previously had with the dashboard. We call these groups "performance groups" as they indicate how active a student was during the course. The following alternative hypothesis was tested:

> H_2: *At least one performance group evaluates the dashboard variants differently from the others.*

Finally, we examined the differences in answers to the AGQ between students classified by their first-choice dashboard design. We opted for this approach because we could not group students based on their achievement goal orientation - only some students scored highest on a single orientation, and attempts to cluster students with similar answers using machine learning (ML) techniques resulted in overlapping clusters. Therefore, the following alternative hypothesis was tested:

> H_3: *At least one group of students who rank the dashboards differently score differently on achievement goal orientation constructs.*

The analyses were performed in an IPython Notebook environment. The `scipy` (version 1.10.1) and `skikit_posthocs` (version 0.7.0) libraries were used to perform the Kruskal-Wallis test and Dunn's test, respectively.

5.1.5. Ethical considerations

In order to account for ethics and privacy concerns, the Utrecht University Ethics and Privacy Quick Scan was performed for this research project. Whilst the Quick Scan identified issues, this project was allowed to proceed as it is covered fully by the ethical approval for the supervisor's research line (see Appendix A).

5.2. Results

The following sections present the study's results, addressing the research question and hypotheses outlined in the previous sections. Four dashboard variants were designed that provided information specifically tailored to the achievement goal orientations of students. In order to understand how students contextualise and make sense of these progress visualisations, the four dashboard variants were evaluated at the end of the term with students following the Computational Thinking and Python Programming (CoTaPP) course at Utrecht University. A total of 66 students responded to the survey. Students who did not provide consent (8), did not complete the questionnaire (2) or provided straight-line answers (2) were excluded from the analysis, resulting in 54 included participants.

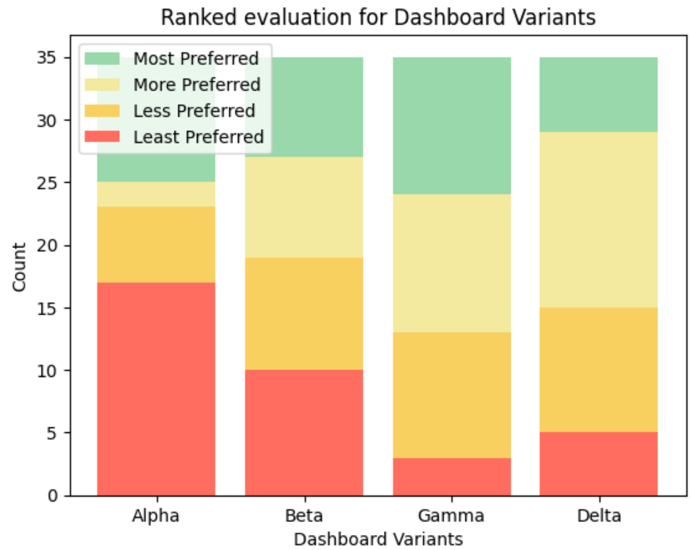
Due to a human error in the survey construction, the dashboard ranking question was optional, and consequently, not all participants chose to answer it. As this number was quite high (19), we decided not to exclude all these participants from the study. Instead, we excluded these participants for the analyses involving the ranked dashboard preference only, resulting in 35 included participants.

5.2.1. *Descriptive statistics*

5.2.1.1. *Performance groups*

Participants were assigned a performance group based on the number of completed activities within StudyLens. Students with less than 100 completed activities were assigned the performance group "low" (*n* = 23), students with 100 to 150 completed activities were assigned the performance group "mid" (*n* = 16), and students with more than 150 completed activities were assigned the performance group "high" (*n* = 15).

Figure 5.1: Overview of the responses to the ranked evaluation



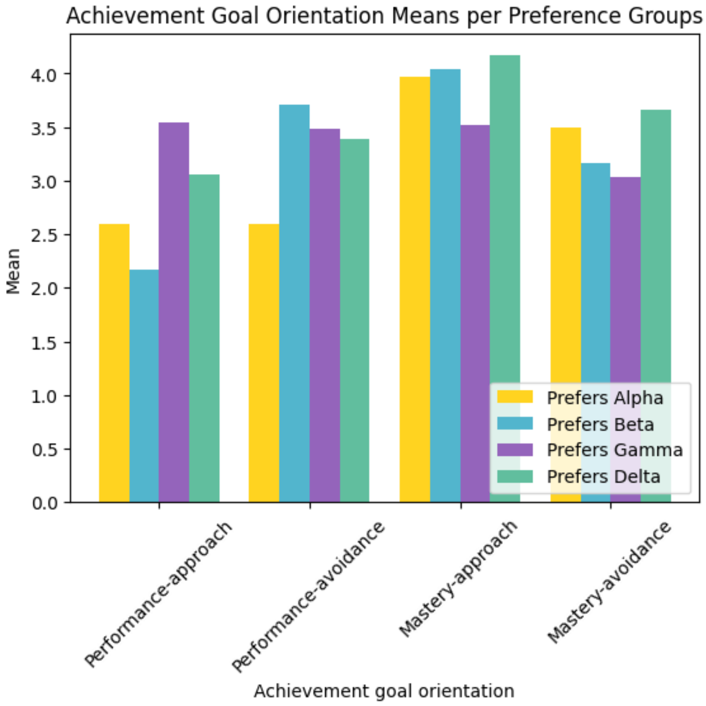
5.2.1.2. *Preferred dashboard*

The achievement goal orientations were not mutually exclusive in the data, and some participants scored the same for multiple orientations on multiple instances. Therefore, students were not grouped based on achievement goal orientation but on dashboard preference, as indicated by the ranking question. As such, the 35 participants who provided a dashboard ranking were grouped based on their first preference dashboard (Figure 5.1). Ten students preferred Dashboard Alpha, eight preferred Dashboard Beta, 11 preferred Dashboard Gamma, and six preferred Dashboard Delta. Interestingly, while receiving the second-most top ratings, Dashboard Alpha was found to be controversial amongst students; the dashboard also received the most bottom ratings out of the dashboards (17).

5.2.1.3. *Achievement goal orientation*

When contextualising the responses to the Achievement Goal Questionnaire (AGQ) with the first preference dashboard (Figure 5.2), a few things stand out or are conflicting with the assumptions of the current study. First, it is striking that the mastery-approach scores are quite high among the overall sample, and performance-approach scores are generally lower. Furthermore, the responses highlight implications for the used designs.

Figure 5.2: Overview of Achievement Goal Questionnaire responses, per first preference dashboard

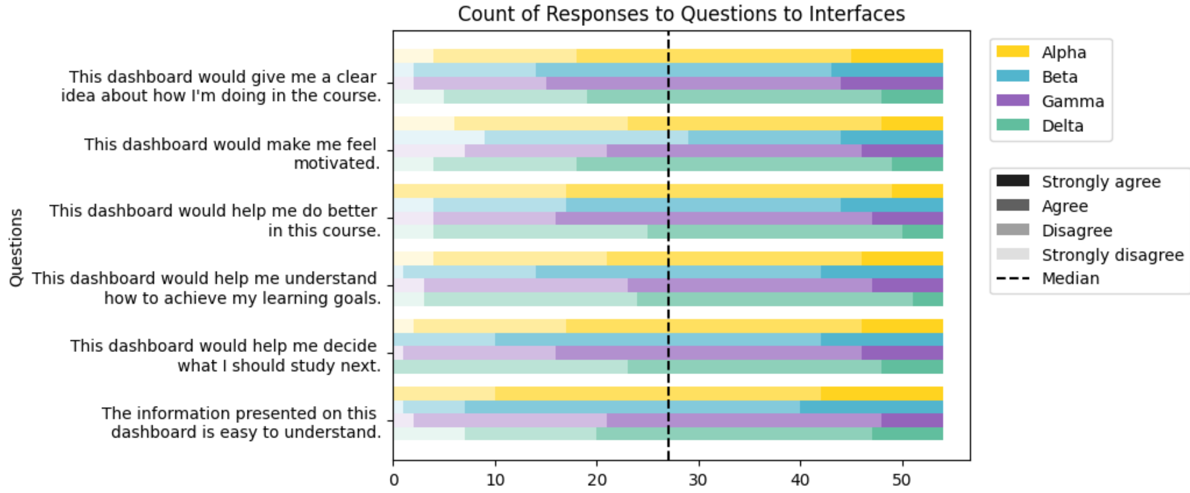


The visualisation seems to confirm our presumption that mastery-oriented students preferred the absolute progress feedback reference frame used in Dashboard Alpha. Students who preferred Dashboard Alpha scored noticeably higher on mastery than on performance scales. The figure also shows that students who preferred Dashboard Beta scored considerably higher performance-avoidance and mastery-approach scales, more so than the mastery-avoidance scales. Lastly, it also stands out that students who preferred Dashboard Delta scored quite high on mastery scales, scoring highest for both the mastery-approach and mastery-avoidance subscales out of all the students.

5.2.1.4. Dashboard evaluation survey

The responses to the evaluation survey (Figure 5.3) show that participants were fairly reserved in their opinion - most responses were either "Agree" or "Disagree". The responses follow a negatively skewed distribution, the median being "Agree" to most questions, indicating a generally positive attitude towards the designs. The only exception is the responses to "This dashboard would make me feel motivated" for Dashboard Delta: the participants' opinion for this statement leaned more towards "Disagree".

Figure 5.3: Overview of the dashboard evaluation responses



5.2.2. *Inferential analysis*

5.2.2.1. *Exploratory correlation analysis*

The relations between achievement goal orientation and evaluation scores were analysed using Spearman's rank-order correlation coefficient (Table 5.2). For this analysis, we took the goal indices (i.e., the means) of the subscales of the Achievement Goal Questionnaire and the mean of the evaluation items for each dashboard variant. For the Cronbach's Alpha values that justified this approach, see Table 5.3. The approach does not allow for in-depth analysis of the evaluation items. However, it offers exploratory insight into the relationship between the dashboard evaluation scores and the achievement goal orientation constructs and between the evaluation scores of each dashboard.

	MAp	***MAv***	***PAp***	***PAv***	***Alpha***	***Beta***	***Gamma***	***Delta***
MAp	—							
MAv	.25	—						
PAp	.05	.03	—					
PAv	-.35*	-.02	.13	—				
Alpha	.15	-.08	-.16	-.09	—			
Beta	.03	-.09	.18	.28*	.10	—		
Gamma	-.11	-.05	.22	.25	-.16	.33*	—	
Delta	.10	.04	.22	.35**	.13	.38**	.55***	—

$* \, p < .05$, $** \, p < .01$, $*** \, p < .001$

Table 5.2: Spearman's rank-order correlation coefficients for the questionnaire.

The coefficients confirm an expected relationship between achievement goal orientations: the significant ($p < .05$) negative relationship between the mastery-approach and performance-avoidance construct makes sense in light of the Achievement Goal Theory.

However interestingly, the mean evaluation scores of all dashboard designs but Dashboard Alpha are also significantly and positively correlated. The correlation between the evaluation scores of Dashboard Gamma and Dashboard Delta makes sense in the current study: the dashboards were designed to cater to performance-approach and performance-avoidance-oriented students, respectively. Except for a subtle difference in the used feedback reference frame, the designs looked similar; thus, similar evaluation scores make sense. However, the significant correlation between both the evaluation scores of Dashboard Gamma and Delta and Dashboard Beta is unexpected in light of the conceptual framework of this study. A possible explanation could be that Dashboard Beta, while designed with mastery-avoidance-oriented students in mind, still used an externally determined feedback reference frame instead of an intrapersonal one, which may not have aligned well with the mastery orientation. This could also explain the significant ($p < .05$) correlation between the evaluation scores of Dashboard Beta and the performance-avoidance achievement goal orientation scores.

Dashboard	***Cronbach's*** α
Alpha	.78
Beta	.87
Gamma	.9
Delta	.89

Table 5.3: Cronbach's α values for the dashboard evaluation items.

Lastly, the exploratory analysis shows a significant ($p < .01$) correlation between the evaluation scores of Dashboard Delta and the performance-avoidance achievement goal orientation scores. This finding suggests that the assumption holds that a downward social feedback reference frame would cater to performance-avoidance-oriented students.

5.2.2.2. Comparison of medians

A Kruskal-Wallis test was selected to compare the median ranking scores among the variants to examine the potential differences in the ranking of the dashboard variants amongst all students. We chose to use the Kruskal-Wallis test as the test included four groups, and the ranking scores were not normally distributed. The results of the Kruskal-Wallis test revealed no significant differences, $H(3, 54) = 7.65$, $p = .054$. This finding suggests that the students who provided a preference ranking did not have a pronounced preference for a particular dashboard.

Kruskal-Wallis tests were also performed to examine if there was a difference in the scoring of individual evaluation questions among dashboards. It was found that students rated the dashboards significantly differently on how easy they were to understand, $H(3, 54) = 15.89$, $p = .001$. The tests to compare the responses to the other questions uncovered no significant differences ($p > .05$).

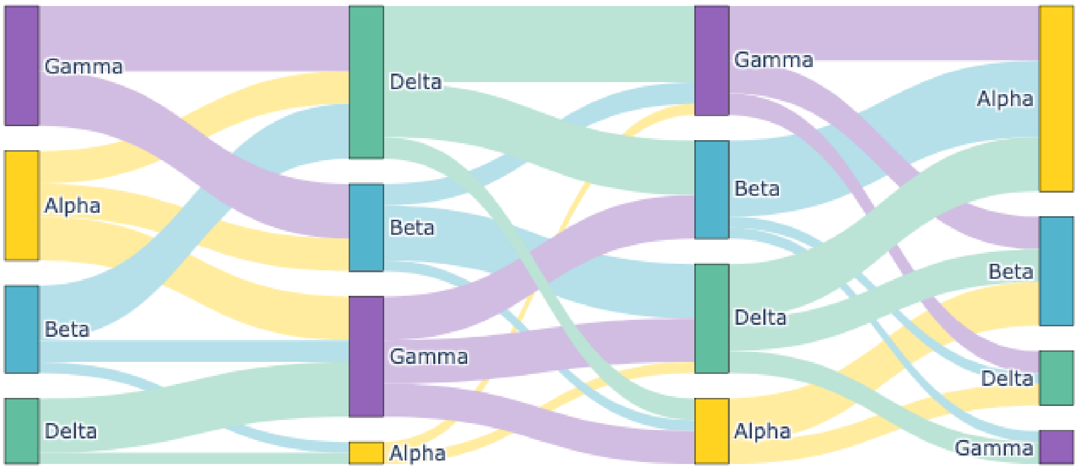
Post hoc Dunn's tests with Bonferroni adjustments revealed that Dashboard Beta was rated differently from both Dashboard Gamma and Delta on how easy it was to understand. The test indicated that the scores of Dashboard Beta ($MD = 3$, $M = 3.11$, $SD = 0.66$) were significantly higher than those of Dashboard Gamma ($p = .01$; $MD = 3$, $M = 2.69$, $SD = 0.72$) and Dashboard Delta ($p = .01$; $MD = 3$, $M = 2.63$, $SD = 0.88$).

To conclude, the performed tests provide sufficient evidence to reject the null hypothesis H_0 and accept the alternative hypothesis H_1*: At least one dashboard variant is evaluated differently from the others*. We found that Dashboard Beta, designed to cater to mastery-avoidance-oriented students, was assessed as easier to understand than Dashboard Gamma and Delta, designed to cater to performance-oriented students.

5.2.2.3. *Dashboard ranking*

A closer look at the dashboard ranking scores (Figure 5.4) provides insight into the most common rankings found in the data. As expected, students who preferred Dashboard Gamma the most did not put Dashboard Alpha second. However, interestingly, these students did seem to like Dashboard Beta: five out of 11 students that put Dashboard Gamma on top of their ranking put Dashboard Beta second. Furthermore, students that preferred Dashboard Alpha the most (n = 10) put the performance-oriented dashboards second quite often (n = 7), which includes the performance-avoidance-oriented Dashboard Delta (n = 3).

Figure 5.4: Flow of the ranked evaluation. Left is most preferred, right is least preferred.



5.2.3. *Subgroup analysis*

5.2.3.1. *Performance groups*

Kruskal-Wallis tests were performed to check for significant differences between performance groups. None of these tests came out significant (p > .05). This finding suggests that the performance groups do not significantly differ in their ranking preference for a dashboard.

Similarly, the performance groups rated none of the evaluation items significantly different for a particular dashboard. Significant results from Kruskal-Wallis tests were observed for the item "This dashboard is easy to understand" for the high, H (3, 54) = 8.23, p = .04, and low, H (3, 54) = 9.8, p = .02, performance groups, indicating that they found a particular variant easier to understand than another. Still, none of the pairwise comparisons using Dunn's test were significant.

To conclude, the performed tests provide insufficient evidence to reject the null hypothesis H_0 and accept the alternative hypothesis H_2*: At least one performance group evaluates the dashboard variants differently from the others.* In the current study setting, the previous interaction with the dashboard does not predict a preference for a certain dashboard variant.

5.2.3.2. *Achievement goal orientation*

Next, we tested for differences in answers to the Achievement Goal Questionnaire (AGQ) between the students with different first-choice dashboard variants in the ranking question – the preference groups. As stated in section 5.2.1., participants were not grouped by achievement goal orientation, as this did not result in distinct groups.

A Kruskal-Wallis test was performed to check for differences in the AGQ item ratings between the preference groups. Significant differences were observed for the performance approach items "It is important for me to do better than other students", H (3, 35) = 10.43, p = .02, and "It is important for me to do well compared to other students", H (3, 35) = 8.73, p = .03, as well as for the mastery approach item "I want to learn as much as possible from this class", H (3, 35) = 8.82, p = .03.

Item	***Prefers Alpha***	***Prefers Beta***	***Prefers Gamma***	***Prefers Delta***
It is important for me to do better than other students	2.5	2.5*	4	3
It is important for me to do well compared to others in this class	2.5	2.5*	4	3
My goal in this class is to get a better grade than most of the other students	2	2	3	3

$*$ Pairwise comparison with group "Prefers Gamma" using Dunn's test significant on .05 level

Table 5.4: Overview of the median answers to the performance-approach items in the Achievement Goal Questionnaire, per preference group

Using post hoc Dunn's tests, we found that Dashboard Gamma seems to cater to students who score high on the performance-approach items of the AGQ. For two out of three AGQ items associated with the performance-approach goal orientation, participants that preferred Dashboard Gamma scored higher than all other preference groups when looking at the median and significantly higher than participants that preferred Dashboard Beta (Table 5.4).

Weaker evidence was found that Dashboard Alpha caters to students who score high on mastery-approach items. One AGQ item on the mastery-approach scale was scored significantly higher (p = .04) by students who preferred Dashboard Alpha than students who preferred Dashboard Gamma (Table 5.5).

Item	***Prefers Alpha***	***Prefers Beta***	***Prefers Gamma***	***Prefers Delta***
I want to learn as much as possible from this class	5	4	4*	4
It is important for me to understand the content of this course as thoroughly as possible	4	4	4	4.5
I desire to completely master the material presented in this class	3.5	4	3	4

$*$ Pairwise comparison with group "Prefers Alpha" using Dunn's test significant on .05 level

Table 5.5: Overview of the median answers to the mastery-approach items in the Achievement Goal Questionnaire, per preference group

To more confidently conclude that a particular achievement goal orientation group indeed preferred a particular dashboard, we followed up this analysis by averaging the items of the subscales of the Achievement Goal Questionnaire as described by Elliott and McGregor [9, p. 4] to derive goal indices. As the achievement goal indices followed a normal distribution (W = .98, p > .05), a one-way ANOVA and Tukey's HSD test were chosen as the methods to compare the means. A one-way ANOVA to compare the performance-approach achievement goal scores of the four preference groups held significant results, F (3, 35) = 4.03, p = .02, with the post hoc Tukey's HSD test revealing a significant (p = .01) difference in the mean of students that preferred Dashboard Gamma (M = 3.55) and students that preferred Dashboard Beta (M = 2.17). One-way ANOVAs to compare the other achievement goal scores held no significant results (p > .05).

To conclude, the performed tests provide partial evidence for the alternative hypothesis H_3*: At least one group of students who rank the dashboards differently score differently on achievement goal orientation constructs*. We found that students who preferred Dashboard Gamma (upward social feedback reference frame) had significantly higher mean performance-approach scores than those who preferred Dashboard Beta (normative achievement feedback reference frame). Analyses on item level revealed that one out of three items associated with the mastery-approach achievement goal orientation was scored significantly higher by students who prefer Dashboard Alpha (absolute achievement feedback reference frame) than those who prefer Dashboard Gamma (downward social feedback reference frame).

Chapter 6

Discussion and Conclusions

This thesis builds on existing work on the interaction between achievement goal orientations and feedback reference frames in learning analytics dashboards (LADs). It aims to answer how the achievement goal orientation of a student affects their preferences in progress visualisations in a learning analytics dashboard. Because particular feedback reference frames may not be suitable for everyone [5], the goal of this study was to pave the way to individualised feedback reference frames based on students' achievement goal orientations. Previous work found that social feedback reference frames are linked to performance-oriented achievement goals, and progress or achievement feedback reference frames are linked to mastery-oriented achievement goals [10, 11].

The current study aimed to solidify and further build on these findings by also investigating the interaction between feedback reference frames and the achievement goal orientation's valance, i.e., approach and avoidance. To this end, we created four alternative dashboard designs to cater to each of the achievement goal orientations in the framework by Elliot and McGregor [9], i.e., mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance. We found that the dashboard that was designed to cater to mastery-avoidance-oriented students and did not include a social feedback reference frame was assessed as easier to understand than the dashboards that included a social feedback reference frame. Furthermore, we found that students who preferred a dashboard with an upward social feedback reference frame had statistically significantly higher performance-approach scores than those who preferred a dashboard with a normative achievement feedback reference frame. Weaker evidence was found that students who preferred a dashboard with an absolute achievement feedback reference frame had higher mastery-approach scores than those who preferred the dashboard with an upward social feedback reference frame.

These findings, while limited, align reasonably well with earlier work. As described in the work by Elliott and McGregor on achievement goals, performance-approach-oriented students evaluate their goals based on the performance of others [9]. In this study, students who scored high on performance-approach scales evaluated a dashboard with an upward social feedback reference frame more positively than one without. This finding supplements the previous finding by Aguilar [75] that students who were shown feedback in an upward social feedback reference frame reported lower performance-avoidance scores. We also found limited evidence that an absolute achievement feedback reference frame caters to mastery-approach-oriented students. This finding also aligns with achievement goal theory, both from the framework itself and empirical research showing that a progress feedback reference frame may help foster a deeper understanding of the task [11].

The current study did not find a relation between negatively valenced achievement goal orientations and preference of feedback reference frame. We may not have found a relation in this study since the designs used fictional data in the visualisations that were not meaningful to the student. Furthermore, because, to our best knowledge, no directed efforts exist to cater LADs to negatively valenced achievement goal orientations, our design decisions may need to be better informed. We encourage future research to further explore how to design LADs towards negatively valenced achievement goal orientations.

6.1. Strengths and limitations

Our study exhibited several limitations worth considering. One limitation was the relatively small number of participants, with a total of 54 students and 35 students considered for the analysis with achievement goal orientations. This limitation resulted in limited statistical power, constrained the generalizability of our findings and may have hindered our ability to detect subtle effects. Additionally, the executed experiment was set up relatively quickly, limiting the data available for analysis and the depth of insights we could draw from the study.

Another limitation of the study applies to the dashboard designs used in the experiment. These dashboards did not incorporate real data that held genuine meaning for the students. Consequently, the underlying concept of the dashboard design might not have been effectively communicated, especially for the performance-oriented dashboards. This limitation could have potentially impacted the validity of our results. Our original research design, which could be executed in the future, accounts for this.

6.2. Directions for future research

Building upon our findings and addressing the limitations outlined above, several directions for future research in the field of learning analytics and learning analytics dashboards can be considered.

Firstly, it would be valuable to further explore how LADs can be designed to cater to negatively valenced achievement goal orientations. Existing work primarily focuses on the general performance and mastery constructs, and expanding our understanding of how LADs can be optimized for students with different achievement goal orientations, including those of negative valence, would provide a more comprehensive perspective.

Additionally, it is essential to consider revisiting the originally planned experiment, considering the limitations we encountered in the current study. By conducting a follow-up experiment with a larger and more diverse participant pool, additional communication to the involved parties, and a participation incentive, we can gain insight into how changing achievement goal orientations shape interaction with a LAD and gain a deeper understanding of how to support learners.

6.3. Conclusion

This thesis emphasised the need for progress indicators that are individualised to the student based on their achievement goal orientation. While we found some significant effects for performance-approach and mastery-approach-oriented students, no effects were found for the achievement goals of negative valence. This finding shows that while the conceptual distinction between approach and avoidance achievement goals is solid, understanding its implications in the design of LADs may prove difficult. Understanding and addressing these nuances is vital to accommodate every learner effectively [66].

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Appendix A

Results of the Ethics and Privacy Quick Scan

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:**

UU students following the Computational Thinking and Programming with Python (CoTaPP) course, which consists of students enrolled in Programming in Python (BETA-B1PYT), Programming with Data (INFOB2PWD), and Computational Thinking (INFOMCTH).

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 the website.)

- 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

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 University's privacy information. Please see the guidance on the ICS Ethics and Privacy website on what happens on submission.

Z0. Which is your main department?

- Information and Computing Science

Z1. Your full name:

L.J.A. van der Zandt

Z2. Your email address:

l.j.a.vanderzandt@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

- Human-Computer Interaction

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):

graduation.hci@uu.nl

Z8. Title of the research project/study for which you filled out this Quick Scan

Designing for Success: Exploring the interplay between achievement goals and progress visualisation preferences in a learning analytics dashboard

Z9. Summary of what you intend to investigate and how you will investigate this (200 words max):

Creating and evaluating alternative designs of a learning analytics dashboard that cater to different achievement goal orientations. We collect the achievement goal orientation scores of students, and their evaluation responses to the designs.

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