MASTER

Reflection and Resource-Related Prompts on Student-Facing Dashboards

Vleeshouwers, Cahelle S.J.M.

Award date:
2023

EINDHOVEN UNIVERSITY OF TECHNOLOGY

Department of Human-Technology Interaction

Reflection and Resource-Related Prompts on Student-Facing Dashboards

MSc Thesis

by

Cahelle S. J. M. Vleeshouwers

Eindhoven, August 4, 2023

Reflection and Resource-Related Prompts on Student-Facing Dashboards

Cahelle S. J. M. Vleeshouwers

Technical University of Eindhoven

in partial fulfillment of the requirements for the degree of

Master of Science in Human-Technology Interaction

Supervisors

dr. Uwe Matzat

prof. dr. Chris C.P. Snijders

Acknowledgements

As part of my master thesis project for the master's program Human-Technology Interaction, I am presenting this thesis with great pleasure. However, I could not have done this without the support of some very important individuals.

Therefore, I would like to thank my supervisors Uwe Matzat and Chris Snijders, for their support throughout the process and the expertise they brought to bring this thesis to a higher level. Additionally, I would like to thank Ad Kleingeld for assisting through feedback during part of the project.

Furthermore, I would like to thank Jeroen Bovend'eerdt, Isa Vogten, and Stijn Franken from the IMS department at the Technical Universiteit of Eindhoven. Without their extensive support, knowledge, and effort, I would not have been able to create the administered learning dashboards.

Last but not least, I would like to thank my friends and family for supporting me throughout the master thesis project. Especially, I want to express my gratitude towards those who took the time to proofread this master thesis.

Cahelle Vleeshouwers

August, 2023

Abstract

In this study, textual feedback in the form of prompts, also called nudges, is incorporated in student-facing dashboards. Specifically, the effects of two types of integrated prompts (reflection and resource-related) on engagement and motivation are examined. The two experimental conditions were compared to a control condition. Measurements were conducted through surveys at three points in time (pre-, week 1, week 2). Results showed no significant differences between the dashboard conditions. However, findings did show significant changes in both motivation and engagement over time. Moreover, a main effect of autonomy was found on engagement. Additionally, an interaction effect was observed of autonomy and time on motivation. Learning strategies showed no increase after dashboard administration. Although no effects of the dashboards were found, written help-seeking was positively correlated with engagement. The findings indicate the importance of considering learner characteristics as well as investigating underlying mechanisms of prompts. Qualitative dashboard evaluations also provided suggestions for approvements in future dashboard designs.

Table of Contents

1. Introduction

Many educational institutions use online environments to present course material, show grades, and sometimes have additional features like online quizzes and forum discussions. Oftentimes, these online environments make use of learning analytics. Learning analytics includes measuring, collecting, analyzing, and reporting data of the learners of a system and their contexts. The objective of learning analytics is to understand and optimize learning and learning environments (Bodily & Verbert, 2017). The data that can be used are for example forum posts, assessment results, and login and clickstream data (Clow, 2012). After generating and capturing the data, it needs to be processed to gain insight into the online learning process of one student or all students combined. Oftentimes, the data is processed into textual feedback, recommendations, visualizations, or dashboards, and then presented to the course administrator (Bodily & Verbert, 2017).

Learning dashboards give a quick and grand overview of the learning process. As defined by Schwendimann et al. (2017), "a learning dashboard is a single display that aggregates different indicators about learner(s), learning process(es), and/or learning context(s) into one or multiple visualizations." After viewing these indicators on the dashboard, the administrator or teacher can decide to act on the reported data to guide students toward improvement or prevent them from dropping out (Clow, 2012).

Teachers are not the only stakeholders in learning analytics, as another major group of stakeholders is the learners themselves (Greller & Drachsler, 2012). However, many learning environments that use learning analytics show the generated data to the course administrators/teachers and often do not directly report back to the student with personalized feedback (Schwendimann et al., 2017). Student-facing dashboards can be used to facilitate a student’s learning process by reporting the learning analytics back to the student.

There are multiple types of learning dashboards, for instance, visualization and enhanced visualization types (Bodily & Verbert, 2017). The difference between these two is the degree of data specification. Enhanced visualization dashboards can produce class/learner comparisons, interactivity, and more module-specific data instead of global (course) data. Furthermore, if the dashboard includes recommendations, it is a recommendations or recommender system type. Another type of learning dashboard is a data mining type in case data mining took place before reporting to the dashboard users (Bodily & Verbert, 2017).

Bodily and Verbert (2017) suggest that future systems should move from passive displays presenting the data to systems that support students to take immediate action using textual feedback or visualizations. A way to incorporate such feedback into a learning dashboard is through prompts. Wirth (2009) describes prompts as “short hints or questions presented to students in order to activate knowledge, strategies, or skills that students have already available but do not use spontaneously” (p. 92).

The current study will examine these prompts on student-facing dashboards. As studies in authentic learning settings are minimal, Schumacher and Ifenthaler (2021) suggest that using trace data and reactions to distinct prompts in these settings could be beneficial. Therefore, the focus will be on reflection and resource-related prompts; reflection prompts will contain questions to prompt the participant to reflect on their learning, whereas the resource-related prompts will direct the participants to resources in the online learning environment. Whereby the two types of prompts will be investigated to determine the different effects of these types if there are any.

Overview

The theoretical background for this study is discussed in Chapter 2. This includes theories about motivation and engagement, as well as findings from prior studies on learning dashboards and prompts. Furthermore, the dashboard and prompt designs are addressed in Chapter 3. The literature, on which the visuals and prompts are based, is discussed alongside the practical implementation of both. In Chapter 4, the research methods used to test the hypotheses of the current study are described. Chapter 5 dives deeper into the results of the analyses which are further discussed and examined through the findings in previous studies in chapter 6.

2. Theoretical Background

Prior Research on Student Dashboards

Many papers concerning learning dashboards do not report the usability nor the outcomes on student behavior, achievement, learning gains, or skills (Bodily & Verbert, 2017; Schwendimann et al., 2017). An example of a paper on learning analytics, which are the background processes of learning dashboards, is the paper by Hu et al. (2014) in which they discuss the design of an early warning system. This research describes data-mining techniques that are used to recognize at-risk students and methods to predict students' learning outcomes. They additionally found that time-dependent variables, such as the average time students viewed online course material, were fundamental to detecting a student's online learning performance. A non-technical example of a design paper is the paper by Sedrakyan et al. (2020), in which a conceptual model is proposed for the design of learning analytics dashboards. They suggest in their model that "feedback can be constructed based on learner profiles" and automated feedback could help to form an action plan to reach the personal learning goals of the specific learner. Other papers considering student-facing dashboards often focus on dashboard development or design. However, only a few papers consider performance, self-regulated learning, and behavioral changes (Bodily & Verbert, 2017; Jivet et al., 2018; Schwendimann et al., 2017). Using a form of automated feedback, Duan et al. (2022) administered a dashboard with actionable feedback through visuals of the learning process. They found that the dashboard positively correlated with course performance and homework submission time. Additionally, students who viewed the dashboard had higher course ranks. However, in their qualitative findings, students had mixed feelings about motivation and anxiety. Another study on actual dashboard effects by Wang and Han (2020), examined the effects of their process-oriented learning analytics dashboard on students' learning through a quasi-experiment. Through a pre- and post-test, they found that students who received their dashboard experienced better learning effectiveness than students who did not. Students with low-level prior knowledge also improved in skill learning effectiveness with the help of this dashboard. A study by Lonn et al. (2015) investigated performance-oriented dashboards instead of the process-oriented approach and found that learners' subject mastery orientation decreased. A possible reason for this is that it pushed the learner to focus more on performance instead of the mastery process. To dive deeper into learner characteristics and their preferences for dashboard indicators, Jivet et al. (2021) investigated whether learner goals or self-regulated learning skills influenced the indicators that students selected for their customizable learning dashboard. In their study, learners most often chose indicators that considered completed activities. Furthermore, they found no correlation between learner goals and indicator selection. However, they discovered that help-seeking skills predicted the learners' choice to monitor their discussion engagement. Additionally, time management skills predicted the choice in procrastination indicators. These studies show that there is prior research to build on; still, there is a limited number of studies examining the actual effects of learning dashboards on student behavior and the underlying processes. Therefore, it is beneficial to broaden the knowledge on this topic (Bodily & Verbert, 2017; Jivet et al., 2018; Schwendimann et al., 2017). To do so, the effects of certain elements on a student-facing dashboard on motivation and engagement will be the focus of the current study.

Motivation and Engagement

To motivate students and people in general, the self-determination theory can be of use (Williams et al., 1998). Self-determination theory (SDT) is an "empirically derived theory of human motivation and personality in social contexts that differentiates motivation in terms of being autonomous and controlled" (Deci & Ryan, 2012). Autonomy seems to have an impact on intrinsic goal orientation, task value, and self-efficacy, which are elements of motivation (Garcia & Pintrich, 1996). The SDT also includes statements about how less autonomy and thus more control can result in less intrinsic motivation, but more extrinsic motivation and vice versa. Intrinsic motivation is considered an internalization, a motivation that comes from within the individual's interests and enjoyment (Ryan & Deci, 2020). Extrinsic motivation comes from external factors such as rewards. Intrinsic motivation is more effective in terms of higher and long-term achievement, as the rewards that fuel extrinsic motivation may cause the individual to have a decreased interest in the topic they were interested in before. However, it is important to understand that a balance is needed between autonomy support and reinforcement to foster a learning environment that both produces the necessary skill set for the future and likewise supports intrinsic motivation (Ryan & Deci, 2020).

The SDT is also connected to the self-regulated learning (SRL) theory (Schumacher & Ifenthaler, 2018a). The highest level of self-regulation involves performing activities for learning purely out of interest or importance to the individual. In contrast, the lowest level of self-regulation is purely externally pressured onto the individual (Deci et al., 1996). Noticeably, this relates to the mechanisms of intrinsic and extrinsic motivation. Goals are likewise an aspect of both the SDT and the SRL theory (Deci et al. 1996; Deci & Ryan, 2012; Schumacher & Ifenthaler, 2018a). Based on an individual's learning goals, they might choose different learning strategies for goal setting, organizing, task approach, regulation, and evaluation (Pintrich, 2000).

Motivation also has a relationship with engagement. As discussed within the SDT, motivated people also tend to engage more in the activity that interests them, and their motivation makes the activity something of interest (Deci & Ryan, 2000). Engagement can thus also be seen as an externalization of motivation, especially when engagement is behavioral (Stroet et al., 2013).

Next to behavioral motivation, thus the observable output, engagement can also be emotional and cognitive (Fredricks et al., 2004). Behavioral engagement considers participation in learning and extracurricular activities. Emotional engagement is concerned with the positive and negative reactions to the learning activities, as well as the people and methods involved. Cognitive engagement encompasses the investment of a learner, which includes the consideration and willingness to put effort into understanding and mastering ideas and skills (Fredricks et al., 2004). For academic achievement, engagement in a course can be beneficial as positive correlations have been found between engagement and grades (Lear et al., 2010; Phan et al., 2016).

Self-efficacy, which mainly involves beliefs about one's competence, expertise, and skill, can also influence motivation and engagement (Linnenbrink & Pintrich, 2003). Thus, if a student feels confident that they are capable of performing and completing a task, they are more likely to be motivated and in fact, engage with the task at hand. Therefore, Linnenbrink and Pintrich (2003) advise to maintain high self-efficacy beliefs through accurate and specific feedback, challenging tasks that most students can successfully complete when they exert effort, and fostering a growth mindset that acknowledges that competence and ability can be developed.

The study by Schumacher and Ifenthaler (2018a) attempts to link this motivational theory to learning analytics. Specifically, they investigated goal orientations and found that performance-avoidance and work-avoidance orientations do not predict feelings of support from learning analytics. Furthermore, they found that learning analytics can provide support, especially for low-achieving students. However, more research that investigates motivation and SRL in combination with online learning is needed to investigate actual effects (Schumacher & Ifenthaler, 2018a; Gentner & Seufert, 2020).

In combination with online course environments, engagement has been studied with both trace data or clickstream data and self-reports (Vytasek et al., 2019). Self-reports can be used for all three types of engagement, where trace data may be a more accurate representation but can only account for behavioral engagement. In the study by Dixson (2015) a combination of trace data and self-reports through the Online Student Engagement Scale (OSE) was used. The OSE can be used to create a broader understanding of cognitive and emotional engagement in which the trace date would not succeed. Dixson (2015) found that the trace data and self-reports were correlated with interaction behaviors in the online learning environment such as forum posts or taking quizzes, but not with observation behaviors such as reading and listening to lectures. Li et al. (2020) found that clickstream data was significantly correlated with the self-reported measures of time management, the effort regulation of students, and the post-course, but not with the pre-course. Thus, estimations of engagement in reflection after the course had connections to the actual observable data. They suggested that clickstream data could help identify students who are not engaging in the online course. Moreover, the study by Phan et al. (2016) measured active engagement in an online course with submission of at least one assignment, and discussion forum interactions. This active online course engagement was positively correlated with performance.

In the randomized controlled experiment by Hellings and Haelermans (2022) concerning a student-facing learning dashboard, trace data was also used to measure engagement in the online learning environment. Engagement measures consisted of completed online practical assignments, online quizzes, and the average mastery score of online exercises. Every week a personalized link was sent through an e-mail pointing to a dashboard with visuals of their performance and the student average. They found that both e-mail and dashboard use had positive effects on online engagement measures.

Feedback

Feedback can have positive effects on a student's motivation when presented properly (Banihashem et al., 2022; Hattie & Timperley, 2007; Jivet et al., 2018). However, it is important to note that feedback in general and on dashboards could also undermine a student's motivation if not provided appropriately. To properly present feedback, both Shute (2008) and Hattie and Timperley (2007) proposed guidelines and recommendations based on prior research to facilitate feedback to improve the learning experience and not undermine it. A general recommendation about feedback is that it should happen promptly. Hence, the student needs to be able to use the feedback for growth in skill before the end of a program, thus intermediate feedback could be helpful. Real-time feedback is often recommended, but delayed feedback can be beneficial when immediate feedback "can detract from the learning of automaticity" (Hattie & Timperley, 2007). Feedback should aim to assist in identifying where the student is going and how they are going as well as providing alternatives or steps about where to go next. The most beneficial form of feedback is found to be cueing or reinforcement to learners. This feedback should be given through video-, audio-, or computer-assisted instructional feedback and/or relate to the learner's goals.

Furthermore, Hattie and Timperley (2007) proposed four levels of feedback, namely: task, processing, regulatory, and self-level. The task level entails feedback about the task or product, for instance, whether the work is correct or not. This level can also contain advice on obtaining additional, different, or correct information. Feedback on the task level is most effective when it supports someone in identifying incorrect information which in turn leads to more effective and efficient strategies for processing and comprehension of the learning material. The process level involves feedback directed at processing and understanding information and completing the task itself. This level is applicable when a learner needs to adjust learning or working strategies.

Feedback at the process level is most beneficial when it supports rejecting flawed assumptions and can provide “cues to directions for searching and strategizing” (Hattie & Timperley, 2007). The regulation level includes feedback for self-regulation specifically. This level encourages students with strategies on how to continue the task as autonomously and effortlessly as possible and can increase self-regulatory and self-efficacy skills as well as self-beliefs. Furthermore, feedback on the regulation level can increase engagement with the task and can lead “to attributions that the feedback is deserved and earned” (Hattie & Timperley, 2007). The self-level or personal level involves feedback about the learners themselves including affective evaluations such as praise. This type of feedback is often ineffective and rarely enhances learning itself as it evaluates the learner on a personal level and does not touch upon improvements for the process, task, or strategies (Hattie & Timperley, 2007). Thus, when considering feedback on student-facing dashboards, it is important to use task, process, or regulated level feedback in the form of cues or reinforcement while helping the student understand their current performance, their objectives, and how to get there.

A dashboard is already a form of feedback, the visuals and text presented can be used for students and teachers to make inferences about where the student is in the learning process, where they are going, and additionally, combine this information to create or revise a strategy to reach learning goals. To offer feedback to the student, a student-facing dashboard can present different indicators specific to the user such as performed actions, content production or interaction, outcomes, context of learning environment, and social relation of their data to others (Schwendimann et al., 2017). Brdnik et al. (2023) investigated the expectations of a learning analytics dashboard for students in Slovenian higher education. The expected effects of the dashboard on motivation were explored through both questionnaires and focus groups. They found that for average and above-average students an increase in motivation was predicted. However, for underperforming students, it could lead to a decrease in their motivation (Brdnik et al., 2023). Prior studies about social comparisons have also shown mixed results. Davis et al. (2017) found that social comparison increased course completion but was mostly beneficial for highly educated learners. Social comparison can motivate students to perform better but can also have negative consequences for their motivation depending on their grades, personality, and other factors. Specifically, high-performing students can be motivated by their peers, while for students who are below average, peer comparison can be intimidating and stressful (Tan et al., 2018). In contrast, Kim et al. (2015) found that high achievers may not be motivated by comparison with peers. They also found that low achievers were more motivated without social comparison. Furthermore, performing slightly above average can result in the student being content and as a consequence does not motivate them to perform better (Corrin & de Barba, 2015). Rather than referencing a norm, students who became demotivated in the study by Tan et al. (2018) preferred self-referenced data such as their prior results.

A more self-referenced manner to provide feedback is through predictive dashboards. These dashboards use self-referenced data to draw inferences about a student's progress and predict their possible outcomes if they keep up the current way of working (Valle et al., 2021). Predictions often include performance predictions like grades. Valle et al. (2021) reported significantly reduced anxiety in a statistics course when interpreting statistical results as well as effects on intrinsic motivation when using a predictive dashboard. To elaborate, motivation for learners who initially had lower motivation also had reduced motivation after using the predictive dashboard, while it had a positive influence on learners with higher initial motivation. As predictive dashboards could be both beneficial and detrimental to a student's motivation, the usage of predictive dashboards should be considered carefully. data such as their prior results.

According to Schumacher and Ifenthaler (2018b), other ways to motivate learners through learning analytics is employing integrating just-in-time performance feedback and/or letting students adapt their learning activities according to recommendations and in turn facilitate more successful learning. There are different types of feedback to consider regarding a student dashboard, for example, textual feedback from a teacher, correct test answers, grades, and course progress (e.g., finished modules) (Jivet et al., 2021). Not all types of feedback are easy to generate automatically as some require thoroughly thought-out textual feedback written by a teacher. Even though this would potentially be the most motivating type of personalized feedback, in most cases it would be hard to create in a timely manner, especially in courses with many students. Possible automated feedback on a student-facing dashboard would be among others: cues, visualizing progress (e.g., grade progression, progress bar for finished course content), showing correct/incorrect online test answers, and average completion time for activities. Although a student-facing dashboard is a combination of indicators to present the student with feedback, Bodily and Verbert (2017) state that there is a limited number of studies on dashboards with actionable feedback and their effects. Additionally, they suggest that future systems should move from being passive displays that present the data, to systems that support students with feedback that prompts immediate action. Sedrakyan et al. (2020) likewise propose that process-oriented feedback could be especially beneficial for learning dashboards to guide them towards improving their learning.

Prompts

A type of actionable feedback that could be used on student-facing dashboards is prompting. Shute (2008) defines prompts and cues as the same concept, stating that they are "elaborated feedback guiding the learner in the right direction." Wirth (2009) describes prompts as "short hints or questions presented to students in order to activate knowledge, strategies, or skills that students have already available but do not use spontaneously." In other words, a prompt, sometimes called a nudge, is a type of feedback that encourages people to take action. Rather than pushing the learner to do something, nudging, or suggesting something is deemed to be more effective (Lodge et al., 2018).

A nudge is a form of prompting that is connected to nudge theory. Nudge theory was made popular through a book by Thaler and Sunstein (2008). In this theory, they acknowledge that people do not always act and make choices that are most beneficial to them. To improve this behavior, people sometimes merely need a 'nudge'. This nudge is meant to provide choices to change behavior for the better, "without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein, 2008).

Further investigations into the effects of prompts have pointed out that prompts could be beneficial for the learning process of students. For instance, Berthold et al. (2007) studied the effect of reflection prompts on learning strategies and outcomes. Specifically, cognitive and metacognitive prompts were administered which are meant to trigger (self-)reflection. Cognitive prompts consider the learning process and strategies (in this study particularly, organization and elaboration strategies), whereas metacognitive prompts, prompt for knowledge and awareness of the learners' cognitive processes. Berthold et al. (2007) let participants watch a video lecture, then showed either no prompt or a cognitive, metacognitive, or combination prompt of the prior. The results showed an increase in cognitive and metacognitive learning strategies when prompted. However, only the cognitive or combination prompt conditions led to better learning outcomes, which were mediated by cognitive learning strategies. Specifically, the understanding was better than in the other two groups immediately after the stimulus was given. Retention was also better for the cognitive and combination prompt conditions, but only after one week (Berthold et al., 2007). Hawthorne et al. (2015) likewise studied the effects of prompts on students. In their study, the focus lay on generic, personal, and mixed motivational prompts and their effects on motivation, effort, and performance. The prompts were given by an instructor and in writing. Results only indicated significant effects on performance in the motivational prompt conditions compared to the control condition with the generic prompts. Furthermore, participants in the personal motivational condition performed better than the other groups. Schmidt et al. (2012), also found effects of prompts on motivation as well as comprehension. However, this study compared the effect of cognitive and metacognitive prompts (control group) versus the same mix of prompts with additional prompts considering personal utility (experimental group). Thus, the control group for this study also received prompts. They found that prompting German secondary school students to write about the personal utility of the learning content resulted in higher learning motivation and comprehension scores in comparison to the control group.

Prompts have also been studied in combination with devices and online environments. In the study by Bannert (2006), students received the task to learn concepts of operant conditioning in a hypermedia environment. A reflection prompt group was instructed to verbally state why they chose certain learning material, the control group learned without this. Immediately after 35 minutes of learning, measures of learning outcome were taken in which students who received the reflection prompts showed better transfer performance. However, no significant effects were found for recall or knowledge. Bannert et al. (2009) also investigated the effects of metacognitive prompts on learning outcomes. The usefulness of metacognitive activities and how to apply them was explained through a device for the experimental group, whereas the control group received no information about this. During a study session of 60 minutes within a digital learning environment, the experimental group was prompted to apply the learned metacognitive activities. Resembling the study by Bannert (2006), when prompting through texts on paper, Bannert et al. (2009) likewise found better transfer performance for the prompted group. Next to the learning outcomes test, they additionally found increased metacognitive behavior through questionnaire measures.

Prompts have not only been used verbally or on paper but have also been digitalized. Stark and Krause (2009) integrated reflection prompts into the digital learning environment. In the prompting group, learners received a digital reflection prompt for which they were asked to write about why they made certain decisions while working with the learning environment. Next to the reflection prompt group, one group worked with the e-learning environment without prompts and the control did not have access to this e-learning environment. All conditions were part of a statistics course; thus, the control groups could still attend the same lectures as the other conditions to receive information on the course topics. Results showed that the prompt group scored significantly higher for cognitive learning outcomes than the other e-learning group and that both experimental groups outperformed the control group. However, they found no effects on time on task, task choices, and motivation.

Other effects on learning performance have been found when prompting within learning pages of the online learning environment, which resulted in better transfer for the immediate test after learning (Müller & Seufert, 2018). Additionally, effects on self-regulation have been found for learning page integration of prompts in terms of self-efficacy, which was higher for the prompt group than the no-prompt group. Further results of prompts on SRL were found within video learning tasks in an experimental learning session of 45 minutes, comparing a prompt condition to a no-prompt condition (Moos & Bonde, 2016). Administering SRL prompts while watching a learning video can increase engagement in both the video and SRL activities, as well as learning outcomes. Similarly, Sitzmann and Ely (2010) found that messages with SRL prompts throughout a 4-hour online course had a positive effect on recall and reduced attrition. Other effects of prompts were found in the study by Kauffman et al. (2008), in which they investigated the effects of problem-solving prompts and reflection prompts on problem-solving and writing within a web-based instructional module. They found that problem-solving prompts helped with problem-solving and writing clarity. In addition, reflection prompts were positively correlated with problem-solving and writing, but only in a mixed condition with problem-solving prompts. Pieger and Bannert (2018) compared self-selected prompts to be administered to fixed (predefined) prompts and no prompts within pages of the learning environment. They found that prompts created less linear learning behavior but found no main effects. However, they did find that prompts could support students with lower reading skills and verbal intelligence, thus student characteristics can play a role in the effect of prompts in general.

Prompts can also be supported using learning analytics. Through case studies, Blumenstein et al. (2018) found that for data-informed nudges through e-mails or text messages, it is important to consider the context of the course and students such as needs, workload pressures, and teaching methods. Additionally, personalization could result in more positive effects and increase student engagement. Another study that used e-mail reminders to complete additional online quizzes likewise found that students filled in the quizzes more regularly completed more quizzes, and had increased improvements in progress (Nikolayeva et al., 2020). However, they found that short non-personal messages were more effective than longer, more personalized content.

Brown et al. (2022) investigated nudges through iterative designs. They suggested that nudging critical resources can motivate students to study if the nudges are framed in a supportive style. Additionally, Brown et al. (2023) gathered both qualitative and quantitative data to explore the impact of nudging on the learning engagement of 187 students across two disciplines. Comparing data from the previous year to the year in which the nudges were used, they found an increase in levels of engagement in online courses. However, as some nudges were too late, they concluded that the nudges of resources should at maximum occur within one week after they should have been viewed to increase success rates.

To investigate activity in the online learning environment, trace data can be used. Bannert et al. (2015) analyzed a log file and found that more relevant pages were visited, and more time was spent on these pages as well by students who received the prompts. Furthermore, transfer performance was better when self-directed prompts were administered to the students versus no prompts. This effect was even greater three weeks after the learning session. However, the study did not compare these self-directed prompts to other prompts like in the study by Pieger and Bannert (2018), therefore, the results could be the mere effect of prompts instead of this specific type.

Instead of incorporating the prompts in e-mails, SMS, videos, or within the web page, Schumacher and Ifenthaler (2021) presented prompts through pop-ups in the online learning environment. In their study, there were four conditions: a cognitive condition (CP), metacognitive condition (MP), cognitive, metacognitive, motivational, and resource-related condition (AP), and a control group (CG). Results from a test showed a small effect of prompts on declarative knowledge and transfer. Furthermore, they found a significant difference in perceived learning support between the MP and the AP group, for which the MP group perceived more support. Moreover, the MP group perceived more learning support than all other groups. On a descriptive level, the AP group perceived the lowest learning support, had the highest negative perceptions, and found the prompts the least helpful. More than any other group, the AP group also stated that they received too many prompts per item. Note that this study did not separately investigate motivational prompts and resource-related prompts, thus the same results might not occur when separating the prompt types.

Certain triggers in trace data and timings can be used to prompt. Continuous timings throughout a semester were found most effective by Sitzmann & Ely (2010). However, according to Brown et al. (2022), nudging critical resources at the start of the semester can especially help to create motivation to study early on. Additionally, it is important to not overwhelm the learners by prompting them too much which can result in either cognitive or information overload (Moos & Bonde, 2016; Pieger & Bannert, 2018). Nudges can be especially useful to guide students who have not yet used important learning material. Furthermore, students who are handing in assignments late or starting on the due date can be at risk of scoring lower (Feild, 2015). Therefore, nudging them to start working on assignments earlier or improving time management could be beneficial. This was backed up by a predictive model by Macfadyen and Dawson (2010), using trace and other online student-specific data. Predictors for low performance could namely be the number of posted discussion messages, e-mail messages sent, and assessments completed. Thus, when these numbers are low, students can be prompted to act. Brown et al. (2023) likewise suggested that low- or non-engagement could be used to trigger prompts, as well as unused critical resources. As stated before, nudges with resources should not be administered later than one week after they were expected to be accessed. Moreover, prompting within a video on fixed times can potentially be disruptive to the learning process (Pieger & Bannert, 2018). Consequently, when prompting, it should be considered that prompts should either be timed at useful moments or integrated into learning material instead of on top of a video or page (Schumacher & Ifenthaler, 2021).

Research Gap and Current Study

Many of the studies discussed investigate reflection prompts. These prompts let the learner reflect on something in their learning process, for instance, learning strategies, time management, or areas for skill or knowledge improvements. Nudges have been used to remind students of unseen or important learning resources. However, these resource-related and reflection prompts have not often been compared. Schumacher and Ifenthaler (2021) compared resource-related prompts in a mixed condition only and not as a separate condition. Therefore, the lack of knowledge in this area could be broadened by investigating the difference between prompting to use learning material and prompting to reflect on learning material. Furthermore, there is a knowledge gap regarding the effects of prompts on student-facing dashboards as other studies mainly investigate prompts that are presented through e-mail, SMS, integration in learning pages, pop-ups on top of learning pages, and within videos. Especially when considering the growing usage of student-facing dashboards and the lack of actionable feedback on them (Bodily & Verbert, 2017; Jivet et al., 2020), it can be beneficial to investigate whether the effects of prompts that are found in prior studies translate to student-facing dashboards. Likewise, authentic settings and reactions to specific prompts that are technology driven are not largely studied (Matcha et al., 2020; Schumacher & Ifenthaler, 2021). Hence, performing such a study within an authentic situation, thus a course with actual enrolled students can broaden knowledge in this area. Studies also found prompts to be disruptive when being timed at a certain point within online material such as a video (Pieger & Bannert, 2018). Since the students have the freedom to access the dashboard when they find it convenient, this should create a less disruptive environment as they are not pulled out of focus. Therefore, this could potentially prevent the negative effects of fixed prompts, while preserving the positive effects from prior research on engagement and motivation. Consequently, the results of this study can support future practical applications to increase learner support through student-facing dashboards. Additionally, for future research, the findings can create more in-depth knowledge about the effects of textual feedback through prompts. To investigate if the effects of prompts are transferable to a student-facing dashboard setting, the following question is posed: "*How do reflection and resource-related prompts on a student-facing dashboard affect course engagement and learning motivation?"*

The primary hypotheses for this research question examine the global effect of prompts on a student-facing dashboard. Texts of the prompts will be based on research in which an effect was found, which will be further discussed in Chapter 3. Therefore, it is expected that the effects of the prompts also occur in a student-facing dashboard environment, resulting in H1 and H2.

H1: Presenting prompts on a student-facing dashboard will improve course engagement.

H2: Presenting prompts on a student-facing dashboard will increase learning motivation.

To examine the potential underlying mechanisms that the question indicates, secondary hypotheses have been developed. H3 and H4 are based on the SDT stating that greater perceived autonomy is central to learning motivation; higher perceived autonomy relates to increased motivation (Deci et al. 1996; Deci & Ryan, 2012; Ryan & Deci, 2020; Schumacher & Ifenthaler, 2018a). Additionally, reflection is a part of SRL, which can lead to altered levels of self-efficacy, value, and interests (Pintrich, 2000). SRL could support motivation and engagement by encouraging the student to look within themselves and reflect to improve future strategies instead of handing them a direct external solution. Direct links to resources therefore may be perceived as less autonomous and less supportive of self-regulation than receiving a reflective question. To explore this theory, perceived autonomy, and most related SRL strategies will be measured. The mechanisms of the SDT and SRL theories lead to the following hypotheses:

H3: Reflection prompts will lead to a stronger increase in course engagement than resource-related prompts.

H4: Reflection prompts will lead to a stronger increase in learning motivation than resource-related prompts.

As learning characteristics, such as SRL skills, can influence the impact of prompts (Pieger & Bannert, 2018), H5 and H6 investigate skills relevant to the specific prompt groups used. Kim et al. (2015), observed differences in motivation between high and low-achieving individuals, whereas low-achievers had a more pronounced positive effect. Pieger and Bannert (2018) found that learners with low skills benefited more from metacognitive support than highly skilled individuals. Thus, a student who engages more in written help-seeking behavior may benefit less from the resource prompts, as they already perform the action in their regular studies. Similarly, reflection prompts may be less beneficial for students scoring high on active reflection. Warr and Downing (2000) likewise found a positive correlation between motivation and active reflection; this might indicate that learners who score high on active reflection may already be more motivated and thus reflect more. Therefore, the effect of the prompts may be less pronounced as their motivation is already high. This results in the following hypotheses:

H5: Reflection prompts will have a larger positive effect on students scoring low on active reflection.

H6: Resource prompts will have a larger positive effect on students scoring low on written help-seeking.

3. Dashboard Design

The experiment considered a control group and two experimental groups using prompts, which are discussed in Chapter 4. Each group received a different dashboard, all presenting the same visual information; however, the two experimental groups received textual prompts on the dashboard whereas the control group (dashboard A) did not receive prompts. The reflection prompt dashboard (dashboard B) presented a question at the top of the dashboard to prompt reflective thinking. The dashboard for resource-related prompts (dashboard C) included a statement that directed the student to online learning materials that could be beneficial for their learning process. Both the visualizations and the prompts were based on Canvas data. The dashboards were developed in Microsoft PowerBI using Canvas course data and interaction data of the students. The dashboards were developed in collaboration with the Information Management Services (IMS) department at the Technical University of Eindhoven.

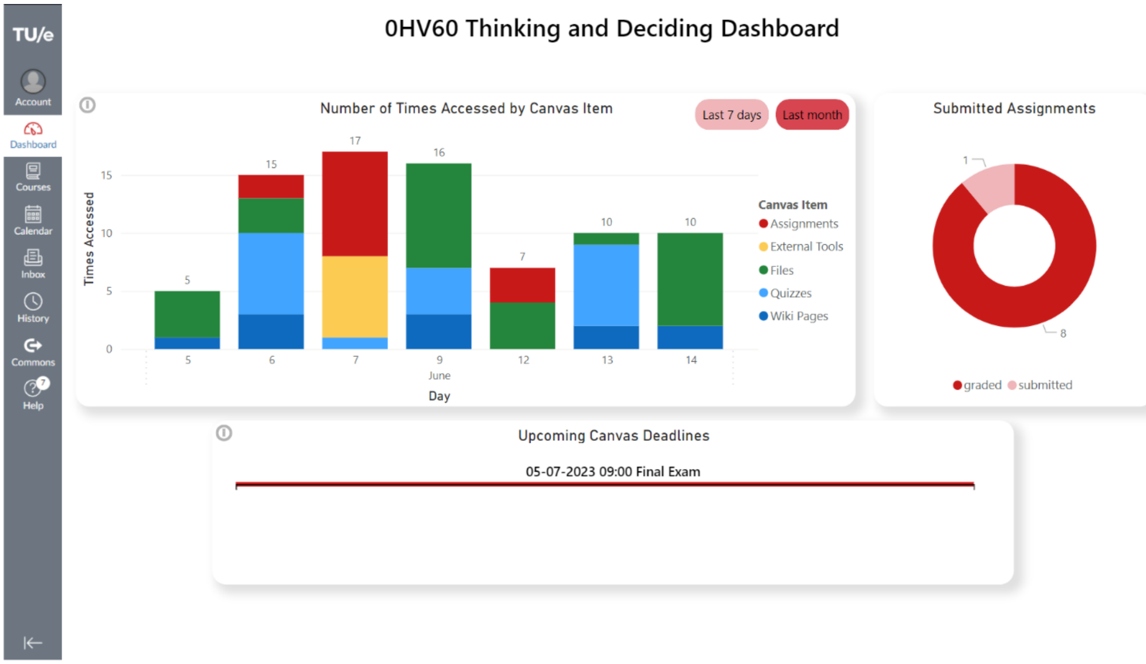
Visuals

To design equal features for the dashboard for both the control and the experimental groups, existing Canvas features were taken into account. The Canvas environment itself is already able to show a box plot with the class results for grades. However, as the literature has mixed results in this area as discussed in the literature review (chapter 2), this feature was not used for the dashboards. Examples of other features already existing within the Canvas environment are the average grade, upcoming deadlines, submitted assignments, and the online course material itself. To not demotivate learners with a low average, the average grade was not considered for the dashboard.

As it was also important to encourage students to use the dashboard, not only already accessible features were considered, but also additional features based on literature. In the study by Jivet et al. (2021) where students were able to choose the indicators to be shown, learners picked indicators about completed learning activities the most. Ott et al. (2015) also found that the number of laboratory tasks completed was an indicator of student performance. Thus, showing the number of completed assignments could give students more insight into their performance. Additionally, in a qualitative exploratory study, Schumacher and Ifenthaler (2018b) investigated which features were desired to have on student-facing dashboards. Features that students desired included but were not limited to: time spent online, learning recommendations (e.g., important subjects, content revision), prompts for self-assessment, ratings for learning material, expected task completion times, and reminders for deadlines. As the experimental groups already consist of one condition for recommendations in resources/learning material and the other for reflection/self-assessment, this feature could not be implemented as a visual presented to all conditions. Furthermore, ratings of material and time estimations for tasks need either input from teachers or other students and thus could not be implemented within the scope of this study. Time spent online and reminders for deadlines were possible candidates. As the Canvas tables did not give a time estimate automatically, but merely points in time when a page or resource was visited, simple calculations would result in possible unreliable or untrue visualizations of time spent online. Sedrakyan et al. (2020) stated that “actual use of learning resources can to a certain extent be indicative of learning outcomes.” As it is unsure if giving a list of names of the resources might affect the resource-related prompt outcomes, in this study, only the number and types of resources can be visualized. Brown et al. (2023) also reminded students of the deadlines for the week, which increased online engagement. Therefore, adding this already available feature in a more confined and straightforward form than the existing monthly Canvas calendar could be useful.

Figure 1

Control dashboard (Dashboard A) containing the visuals available for all conditions.

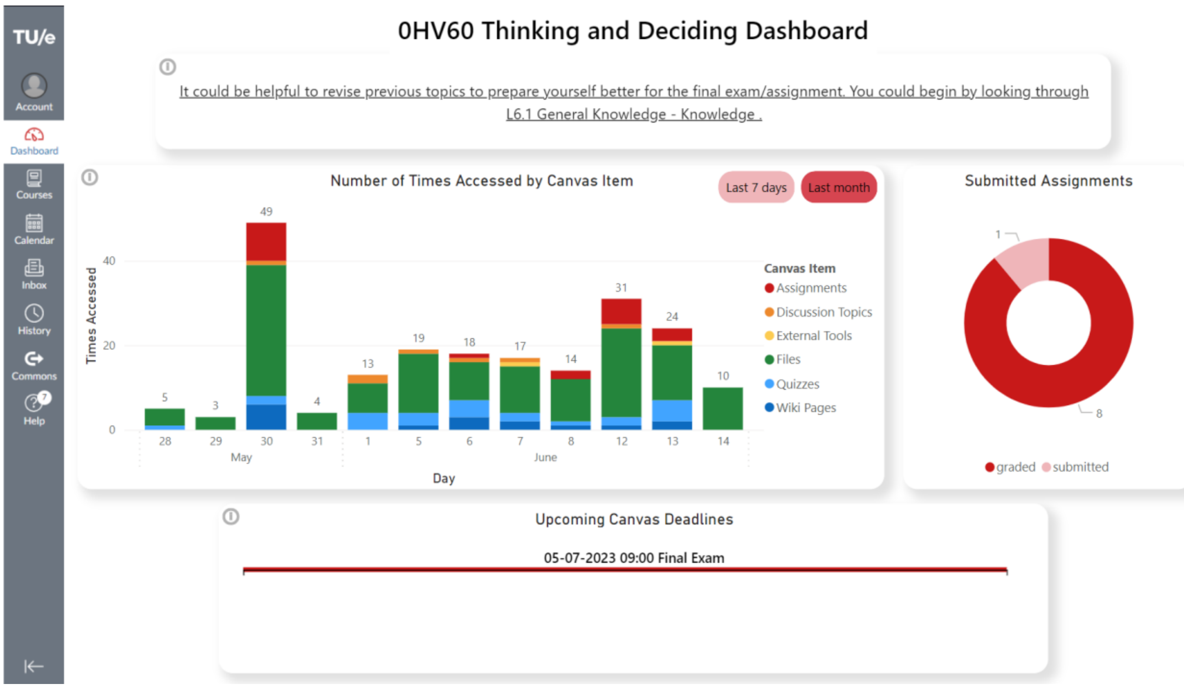


The three final features that became visuals for dashboards in all conditions were based on both the literature and existing accessible Canvas features. To still implement a similar feature to time spent online (Schumacher & Ifenthaler, 2018b), the number of times the learner accessed online material was used to incorporate a new feature on the dashboard. For more in-depth coverage of this behavior, the type of resource accessed was also shown (e.g., file, external tool, wiki page, discussions) (Sedrakyan et al., 2020). This feature was new to the student and could potentially draw them to use the dashboard. Additionally, the number of completed and graded assignments was shown on the dashboards as visuals (Jivet et al., 2021; Ott et al., 2015). Finally, the third feature was a quick overview in the form of a horizontal timeline of the upcoming deadlines for the next 30 days (Brown et al., 2023; Schumacher & Ifenthaler, 2018b). Additionally, as fields could be empty if no online interactions occurred or no deadlines were upcoming, an icon with an “i” provided more information, stating that if the field was empty, no data was available. The final design of the visuals on the dashboard is shown in Figure 1.

Prompt Texts

Figure 2

Resource-Related dashboard (Dashboard C) including a clickable prompt with URL.



All prompts that were administered in this study were based on the literature on prompts. A distinction was made between reflection prompts and resource-related prompts. Reflection prompts hereby include metacognitive, cognitive, personal utility, and other types of prompts that pose a question that is aimed at letting the learner reflect on their learning. Resource-related prompts provide texts that direct the learner to a specific online resource that can be used to study for the course. The dashboard for the resource-related prompts is shown in Figure 2, this looks visually the same as the reflection dashboard, but the reflection dashboard received other prompts discussed further within this chapter. A prompt was only underlined if it was clickable. This occurred when a specific Canvas resource, of which a URL was known, was connected to the prompt. Thus, other prompts without a prompt and URL connected were not underlined and were not clickable.

Reflection Prompts

For reflection prompts, Berthold et al. (2007) found a significant effect of their prompts on cognitive learning strategies in a laboratory experiment in which they used both metacognitive and cognitive prompts. Sitzmann et al. (2009) likewise found that reflection prompts for self-regulation improved performance over time. This result was found in online settings as well as work-related training and laboratory settings. In the study on prompts for personal utility in a classroom setting, Schmidt et al. (2012) found that students who received this type of prompt in addition to metacognitive and cognitive prompts from the study by Berthold et al. (2007), had a higher level of motivation and comprehension scores. Finally, the study by Moos and Bonde (2016), which was conducted in an experimental setting that included SRL prompts in a video, found significant differences in learning outcomes and SRL processes. Prompts originating from these four studies were administered in the current study with some adjustments to make them relevant for the specific course and setting. A few examples of the prompts are shown in Table 1 and the full prompts list can be found in Appendix E.

Table 1

Examples of textual reflection prompts and the studies they were based on.

Based on the study by	Prompt text
Berthold et al. (2007)	Which main points about [*topic*] do you already understand, and which do you not understand yet? What can you do to improve your knowledge in these points?
Sitzmann et al. (2009)	Did you set any goals and/or make a plan to ensure you have a thorough understanding of the course material?
Schmidt et al. (2012)	How is the course material personally relevant for you at present or in the future outside of university? (Making these connections may help you remember the content better)
Moos and Bonde (2016)	Do you need to go back to any of the videos on [*title of video material*] and fill any gaps in understanding?

Resource-related Prompts

The resource-related prompts are based on the research by Feild (2015), Schumacher and Ifenthaler (2021), and Brown et al. (2023). Schumacher and Ifenthaler (2021) studied both reflection prompts and resource-related prompts; however, the latter was only administered in a combined group with other prompt types. They found that other groups outperformed this combined prompt group and that this group did not perceive the prompts as helpful. The study by Feild (2015) investigated what nudges could be beneficial for underperforming students and suggested that prompting them to stick to deadlines and giving oneself enough time for assignments could help students to perform better. Brown et al. (2023) assessed the impact of a nudging intervention that prompted students through e-mail messages to use online learning material that was important to consider that week. They found that online engagement increased compared to data from the previous year. The resource-related prompts in the current study are based on the three studies discussed, though some adjustments were made to create more relevance to the course or the dashboard setting. For example, as texts in some studies were extensive and would be too long for a student dashboard (more than two sentences), the texts were partially used or administered in parts. In Table 2, examples of resource-related prompts are shown. The complete prompts list can be found in Appendix E.

Table 2

Examples of textual resource-related prompts and the studies they were based on.

Based on the study by	**Prompt text**
Feild (2015)	Turning in assignments late can result in lower or missing grades. Start with [*title of assignment*] soon, to make sure you have enough time to put in the effort.
Schumacher and Ifenthaler (2021)	There are additional resources on Canvas in [*title of page*] you can use to deepen your knowledge on the topics of this week.
Brown et al. (2023)	To prepare yourself in time for the upcoming topics and the exam, you can start watching [*title of video material*] to familiarize yourself with the content.

Technical implementation of visuals

The online learning environment Canvas continuously collects student data, including for example clickstream, login, assignment submissions, and grades. As discussed in the literature, this data can be utilized as indicators for a student-facing dashboard. Due to the sensitivity of the data, the data of the participating students was pseudonymized by the IMS department of the Technical University of Eindhoven to prevent the researcher from being able to directly trace the data back to the individual student. All participants consented to the usage of their data within this study. The pseudonymized Canvas data was connected to Microsoft PowerBI through an Azure Databricks connection, resulting in tables of Canvas data. In turn, these data were used to provide all three dashboards with real student data. To make sure participants could only view their own data, roles were created in PowerBI that filtered tables based on the pseudoID for the student as well as the course they were in. The IMS department connected the pseudoIDs to the student accounts to facilitate logging into their personal dashboard through their university account.

To prepare the dashboards for the experiment, the Canvas tables were first manipulated through Power Queries within the PowerBI environment. The documentation for these tables is provided through the Canvas Data Portal (n.d.). A list of the most prominent Canvas tables that were used can be found in Table 3.

Table 3

Listing of the most prominent Canvas tables used in Microsoft PowerBI

Table name	Data
canvas_enrollment_dim	Student enrollment in the courses
canvas_course_dim	Course-specific information (e.g., course name)
canvas_module_dim	Information on the modules within a course
canvas_module_item_dim	Items (e.g., wiki pages, learning material, assignments) within the modules
canvas_quiz_dim	Quiz information (e.g., quiz name, deadlines)
canvas_assignment_dim	Assignment information (e.g., assignment name, deadlines)
canvas_requests	HTTP requests made by the students (e.g., page clicks, items opened)
canvas_submission_dim	Submitted assignments

The *canvas_requests* table consists of the clickstream data of the students, which was the table indirectly used for the dashboard visual of accessed items. However, as this table was too large and caused overhead, a new table (*_filtered_canvas_requests*) was derived from this table through Power Query, including only relevant Canvas requests. This resulted in a table with HTTP GET requests for wiki pages, files, quizzes, assignments, discussion topics, and external tools (e.g., Panopto, which supports integrated video lectures). In the PowerBI report view, the visual was filtered on a certain timestamp. This filter could in practice be adjusted by the participant, to view either their activity for the last week or the last month. For the dashboard visual of submissions, the *canvas_submission_dim* table was used directly. The visual used the number of assignments submitted and the so-called “workflow_state” column, which included information about the state in which the grading process of the assignment was (e.g., submitted or graded). As directly connecting the *canvas_assignments_dim* to the timeline visual resulted in issues of presenting wrongful data due to cluttered and missing Canvas data, this timeline was connected to the DAX code aggregated table *_connected_prompts_list*. From this table, the names of the assignments and quizzes and their corresponding deadlines were derived to present in the timeline. The *_connected_prompts_list* table is interconnected with other tables to administer the reflection and resource-related prompts to the students. Implementation of the prompts will be further discussed in the section considering the technical implementation of the prompts. Since students of the 0HV60 course did not have any online assignments or quizzes near the end of the semester, the *_manual_exams* table was created to add the final exam and its date on top of the timeline visual as it would otherwise continuously be empty during the experiment. All tables created in Microsoft PowerBI, which are aggregated from the original Canvas tables are listed in Table 4.

Table 4

Listing of the tables created in Microsoft PowerBI

Table name	Data
_filtered_canvas_requests	Reduced Canvas request table for the activity visual
_connected_prompts_list	Full prompt texts including resources and URLs
_prompt_resources	List of Canvas items to be used for the prompts
_prompts_tests	Prompt texts without resource connections
_manual_urls	Manually added URLs for Canvas items
_manual_exams	Manually added exams (specifically for offline exams)

Technical implementation of the prompts

The prompts have been made course-specific using resources in the online environment. For instance, the topics or specific online materials that were found in the 0HV60 course such as “perception” were used in the reflection prompts to let them reflect on what they learned about this topic so far and how they could improve their knowledge. For resource-related prompts, the specific material was used to directly point to it, for instance, extra practice material was pointed out, as well as reading material or assignment descriptions that were applicable in the current week.

Furthermore, for both prompt types, topics, and material from previous weeks were also included for review purposes. This also assured that prompting was still possible late in the semester without repeating the same prompt or resource on consecutive days. The prompts were partially automated as the resources were derived from the Canvas tables. As a first step towards automation, the *_prompt_resources* table was created using Power Query. This table merged the *canvas_assignment_dim*, *canvas_module_item_dim*, and *canvas_quiz_dim*, to create a list of Canvas resources including learning material, assignments, and quizzes. Due dates were taken from the course schedule and added for all items with an empty deadline. The deadlines for the learning materials were set to the end of the week in which they were supposed to be covered. Additionally, a column was added through a Power Query to check if a deadline was in the past or in the future, to prompt resources correctly. The URLs or Canvas resources were only available in the *canvas_requests* table. However, no simple connection between these resources was possible as the requests table did not include names, nor IDs of the resources inherently. Nonetheless, the URLs contained the specific IDs that Canvas used to identify the resources. Therefore, the URLs were split into parts using Power Query to obtain the Canvas IDs. This made it possible to match the resources based on IDs and add the URLs to the *_prompt_resources* table through DAX code. If no automated URLs were found for seemingly important resources, they were manually added in the *_manual_urls* together with the Canvas IDs, which could be connected using the same method as the other URLs. The *_prompts_texts* table was manually filled with the texts as discussed in the prompt texts section of this chapter. Through the table *_connected_prompts_list*, created through DAX code, the *_prompts_texts,* and the *_prompt_resources* tables were merged. An additional DAX measure was created with HTML and CSS code containing the now automated text to be displayed. To make the prompts visual, this measure with code was connected to an

HTML Content widget in PowerBI. To show only one prompt at a time identification numbers were randomly assigned to the prompts. A column was added through DAX code to select a prompt with a specific ID from the available prompts list. Due to PowerBI restrictions and time constraints, prompts with certain IDs were first set to be shown on specific dates. However, as prompt IDs were randomly assigned and were refreshed when resources were changed or added by the teachers, this resulted in actual random instead of controlled prompting. This was changed after one week and set to hardcoded texts in prompts to prevent wrongful prompting. The prompts were selected based on the course in which the participant was enrolled and in which prompt group they were assigned to. To not overload the learner with prompts, only one prompt was displayed per day, resulting in 15 prompts in total.

4. Methods

Experimental Design

This study followed a randomized, mixed (within-between, 3x3) experimental design. The three dashboards discussed in Chapter 3 were used for the corresponding groups, namely the control group (Dashboard A), reflection prompt group (Dashboard B), or resource-related prompt group (Dashboard C). Participants were randomly assigned to one of the three groups. For the main hypotheses, the following differences between the three measurements in time (within factor) and between the groups (between factors) were measured: engagement (surveys) and motivation (surveys). The reason behind the three measurements in time is that prompts may cause different effects at different times (Berthold et al., 2007).

Those three moments in time took place prior to exposure to the dashboard (T0), after three days of access to the dashboard (T1), and after 10 days of access to the dashboard (T2). For H5 and H6, all surveys measured written help-seeking and active reflection. Furthermore, surveys two and three included feelings of autonomy while using the dashboard for underlying mechanisms considered by H3 and H4. Additionally, the third survey included measurements of time spent on the dashboard, usability, and perceived usefulness of the dashboard, alongside open questions for dashboard feedback. To create deeper insight into participant characteristics, the second survey also asked for additional data participants could opt out of, such as age, gender, study program, and years studying in higher education.

Privacy and Security

Canvas-interaction data (e.g., click-stream data), Panopto-interaction data (e.g., video views), and dashboard-interaction data were tracked automatically during the weeks that participants have access to the learning dashboard. Measurements of the data were conducted daily and were pseudonymized (e.g., student IDs, names, e-mail addresses, and personal comments/feedback were removed) to prevent directly identifiable data from being presented to the researcher. The study proposal was approved by the Ethical Review Board of the TU/e. Furthermore, a Data Protection Impact Assessment (DPIA) was drafted and approved through the privacy protocols of the university. Alongside the DPIA, an informed consent was drafted and approved (Appendix B). An additional Annex was also drafted and approved to incorporate the participant characteristics of gender, age, study year, and study program (Appendix C).

Participants

Prior to recruitment, a sensitivity analysis was executed using G*Power 3.1.9.4. The participants possible within the scope of the study would be N=83. The sensitivity analysis (ANOVA, repeated measures, within-between interaction effect, option "as in SPSS") indicated that with 83 participants, a medium effect size of f(U)=.31 (corresponding to d=.62) could be found.

Participants of this experiment were full-time students at the Technical University of Eindhoven in the fourth quartile of the academic year 2022-2023, following either the course Thinking & Deciding (0HV60) or USE Basic Theme: Ethics of Digital Futures and AI (0SAB0-EDF). The students were familiar with the university's online learning platform Canvas. All participants were at least 18 years old and could only participate in the experiment through either OHV60 or 0SAB0-EDF if they were enrolled in both. In total 41 participants registered and completed the first survey, of which 39 received a dashboard due to a technical issue and an error in one participant's student ID input. The 39 participants were randomly assigned to the control, reflection prompt, or resource-related prompt group, resulting in 13 participants per group. A total sample size of N=31 completed all three surveys (control: N=10; reflection: N=9; resource: N=12). This was less than the sensitivity analysis indicated, thus the power of this study will be low.

Measurements

Measurements for this study were conducted through the three surveys as discussed in the experimental design. An overview of which measures were conducted in which survey is presented in Table 5. In this section, the details of the measurements are described. All constructs with the specific scale items of the survey measurements can be found in Appendix D.

Table 5

Measurements per survey at T0, T1, and T2.

Survey 1 (T0)	**Survey 2 (T1)**	**Survey 3 (T2)**
Motivation	Motivation	Motivation
Engagement	Engagement	Engagement
Learning Strategies	Learning Strategies	Learning Strategies
Course Participation (0HV60 or 0SAB0-EDF)	Autonomy	Autonomy
	Age	Perceived Usefulness Dashboard
	Study Year	Perceived Usefulness Prompts (Prompt conditions only)
	Gender	Prompt Interaction Times (Prompt conditions only)
	Study Program	Dashboard Interaction Times
		Dashboard Usability
		Open questions

Motivation

Measurements of motivation were executed in surveys 1, 2, and 3. For this measurement, a combination of the Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich, Smith, Garcia & McKeachie (1991) was used together with the Situational Motivation Scale (SIMS) by Guay, Vallerand, & Blanchard (2000). The MSLQ was used to measure both intrinsic ($\alpha = .74$) and extrinsic goal orientation ($\alpha = .62$), for intrinsic and extrinsic motivation. Furthermore, the

SIMS was used to create a deeper measurement of intrinsic motivation with the intrinsic motivation subscale (α = .95).

Engagement

To measure engagement in the students, a combination of the MSLQ (Pintrich et al., 1991), the effort scale by Li (2012), and the Student Course Engagement Questionnaire (SCEQ) (Handelsman et al., 2005) was used. All three surveys included these same measurements. As not all statements were relevant to both courses, only statements relevant to both settings were selected. For example, in the 0SAB0-EDF course, there was no final exam, in this case, the reading material was mostly applied to current assignments instead of thoroughly studied throughout the course. Furthermore, the most important items were selected to keep the survey as brief as possible. The skills engagement (α = .82) and emotional engagement (α = .82) factors were used from the SCEQ. From both factors, the three most relevant items for the current setting were selected. For behavioral engagement, Li's (2012) effort scale (α = .85) was used together with the effort regulation subscale of the MSLQ (α = .69). Three items of the effort scale (Li, 2012) and one item from the MSLQ effort regulation subscale were selected to measure behavioral engagement. All levels of engagement (skill, emotional, and behavioral) together formed the engagement scale.

Learning Strategies

Learning strategies were measured through the learning strategy factors used in the study by Warr and Downing (2000) with a median Cronbach's alpha coefficient of .85 and .79 for two samples. The relevant factor for reflection was the active reflection factor, whereas the written help-seeking scale is relevant for actively seeking written material to study with. To keep the survey as brief as possible for the students, not all 10 items for active reflection were used. As Warr and Downing (2000) used the MSLQ elaboration (α = .76) and organization subscales (α =

.64) (Pintrich et al., 1991), the five items with the highest lambda-ksi scores were used (items 64, 69, and 81 for elaboration; items 32 and 62 from organization). For written help-seeking, all 5 items were kept. Learning strategies were also measured in all three surveys.

Autonomy

Measurements of autonomy were based on the autonomy scale by Betoret and Artiga (2011). The study based the autonomy scale on the SDT and found an internal consistency of α = .76. For the current study, the scale was slightly altered to make the questions relevant to the learning dashboard instead of a subject. The autonomy measurements were conducted in surveys 2 and 3.

Usability

Usability was exclusively measured in the third survey. The shortened System Usability Scale (SUS) by Lah and Lewis (2016) was slightly altered to be relevant to the study, meaning that the word *system* was replaced by the word *dashboard*. Lah and Lewis found that the 8-item scale had effects that were consistent with the original 10-item scale which has a reliability around α = 85 (Lewis & Sauro, 2009). Six items were selected to shorten the measurements and prevent irrelevant questions, for example, item 4 includes the “technical person”, but as the study was conducted at a technical university, thus the participant could already be considered as technical.

Perceived Usefulness

Hwang et al. (2013) used six items of technology perception from the study by Chu et al. (2010) to measure perceived usefulness, which had a Cronbach’s alpha of .95. Four items of the scale were used to measure both perceived usefulness of the overall dashboard and the perceived usefulness of the prompts. For this purpose, the text was also altered to state “learning dashboard” or “prompts” for relevance. The measurements of perceived usefulness were only included in the third survey.

Open Questions

In addition to the usability and perceived usefulness measurements in the third survey, open questions were posed to obtain the subjective experiences of the participants. These findings could be useful for future studies to improve student-facing dashboards and to investigate what the students liked, disliked, and would add to better support their learning experience.

Participant Characteristics

In the first survey, participants were asked to register through either the 0HV60 or 0SAB0-EDF course. This could additionally be used to investigate whether an effect exists for one course, but not the other. Furthermore, in survey 2, participants received an annex to the original informed consent, which asked for consent to additional information. If participants opted out of this, they could still participate in the study, but the additional questions were not posed. Additional data included gender, age, years studying in higher education, and study program. The purpose of this extra data was to explore the effects of prompts on students with certain characteristics.

Estimated Interaction

In survey 3, participants were asked to estimate the number of dashboard interactions as well as the minutes spent on the dashboard. Prompt groups additionally received these questions about prompt interactions.

Prompt Perception

The prompt conditions received two other additional questions asking how difficult they found the prompts and how much they trusted the prompts. Both questions could be answered on a 5-point Likert scale.

Procedure

The experiment ran fully online in the span of two weeks. Students at the Technical University of Eindhoven who were following the course 0HV60 or 0SAB0-EDF in the spring semester of 2023 were invited to participate. Students were made aware of the experiment by means of a short presentation in class and were later officially invited to register through an announcement on Canvas. Registration consisted of an information sheet and informed consent form (Appendix B), alongside the first out of three surveys in LimeSurvey. After 12 days registration closed and participants were randomly assigned to one of the three groups (control, reflection prompt, resource-related prompt). On Monday after closing of the registration, the participants received an e-mail with a link to their personal dashboard and were reminded of the dashboard link after one week. The dashboard was a Microsoft Power BI-based application embedded in a webpage and was accessible until Monday two weeks after the dashboard link was first received. The first day of the dashboard started on a Monday after lecture/working hours, therefore, instead of ending on Sunday, the dashboard was last updated on a Monday. Participants could access their personal dashboard through logging in with the student account of the TU/e. After having access to the dashboard for three days, the participants received an e-mail asking them to fill in the second survey. Prior to filling in the survey, they were asked to make sure they had interacted with the dashboard for at least five minutes. The second survey closed after 6 days and near the end of the second week of the study, the third survey opened. As late responses could result in a short time in between survey 2 and 3, participants were asked to make sure there were at least three days in between filling in these surveys. Again, participants were also asked to interact with the dashboard for at least five minutes prior to answering the third survey. Survey 3 closed after 6 days, which marked the end of the experiment. Only after completion of all three surveys, participants received 10 euros as compensation.

Data Preparation

The data was prepared and analyzed in StataBE 17.0 (StataCorp, 2021). Responses from the three conducted surveys were merged into one dataset. The data was arranged into long-format, resulting in one row for each measurement in time, thus three in total, for each participant that finished the study. For each scale, the interitem covariance was analyzed to inspect the reliability of the measurements. This was done for each point in time separately. Cronbach's alpha for each variable is shown in Table 6. A pairwise correlation comparison was executed to investigate whether particular items yielded low scores. For the engagement scale, the third behavioral engagement item ("*when course work is difficult, I give up or only study the easy parts*") had low correlation and Cronbach's alpha (α) for the scale consistently increased when it was removed. As this changed the $\alpha \approx .04$ for survey three, this item was removed for the analysis. Other scales remained intact due to low numbers of items, negative changes after item removal, or adequate interitem covariance. Only active reflection had $\alpha < .70$, though the Cronbach's alphas were slightly low, they were still acceptable to use for analysis. For all measurements, the mean score of all items combined created the variables to be used for analysis. Two items that were worded negatively for usability were reversed, however, based on the literature, no other items were reversed.

For the purpose of analysis of H5 and H6, active reflection and written help-seeking scores were divided into two groups, namely a high and low scoring group. Groups were separated at the median with the high group including the median number itself. This was performed with both the pre-survey measurements and the combined mean of all three measurements in time. As will be further discussed in the descriptive statistics of chapter five, the difference in motivation was investigated between the time points due to there being a significant difference between the control and resource-related condition in the pre-survey. Therefore, results from motivation in the second survey (T1) were subtracted from the motivation results from the first survey (T0). This was also executed for survey two (T2) minus survey one (T0). These calculations were performed in wide format, then for analysis, the long format was reinstated.

Table 6

Cronbach's alphas (α) of the survey scales per measurement, rounded up.

	Survey 1 (T0)	Survey 2 (T1)	Survey 3 (T2)
Motivation	.84	.86	.91
Engagement	.84 (incl. item 3: .83)	.81 (incl. item 3: .81)	.76 (incl. item 3: .72)
Active Reflection	.69	.67	.87
Written Help-Seeking	.71	.84	.87
Autonomy	*Not measured*	.81	.82
Usability	*Not measured*	*Not measured*	.86
Perceived Usefulness Dashboard	*Not measured*	*Not measured*	.91
Perceived Usefulness Prompts	*Not measured*	*Not measured*	.90

Prior to the analyses, normality, outliers, and homogeneity of variances were checked for the measured variables. Normality was tested for all variables, however, for the mean difference variables, both Stata's standard skewness and kurtosis test for normality and the Shapiro-Wilk W test rejected normality for the mean difference of T0 – T1. Through Tukey's ladder of powers transformations, no suitable transformation was given to transform for normality. Normality for engagement could also not be assumed according to these tests for normality. After multiple transformations that were given by Tukey's ladder of powers transformations, normality was still rejected. Homogeneity of variance was tested through Levene's test for the equality of variances. All variables showed equal variance except for the written help-seeking learning strategy at T2.

However, this was between dashboards, which was not relevant for testing of the current hypotheses. Outliers were tested at -2.5 to 2.5 in standardized scores for all variables. The outliers were checked separately for all time and dashboard combinations (e.g., control at T0, control at T1, etc.). Only the mean difference motivation variable of T0 – T1 showed one outlier in the resource-related condition. Exclusion of this outlier resulted in normality for the resource-related condition, which could not be assumed before. Therefore, it was excluded in tests for the T0 – T1 mean difference. Still, the reflection condition remained non-normal for this variable. For other variables, no outliers were discovered.

Data Analysis

To test whether prompts had an effect on motivation and engagement, various mixed-effects linear regression analyses were conducted. Where necessary, robust mixed-effects linear regressions were executed. For motivation the mean differences over time were compared between groups. This results in two separate variables to be tested against only two groups. An independent samples t-test was performed for the mean difference variable of which normality was assumed. For the mean difference variable that violated the normality assumption a non-parametric Wilcoxon rank sum test (Mann-Whitney test) was conducted. As engagement likewise violated the normality assumption, the “ehm” package (“Extended Mantel-Haenszel (Cochran-Mantel-Haenszel) Stratified Test of Association”) was installed in Stata to perform the non-parametric Friedman test. When statistically significant effects were found, post estimation tests were conducted using pairwise comparisons. Through one-way ANOVAs exploratory analyses were performed to investigate connections between variables such as student characteristics.

5. Results

Descriptive Statistics

In this section, the descriptive statistics of the variables are reported. Table 7 presents the unstandardized values of the variables for the pre-survey (T0). These descriptive statistics of the surveys at T1 and T2 can be found in Appendix F. Additionally, descriptive statistics of usability and perceived usefulness of the dashboard as well as perceived usefulness of the prompts are shown in Table 8.

The overall mean of estimated time in minutes spent on the dashboard was 13.5 minutes for all dashboards combined. For each dashboard separately, this was 14.8 minutes for the control condition, 13.4 for the reflection prompt condition, and 12.5 for the resource related prompt condition. Further descriptives of estimated time and numbers of interactions are presented in Table 9. More details about course division, gender, and other participant characteristics as well as boxplots of the scale variables are located in Appendix F.

Table 7

Descriptive statistics of the pre-survey measurements, with “DA” as control dashboard, “DB” as reflection prompt dashboard, and “DC” as resource-related prompt dashboard.

		Range	M	Mdn	SD	Var.	Skew.	Kurt.
Motivation	DA DB DC	1.5 – 5 3.75 – 5.42 3.33 – 6.33	3.83 4.49 4.68	3.92 4.42 4.63	1.01 .6 .89	1.01 .36 .8	-1.09 .36 .3	3.95 1.92 2.42
Engagement	DA DB DC	1.89 – 5 3.11 – 5.25 2.22 - 5	3.94 4.18 3.94	4.28 4.11 4.06	.96 .62 .88	.92 .38 .78	-1.18 -.003 -.58	3.22 2.6 2.18
Active Reflection	DA DB DC	2.8 – 5.8 3.2 – 7 4.4 – 6.6	4.4 5.22 5.52	4.4 5 5.5	.74 1.08 .67	.55 1.16 .67	-.38 -.23 -.05	4.25 2.92 1.86
Written Help-Seeking	DA DB DC	2.4 – 4.4 2.6 – 4 1.8 – 4.2	3.34 3.11 3.08	3.1 3 3.3	.7 .51 .81	.49 .26 .66	.49 .72 -.38	1.9 2.09 1.83

Table 8

Descriptive statistics of the usability and perceived usefulness measurements in the third survey (T2), with "DA" as control dashboard, "DB" as reflection prompt dashboard, and "DC" as resource-related prompt dashboard.

		Range	M	Mdn	SD	Var.	Skew.	Kurt.
Usability	DA DB DC	1.17 – 4.17 2.67 – 4.67 1.33 – 4.83	3.02 3.65 3.26	3.42 3.83 3.67	1.01 .68 1.14	1.02 .46 1.3	-.8 -.1 -.38	2.34 1.76 1.87
Perceived Usefulness Dashboard	DA DB DC	2 – 5 1.5 – 5.25 1.75 – 5.5	3.3 3.56 3.85	3.5 3.5 4.25	.98 1.04 1.33	.97 1.09 1.78	.02 -.45 -.45	2.08 3.17 1.66
Perceived Usefulness Prompts	DB DC	1.25 – 4.75 2 – 5.25	3.31 3.78	3.5 3.88	1.16 1.05	1.36 1.11	-.48 -.42	2.12 2.06

Table 9

Descriptive statistics of estimated minutes measurements in the third survey (T2), with "DA" as control dashboard, "DB" as reflection prompt dashboard, and "DC" as resource-related prompt dashboard.

	DA mean	DB mean	DC mean	Overall mean
Minutes on dashboard	14.8	13.44	12.5	13.5
Times dashboard visited	3.7	3.67	3.67	3.68
Times interacted with prompts	*Not applicable*	3.78	2.5	3.05

Motivation

As the descriptive statistics of motivation already showed substantial differences in mean for the pre-survey, two independent samples t-tests were conducted. The first test compared the control condition to the combined prompt conditions and the second compared the prompt conditions to one another. For the control versus the prompt conditions (received prompt condition) the pre-survey showed a significant effect (t (29) = -2.37, p = .03), but the prompt conditions as opposed to one another did not (t (19) = -0.55, p = .59). Therefore, the mean difference between measurements in time was compared between the control and received prompt group. Mean difference was calculated through subtracting T1 from T0 and T2 from T1. This resulted in two mean difference variables. As the mean difference of T0 – T1 was non-normal, but variances were equal, a two-sample Wilcoxon rank-sum (Mann-Whitney) test was performed. No statistical significance was found between the two groups (z = -.31, p = .76). As assumptions were met for the second mean difference variable (T1 – T2), a two-sample t-test was conducted which likewise indicated that there was no statistical difference between the groups (t (29) = .41, p = .69).

As the pre-survey showed no significance between the two prompt groups a mixed-effects linear regression was performed to investigate the difference between the two over time. No significant difference between the two experimental conditions (z = .49, p = .62), nor an interaction effect of time and condition were found. However, a statistically significant effect of time was found. A postestimation analysis was performed of a pairwise comparison of effects. This showed an effect for both T0 versus T1 (z = -3.04, $p < .01$) and T1 versus T2 (z = 2.12, p = .03), but not between the pre-survey (T0) and the third survey (T2) (z = -.92, p = .36). The effect for T0 versus T1 is negative and the effect of T1 versus T2 is positive as is shown in the margin plot in Appendix G. Furthermore, to explore the underlying mechanisms of autonomy, the centered autonomy variable was added to the model. No main effect was found for autonomy (z = -.02, p = .98), and no interaction effect with the dashboard was found (z = .99, p = .32). However, an interaction effect between time and the centered autonomy variables were found (z = -2.23, p = .03). In a post prediction, the margins showed significant positive slopes for autonomy below and at the mean, Stata output is shown in Appendix G. No effects were found for usability, dashboard usefulness, and prompt usefulness (Appendix G). Merely exploring effects of characteristic on motivation, one-way ANOVAs were performed examining solely T2. No significant differences were found between gender, years studying, course, and study program.

Engagement

Engagement measures showed no statistical difference for the pre-survey, but normality was rejected, thus a Friedman analysis was conducted. The Friedman test comparing the control condition to the received prompt conditions resulted in a non-significant value ($Q\ (1) = .24$, $p = .63$). When comparing the two prompt groups, there was likewise no statistical significance indicated ($Q\ (1) = .04$, $p = .84$). The Friedman test did not allow analysis of interactions. Therefore, the interaction between time and dashboard condition were investigated through a robust mixed-effects linear regression. An effect was found between engagement and time T2 ($z = -10.92$, $p < .001$), but no interaction effect between the dashboard conditions and time was indicated. In a pairwise comparison an effect between T0 and T2 ($z = -11.86$, $p < .01$) as well as an effect between T1 and T2 ($z = -13.08$, $p < .01$) are found. As is shown in the margin plot in Appendix G, both effects are negative. Adding autonomy to this mixed model results in a main effect for autonomy ($z = 2.10$, $p =.04$). A prediction showed that a positive correlation was found between engagement and autonomy (Appendix G). In exploratory models, adding dashboard usability to the original model showed both a main effect for dashboard usability on engagement ($z = 3.35$, $p < 0.1$) as well as an interaction effect for the reflection dashboard ($z = -1.64$, $p = .03$). However, the linear predictions indicated no significant effects for the interactions (Appendix G). Through exploratory one-way ANOVAs at T2, no significant effects were found for gender, age, study year, course, and study program. Connections between motivation and engagement were roughly explored through a one-way ANOVA ($z = 7.43$, $p = 0.01$) at T2, resulting in significant effects.

Learning Strategies

Mixed-effects linear regressions were performed to test whether certain learning strategy scores had an effect on motivation and engagement in combination with the relevant dashboard. As engagement violated normality assumptions, the robust version of the analysis was executed for this dependent variable. For the reflection prompt condition, the active reflection learning strategy was examined. The written help-seeking learning strategy was examined in combination with the resource-related prompt condition. For both learning strategies, the students were divided into two groups divided at the median (low and high). This was executed for both the pre-score and the overall mean score of the students. For active reflection, this resulted in 5 low- and 4 high-scoring students in both the pre- and overall score groups for the reflection prompt dashboard. Division in the resource-related prompt group for written help-seeking scores was 5 low-scoring and 7 high-scoring students in the pre-survey. For the overall mean scores of written help-seeking within this dashboard resulted in an equal division of 6 participants per group.

Effects for time were again found in these models for motivation, as they were discussed previously within this chapter, the main effects of time will not be discussed again at this time. No main nor interaction effects were found for active reflection in the reflection prompt dashboard. Likewise, no effects of written help-seeking within the resource-related prompt group were found on motivation. However, main effects on engagement were found for both the pre-scores ($z = 2.73$, $p < 0.01$) and the overall mean scores ($z = 3.36$, $p < 0.01$) for written help-seeking within the resource-related prompt condition. Through a pairwise comparison for the overall mean scores, the contrast of 1.17 ($z = 4.30$, $p < .01$) showed that people scoring high on active reflection also had higher motivation scores. Nonetheless, no interaction effects were found between time and written help-seeking (high vs. low). Results of the ANOVAs are shown in Appendix G.

Dashboard Evaluations

Dashboard evaluations were both carried out through measures of usability and perceived usefulness as well as qualitative findings through open questions. To investigate differences in usability between the dashboards, a one-way ANOVA was performed for which no statistically significant difference was found (F = (2, 28) = .98, p = .39). One-way ANOVAs were also conducted for both the perceived usefulness of the dashboard (F = (2, 28) = .64, p = .54) and perceived usefulness specifically for the prompts (only applicable for the experimental conditions) (F = (1, 19) = .92, p = .35). Through one-way ANOVAs no effects were found for estimations of number of visits, minutes spent on the dashboard, and number of prompt interactions on usability and perceived usefulness measures. Through exploratory analyses conducted through one-way ANOVAs, significant differences were found for prompt difficulty and prompt trust on dashboard usability and dashboard usefulness (Appendix G). Furthermore, a significant effect was found for prompt trust on prompt usefulness (Appendix G). However, for these latter exploratory analyses, all effect sizes were below an eta-squared of .4.

Qualitative Findings

Qualitative findings were investigated through three questions in the third survey (Appendix D). The most prominent results are reviewed in this section. The least liked, most liked, and suggested improvements aspects of the dashboards are discussed through recurring themes within the open questions.

Usability, Interactivity, and Aesthetics

Within the three dashboard groups conflicting statements about the usability of the dashboard were found. Participants from all groups reported having difficulty understanding the dashboard at first, coming from five participants from the control condition, one from the reflection prompt condition, and five from the resource-related prompt condition. One participant said that they “did not like all the other applications on the website. I had no idea if the dashboard was just the overview page or the whole site.” A suggestion by another student was to “maybe host it on its own to remove the confusing PowerBI sidebar.” As the dashboard was hosted in an online Microsoft PowerBI environment instead of a full-page website, this may have caused additional unnecessary distractions. In contrast two individuals from the control, two from the reflection prompt, and two from the resource-related prompt condition stated that the dashboard was clear and concise. Four individuals (1 control, 2 reflection, 1 resource) liked the aesthetics of which one participant stated that “the aesthetic is similar to that of canvas which gives it an air of familiarity.” Multiple participants suggested that for improvement, a short instructional guide could be added to help them understand how the dashboard works. For all three dashboards combined, four participants also stated that they did not like that the dashboard was mostly purely visual instead of interactive. They suggested that as an improvement, more interactions with, for instance more buttons and filters could be made.

Personal Relevance, Usefulness, and Support

The recurring themes of all dashboards were the relevance and usefulness of features. Especially the control condition stated that they could already find most of the information on Canvas and that the dashboard was not relevant for them to use. In general, 5 participants did not find the overall dashboard useful (4 control, 1 resource). Others pointed out specific features such as the submissions visual (1 reflection, 2 resource) and the number of items accessed (reflection 2, resource 4) were not useful. In contrast, participants also liked the submissions visual (1 control, 2 reflection). For example, one participant stated that they “liked the 'donut pie chart' for graded and submitted assignments; it was a really nice overview to have so you can know how many grades are you still waiting for.” Contrasting attitudes about the number of times items were accessed were also observed as some participants indicated they liked the feature (4 control, 4 resource). One individual explained that they liked “the structured way of presenting the different types of educational material I use. In that way, I can observe my learning path and use it properly.”

In the reflection prompt condition one individual stated: “I'm not going to watch the video just because it says, ‘Would you like to see the video of this lesson?’” Three participants in the resource-related prompt condition pointed out that they found the prompts useful with one individual stating: “I had not looked at the week 9: lectures and exam info by myself” though for some “it also gave suggestions of activities I had already done.” A suggestion by a participant from the resource-related prompt group was that an improvement could be “more prompts about the ideal studying schedule, and if the student is on track or not” since “right now, the prompts felt quite random and out of place.” An overall comment from an individual in the resource-related prompt condition was “the dashboard helped me to stay on track with my studies and organized.”

The feature many participants found useful (2 control, 2 reflection, 2 resource) was the timeline with upcoming deadlines, however, as at certain times there were no upcoming Canvas deadlines published, the timeline appeared empty, which two participants pointed out. Suggestions to improve relevance and usefulness were adjustable settings for the visuals (e.g., Canvas usage or deadline period to show). Additional features that were suggested to improve the dashboard were: a timeline of scheduled lectures with the corresponding lecture slides, predictions of the upcoming workload, an overview of all of the course material that should be studied, and percentages of the assignments completed to see how close the learner is to their target score.

6. Discussion

The current study investigated whether incorporating textual feedback through prompts in a student-facing dashboard could have effects on motivation and engagement. Theoretical aspects of the study were largely based on the self-determination theory (SDT) and the self-regulated learning theory (SRL). Furthermore, prior research on feedback and prompts (sometimes called nudges) was incorporated and formed the basis for the texts shown on the dashboards for the experimental conditions. Additionally, a relevant underlying mechanism was examined for each of the two experimental conditions. Compared to a control group, the mere effect of prompts was investigated, as well as the differences between the two prompt groups. The proposed research question to investigate these effects was: “How do reflection and resource-related prompts on a student-facing dashboard affect course engagement and learning motivation?”

Differences in motivation and engagement were expected between the three conditions. As there is limited knowledge about textual feedback on student-facing dashboards and prior literature on prompts does show promising results, this does not mean no such effect exists. Nevertheless, this study observed no such effects. Still, other variables showed statistically significant differences through the linear multi-level effects models and one-way ANOVAs, that are worth exploring further.

General Findings and Connections to the Literature

For the hypotheses H1 and H3, engagement scores of the participants were investigated. The p-values indicated no effects between receiving prompts and not receiving prompts. Likewise, no significant effects were found between the two experimental (prompt) conditions. Therefore, no support was found for either of the hypotheses of H1 or H3. Nevertheless, main effects of time and dashboard usability on engagement were found. There was a significant decrease in engagement over time with students engaging less near the end of the study. Furthermore, usability findings indicated that people who found had higher scores for usability of the dashboard also had better engagement scores. A main effect was found for autonomy on engagement where a positive relationship was found between the variables. Thus, low autonomy scores were correlated with lower engagement scores, and high autonomy scores were correlated with higher engagement scores. According to the literature motivation and engagement are related (Deci & Ryan, 2000; Stroet et al., 2013), whereas engagement may be the behavioral outcomes of motivation. If this is indeed the case, the findings can also be related to the SDT. SDT states that less autonomy results in less motivation, therefore less autonomy could also result in less engagement. However, further research on this interaction is needed to draw inferences.

Motivation scores were examined to investigate support for H2 and H4. However, no significant difference was found between the control versus combined experimental conditions, nor between the two experimental conditions. Thus, no support was found for H2 and H4. Similar to the findings on engagement, effects of time were also found on motivation when comparing the two experimental conditions. However, the effect did not show the same trend as for engagement. Scores had significant changes between T0 and T1 as well as T1 and T2. The post analysis demonstrated a drop in motivation at T1. Thus, somewhere in week one of the experiment, students were less motivated than at the other times. Furthermore, an interaction effect was found between autonomy and time on motivation. This effect predicted that individuals perceiving low and average autonomy had more increase in motivation over time (T1 vs T2). This conflicts with the SDT that suggests that motivation would decrease, when the individual feels less autonomy (Deci et al. 1996; Deci & Ryan, 2012; Ryan & Deci, 2020; Schumacher & Ifenthaler, 2018a). In line with the literature, an effect was found between motivation and engagement (Deci & Ryan, 2000;

Stroet et al., 2013). However, as the variables may have a complex interconnection, thus deeper understanding of this relationship was not in the scope of this study.

For H5 and H6, learning strategies were examined. As the effects of prompts did not significantly change over time, no inferences can be made for increases in motivation and engagement in combination with the learning styles. Thus, no supporting findings were attained for H5 and H6. However, an effect was found for written help-seekers within the resource-related dashboard. Individuals scoring high on written help-seeking had higher engagement scores than low-scoring individuals. Though statement cannot be made about whether the effects occur due to the dashboard, or the prompts like in the study by Pieger and Bannert (2018), the findings do relate to literature stating that learning characteristics may provide different outcomes on motivation and engagement (Linnenbrink & Pintrich, 2003; Pieger & Bannert, 2018; Warr & Downing, 2000). Furthermore, Jivet et al. (2021) found that help-seeking skills predicted the learners' choice to monitor their discussion engagement. Consequently, these learners might be more actively engaging by seeking help through these discussions. Similarly, in the current study, high engagers could seek more help, nonetheless, this requires further investigation.

The dashboard evaluations indicated no significant differences between the dashboards. This could be due to the small difference between the conditions. An effect was found for both prompt trust and difficulty on the usability and usefulness of the dashboard indicating that more trust resulted in a better experience. However, this was only relevant for the two experimental groups. Prompt trust also had an effect on the usefulness of the prompts, as more trust in the prompts is associated with more usefulness. Yet, effect sizes were small and prompt trust and prompt difficulty were only measured through a single item/question. Still, the effects point out that when aiming for behavioral change, trust and difficulty of the feedback should be factors to take into account.

As for the qualitative findings, indicated that participants did not always comply with the reflection prompts. Even though the most prominent statement in these findings was not in line with the received prompts within the reflection condition, it did point out that an explanation of why the prompts could support their learning process might be beneficial. Bannert et al. (2009) explained the usefulness of metacognitive learning strategies prior to exposure to prompts and did find significant effects. As some felt that the resource-related prompts felt random and out of place, similar methods as in the studies by Brown et al. (2022) and Brown et al. (2023) can be applied. Namely, provide material recommended by teachers and tailoring nudges to the specific student's learning process, such as only prompting unseen learning material. The qualitative findings for the visuals indicate that even though the visuals were clear and concise, some would like to tailor them to their specific needs. Other qualitative findings were in line with the study by Schumacher and Ifenthaler (2018b) as students mostly liked learning suggestions and reminders for deadlines and would desire to have workload estimations included. The submissions visual received mixed responses, yet Jivet et al., (2021) do show that students prefer these types of indicators. Since feelings were mixed, more concise indicators of completed learning activities could be more supportive, as no uncompleted assignments were currently presented, but submitted and graded assignments.

Limitations

The current study aimed for 83 participants, which according to a sensitivity analysis could have led to a medium effect size of f(U)=.31 (corresponding to d=.62). However, the actual sample size was N=31 for all three surveys. Due to this, the data was more prone to small changes and could have caused unreliable results. Furthermore, the sample may not be representative of the entire population due to both its size and being sampled from only two courses at the Technical University of Eindhoven. As the groups were randomized by the university's IMS department, the groups were not directly controlled by the researcher. The pre-survey already showed a significant difference in motivation between the control and resource-related condition. Therefore, the data had to be manipulated further to find the mean differences between motivation at the points in time, to investigate whether the changes were significant between groups. This made it more challenging to analyze the data through the intended method. However, for engagement, no effects were found for the pre-survey, thus rearranging groups possibly would have affected this variable if both were not equally considered.

As a result of time constraints, the dashboards were only available for approximately two weeks. In order to see significant effects of such a small difference in stimuli between the groups, a longitudinal experiment could be required. In addition, given that only subjective survey measurements were used and no observational data from the learning environment were analyzed, the measurements could not be verified with factual Canvas data. Through this clickstream data, behavioral engagement can be measured, which could be more reliable than survey data and may show different results.

The dashboard itself was not able to report real-time data. As a consequence of the vast amount of Canvas data streams coming in, the dashboard data had a delay of at least two days. As Hattie and Timperley (2007) stated, real-time feedback could better support learners, thus this may have led to the dashboard feeling less supportive. Moreover, the dashboard was only updated once every day and only on Monday to Friday. Due to constraints of the data connection, updates were manually executed by the IMS department, and this could not be accomplished at consistent times.

The researcher was not able to update and publish the dashboards freely as they had no rights to perform these actions. Therefore, when students visited the dashboard at the same time each day, as a result, the same data could still be presented on two consecutive days. Consequently, this may have lowered the effects of prompts as well as usefulness of both the prompts and the dashboard itself.

While automating the prompt with IDs that were assigned by the Microsoft PowerBI environment, the IDs were changed at every change in the online resources, resulting in actual random prompting. This caused an error in the prompts one day for both prompt groups during the Sunday of the first week. A mix-up occurred between groups and the resource-related condition received a reflection prompt and vice versa. Immediately when this was discovered, this issue was solved on Monday morning. Additionally, a change in DAX code was made to show prompts based on their actual text to prevent further issues. This type of automation is only possible with non-changeable IDs, however, as resources and texts were connected in PowerBI internally, IDs could possibly not be assigned in a set way. Therefore, executing the prompts based on the name of the resource and prompt ID is suggested. This also gives control to course administrators and teachers to show important learning material for specific days. Additionally, through this data connection, published assignments stayed unpublished within the Canvas tables when locally refreshing the Microsoft PowerBI environment, therefore causing out of date information, restricting further automation.

Students might also have received prompts in the resource-related condition that they had previously seen. Though prompting was also done for revision, these revision prompts were not executed for material that was still relevant for the specific week. Verifying whether a student has already viewed a resource is feasible within the environment but was not implemented due to time constraints. Resource-related prompts may be more supportive and effective if they are relevant to the student's learning process, thus adding this could be beneficial.

Implications and Future Research

The current study proposes a setup of prompts on dashboards that was based on prior research that did find significant effects. Therefore, the effects may still be transferable. Significant effects may not have been found between the dashboard groups, but effects were observed between time and motivation as well as time and engagement. As the between-group differences were small, a longitudinal study may be more adequate in examining the between-group differences, as well as differences in motivation and engagement over time, as effects of prompts may differ over time (Berthold et al., 2007). Moreover, a bigger sample size can create more reliable findings. In addition, more specific prompt types may have different results (Schumacher & Ifenthaler, 2021).

The interaction effect between autonomy and time on the dependent variable of engagement, should likewise be investigated further. Moreover, effects of written help-seeking were found on engagement. This shows that it is important to consider individual differences in learning strategies for future studies.

As effects were found for prompt trust and prompt difficulty on both the usability and perceived usefulness of the dashboard within the experimental conditions, future studies could look into which prompts create more trust including the underlying mechanisms. Additionally, instead of a single item, a scale of trust and difficulty should be used to evaluate the prompts for increased reliability.

In future research, clickstream data could be used to measure behavioral engagement and observe behavior combined with subjective survey data (Dixson, 2015; Li et al., 2020; Vytasek et al., 2019). This can also further investigate relationships between learning strategies and online engagement, when measuring learning strategies through surveys and connecting these measures with factual online engagement data. Furthermore, as Hattie and Timperley (2007) also stated, real-time feedback can be more supportive for learners. Thus, creating a dashboard with real-time or at least a consistent daily update with the latest data may be beneficial.

The resources for the prompts in this study were selected by the researcher. As in the study by Brown et al. (2023), to improve support within the specific course, teachers should be included to point out the most important learning materials per week. Consequently, a priority list can be created to show the most important resource first. If a teacher cannot be involved, prompts could be based on high-performers and their most viewed resource. However, it should be considered that when students are aware of this, it may affect motivation and engagement (Corrin & de Barba, 2015; Davis et al., 2017; Kim et al., 2015; Tan et al., 2018).

Additionally, checking whether an individual has viewed the specific resource can increase personalized support. The latter is based on the qualitative findings that indicated that some participants had already viewed certain learning material and had no use for the resource-related prompt pointing to it. Based on the qualitative findings that are in line with previous literature, design improvements can be made in both practical and research applications. Additional support can be provided through presenting an overview of learning material to study as well as workload estimations for specific assignments or exams. At this time, no condition without a learning dashboard existed, thus it could not be examined whether the dashboard already had an effect on student behavior by itself. For future research, the implemented dashboard designs, together with the suggested improvements, can provide serve as a basis to investigate whether this dashboard implementation can support students compared to no dashboard or other implementations.

7. Conclusion

The findings of the current study indicate that both engagement and motivation may change over time. Motivation showed fluctuations and engagement showed decrease as measured in three points in time. An effect of prompt trust and prompt difficulty was observed in relation to dashboard usability and perceived usefulness measures. This indicates that both trust and difficulty are important variables to consider when prompting students to change their behavior. Though learning strategies showed no increase over time, written help-seeking was positively correlated with engagement within the resource-related prompt condition. Furthermore, a positive correlation between autonomy and engagement was observed. Additionally, an interaction effect was found of autonomy and time on motivation, conflicting slightly with previous literature. Furthermore, no statistical evidence was provided for effects between prompts and no-prompts, nor between reflection prompts and resource-related prompts, when integrated in a student-facing dashboard. As this study does provide a new approach and elaborative design description, it is a valuable contribution to the field of learning analytics with respect to learning dashboards. In addition, the study highlights the need for further research to broaden the understanding about underlying mechanisms of effects on the student for both textual prompts and learning dashboards. Dashboard evaluations further provide suggestions on how to improve future dashboard designs.

References

Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. A. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. Elsevier BV. https://doi.org/10.1016/j.edurev.2022.100489

Bannert, M. (2006). Effects of Reflection Prompts When Learning with Hypermedia. Journal of Educational Computing Research, 35(4), 359–375. https://doi.org/10.2190/94V6-R58H-3367-G388

Bannert, M., Hildebrand, M., & Mengelkamp, C. (2009). Effects of a metacognitive support device in learning environments. Computers in Human Behavior, 25(4), 829–835. https://doi.org/10.1016/j.chb.2008.07.002

Bannert, M., Sonnenberg, C., Mengelkamp, C., & Pieger, E. (2015). Short- and long-term effects of students' self-directed metacognitive prompts on navigation behavior and learning performance. Computers in Human Behavior, 52, 293–306. https://doi.org/10.1016/j.chb.2015.05.038

Berthold, K., Nückles, M., & Renkl, A. (2007). Do learning protocols support learning strategies and outcomes? The role of cognitive and metacognitive prompts. Learning and Instruction, 17(5), 564–577. https://doi.org/10.1016/j.learninstruc.2007.09.007

Betoret, F. D., & Artiga, A. G. (2011). The Relationship among Student Psychological Need Satisfaction, Approaches to Learning, Reporting of Avoidance Strategies and Achievement. Electronic Journal of Research in Educational Psychology, 9, 463-496.

Blumenstein, M., Liu, D., Richards, D., Leichtweis, S., & Stephens, J. (2018). Data-informed nudges for student engagement and success. California Digital Library (CDL). https://doi.org/10.31234/osf.io/qjmpn

Bodily, R., & Verbert, K. (2017). Review of Research on Student-Facing Learning Analytics Dashboards and Educational Recommender Systems. IEEE Transactions on Learning Technologies, 10(4), 405-418. https://doi.org/10.1109/TLT.2017.2740172.

Brdnik, S., Podgorelec, V., & Šumak, B. (2023). Assessing Perceived Trust and Satisfaction with Multiple Explanation Techniques in XAI-Enhanced Learning Analytics. Electronics, 12(12), 2594. MDPI AG. https://doi.org/10.3390/electronics12122594

Brown, A., Basson, M., Axelsen, M., Redmond, P., & Lawrence, J. (2023). Empirical Evidence to Support a Nudge Intervention for Increasing Online Engagement in Higher Education. Education Sciences, 13(2), 145. MDPI AG. https://doi.org/10.3390/educsci13020145

Brown, A., Lawrence, J., Basson, M., Axelsen, M., Redmond, P., Turner, J., Maloney, S., & Galligan, L. (2022). The creation of a nudging protocol to support online student engagement in higher education. Active Learning in Higher Education, 146978742110390. SAGE Publications. https://doi.org/10.1177/14697874211039077

Chu, H. C., Hwang, G. J., Tsai, C. C., & Tseng, J. C. (2010). A two-tier test approach to developing location-aware mobile learning systems for natural science courses. Computers & Education, 55(4), 1618-1627.

Clow, D. (2012). The learning analytics cycle. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge. LAK 2012: Second International Conference on Learning Analytics and Knowledge. ACM. https://doi.org/10.1145/2330601.2330636

Corrin, L., & de Barba, P. (2015). How do students interpret feedback delivered via dashboards? In Proceedings of the Fifth International Conference on Learning Analytics And Knowledge. LAK '15: the 5th International Learning Analytics and Knowledge Conference (pp. 81–85). ACM. https://doi.org/10.1145/2723576.2723662

Data Dictionary For The Canvas Data warehouse. Canvas Data Portal. (n.d.). https://portal.inshosteddata.com/docs

Davis, D., Jivet, I., Kizilcec, R. F., Chen, G., Hauff, C., & Houben, G.-J. (2017). Follow the successful crowd. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference. LAK '17: 7th International Learning Analytics and Knowledge Conference (pp. 448–452). ACM. https://doi.org/10.1145/3027385.3027411

Deci, E. L., & Ryan, R. M. (2000). The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/s15327965pli1104_01

Deci, E. L., & Ryan, R. M. (2012). Self-determination theory. In Handbook of Theories of Social Psychology, 1, 416-436. SAGE Publications Ltd.

Deci, E. L., Ryan, R. M., & Williams, G. C. (1996). Need satisfaction and the self-regulation of learning. Learning and Individual Differences, 8(3), 165–183. https://doi.org/10.1016/s1041-6080(96)90013-8

Dixson, M. D. (2015, August 31). Measuring student engagement in the online course: The online student engagement scale (OSE). Online Learning. https://eric.ed.gov/?id=EJ1079585

Duan, X., Wang, C., & Rouamba, G. (2022). Designing a Learning Analytics Dashboard to Provide Students with Actionable Feedback and Evaluating Its Impacts. In Proceedings of the 14th International Conference on Computer Supported Education. 14th International Conference on Computer Supported Education (pp. 318–325). SCITEPRESS - Science and Technology Publications. https://doi.org/10.5220/0011116400003182

Feild, J. (2015, May 31). *Improving student performance using Nudge Analytics.* International Educational Data Mining Society. https://eric.ed.gov/?q=ED560905&id=ED560905

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the Concept, State of the Evidence. Review of Educational Research, 74(1), 59–109. American Educational Research Association (AERA). https://doi.org/10.3102/00346543074001059

Garcia, T., & Pintrich, P. R. (1996). The Effects of Autonomy on Motivation and Performance in the College Classroom. Contemporary Educational Psychology, 21(4), 477–486. https://doi.org/10.1006/ceps.1996.0032

Greller, W., & Drachsler, H. (2012). Translating Learning into Numbers: A Generic Framework for Learning Analytics. Educational Technology & Society, 15, 42-57.

Gentner, N., & Seufert, T. (2020). The Double-Edged Interactions of Prompts and Self-efficacy. Metacognition Learning, 15, 261–289. https://doi.org/10.1007/s11409-020-09227-7

Guay, F., Vallerand, R. J., & Blanchard, C. (2000). In Motivation and Emotion (Vol. 24, Issue 3, pp. 175–213). Springer Science and Business Media LLC. https://doi.org/10.1023/a:1005614228250

Handelsman, M. M., Briggs, W. L., Sullivan, N., & Towler, A. (2005). A Measure of College Student Course Engagement. The Journal of Educational Research, 98(3), 184–192. Informa UK Limited. https://doi.org/10.3200/joer.98.3.184-192

Hattie, J., & Timperley, H. (2007). The Power of Feedback. Review of Educational Research, 77(1), 81–112. https://doi.org/10.3102/003465430298487

Hawthorne, K. A., Bol, L., Pribesh, S., & Suh, Y. (2015). *Effects of motivational prompts on motivation, effort, and performance on a low-stakes standardized test.* Research & Practice in Assessment. https://eric.ed.gov/?q=EJ1064767&id=EJ1064767

Hellings, J., & Haelermans, C. (2022). The effect of providing learning analytics on student behaviour and performance in programming: a randomised controlled experiment. Higher Education, 83, 1–18. https://doi.org/10.1007/s10734-020-00560-z

Hu, Y.-H., Lo, C.-L., & Shih, S.-P. (2014). Developing early warning systems to predict students' online learning performance. Computers in Human Behavior, 36, 469–478. https://doi.org/10.1016/j.chb.2014.04.002

Hwang, G.-J., Yang, L.-H., & Wang, S.-Y. (2013). A concept map-embedded educational computer game for improving students' learning performance in natural science courses. Computers & Education, 69, 121–130. Elsevier BV. https://doi.org/10.1016/j.compedu.2013.07.008

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. The Internet and Higher Education, 47, 100758. https://doi.org/10.1016/j.iheduc.2020.100758

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate. In Proceedings of the 8th International Conference on Learning Analytics and Knowledge. LAK '18: International Conference on Learning Analytics and Knowledge. ACM. https://doi.org/10.1145/3170358.3170421

Jivet, I., Wong, J., Scheffel, M., Valle Torre, M., Specht, M., & Drachsler, H. (2021). Quantum of Choice: How learners' feedback monitoring decisions, goals and self-regulated learning skills are related. In LAK21: 11th International Learning Analytics and Knowledge Conference (pp. 276–285). ACM. https://doi.org/10.1145/3448139.3448179

Kauffman, D. F., Ge, X., Xie, K., & Chen, C.-H. (2008). Prompting in web-based environments: Supporting self-monitoring and problem-solving skills in college students. Journal of Educational Computing Research, 38(2), 115–137. https://doi.org/10.2190/ec.38.2.a

Kim, J., Jo, I.-H., & Park, Y. (2015). Effects of learning analytics dashboard: analyzing the relations among dashboard utilization, satisfaction, and learning achievement. Asia Pacific Education Review, 17(1), 13–24. https://doi.org/10.1007/s12564-015-9403-8

Lah, U., & Lewis, J. R. (2016). How Expertise Affects a Digital-Rights-Management-Sharing Application's Usability. IEEE Software, 33(3), 76–82. Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/ms.2015.104

Lear, J. L., Ansorge, C., & Steckelberg, A. L. (2010). Interactivity/Community Process Model for the Online Education Environment. Journal of Online Learning and Teaching, 6(1). https://jolt.merlot.org/vol6no1/lear_0310.pdf

Lewis, J. R., & Sauro, J. (2009). The factor structure of the system usability scale. In Human Centered Design: First International Conference, HCD 2009, Held as Part of HCI International 2009, San Diego, CA, USA, July 19-24, 2009 Proceedings 1 (pp. 94-103). Springer Berlin Heidelberg.

Li, Q., Baker, R., & Warschauer, M. (2020). Using clickstream data to measure, understand, and support self-regulated learning in online courses. The Internet and Higher Education, 45, 100727. https://doi.org/10.1016/j.iheduc.2020.100727

Lilian K., (2012). A study of the attitude, self-efficacy, Effort and Academic Achievement of City U students towards research methods and statistics. Discovery student E-Journal, 1, 154-183.

Linnenbrink, E. A., & Pintrich, P. R. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. Reading & Writing Quarterly, 19(2), 119–137. https://doi.org/10.1080/10573560308223

Lodge, J. M., Panadero, E., Broadbent, J., & de Barba, P. G. (2018). Supporting self-regulated learning with learning analytics. In Learning Analytics in the Classroom (pp. 45–55). Routledge. https://doi.org/10.4324/9781351113038-4

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. Computers in Human Behavior, 47, 90–97. https://doi.org/10.1016/j.chb.2014.07.013

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. Computers & Education, 54(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Matcha, W., Uzir, N. A., Gasevic, D., & Pardo, A. (2020). A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. IEEE Transactions on Learning Technologies, 13(2), 226–245. https://doi.org/10.1109/tlt.2019.2916802

Müller, N. M., & Seufert, T. (2018). Effects of self-regulation prompts in hypermedia learning on learning performance and self-efficacy. Learning and Instruction, 58, 1–11. https://doi.org/10.1016/j.learninstruc.2018.04.011

Moos, D. C., & Bonde, C. (2016). Flipping the Classroom: Embedding Self-Regulated Learning Prompts in Videos. Technology, Knowledge and Learning, 21(2), 225–242. https://doi.org/10.1007/s10758-015-9269-1

Nikolayeva, I., Yessad, A., Laforge, B., & Luengo, V. (2020). Does an E-mail Reminder Intervention with Learning Analytics Reduce Procrastination in a Blended University Course? In Addressing Global Challenges and Quality Education (pp. 60–73). Springer International Publishing. https://doi.org/10.1007/978-3-030-57717-9_5

Ott, C., Robins, A., Haden, P., & Shephard, K. (2015). Illustrating performance indicators and course characteristics to support students' self-regulated learning in CS1. Computer Science Education, 25(2), 174–198. https://doi.org/10.1080/08993408.2015.1033129

Phan, T., McNeil, S. G., & Robin, B. R. (2016). Students' patterns of engagement and course performance in a Massive Open Online Course. Computers & Education, 95, 36–44. https://doi.org/10.1016/j.compedu.2015.11.015

Pieger, E., & Bannert, M. (2018). Differential effects of students' self-directed metacognitive prompts. Computers in Human Behavior, 86, 165–173. https://doi.org/10.1016/j.chb.2018.04.022

Pintrich, P. R. (2000). The Role of Goal Orientation in Self-Regulated Learning. In Handbook of Self-Regulation (pp. 451–502). Elsevier. https://doi.org/10.1016/b978-012109890-2/50043-3

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). A Manual for the use of the motivated strategies for learning questionnaire (MSLQ). ERIC. https://eric.ed.gov/?id=ED338122

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. Contemporary Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Schmidt, K., Maier, J., & Nückles, M. (2012). Writing about the Personal Utility of Learning Contents in a Learning Journal Improves Learning Motivation and Comprehension. Education Research International, 2012, 1–10. Hindawi Limited. https://doi.org/10.1155/2012/319463

Schumacher, C., & Ifenthaler, D. (2018a). The importance of students' motivational dispositions for designing learning analytics. Journal of Computing in Higher Education, 30(3), 599–619. https://doi.org/10.1007/s12528-018-9188-y

Schumacher, C., & Ifenthaler, D. (2018b). Features students really expect from learning analytics. Computers in Human Behavior, 78, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Schumacher, C., & Ifenthaler, D. (2021). Investigating prompts for supporting students' self-regulation – A remaining challenge for learning analytics approaches? The Internet and Higher Education, 49, 100791. https://doi.org/10.1016/j.iheduc.2020.100791

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research. IEEE Transactions on Learning Technologies, 10(1), 30-41. https://doi.org/10.1109/TLT.2016.2599522.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. Computers in Human Behavior, 107, 105512. https://doi.org/10.1016/j.chb.2018.05.004

Shute, V. J. (2008). Focus on Formative Feedback. Review of Educational Research, 78(1), 153–189. https://doi.org/10.3102/0034654307313795

Sitzmann, T., Bell, B. S., Kraiger, K., & Kanar, A. M. (2009). A multilevel analysis of the effect of prompting self-regulation in technology-delivered instruction. Personnel Psychology, 62(4), 697–734. https://doi.org/10.1111/j.1744-6570.2009.01155.x

Sitzmann, T., & Ely, K. (2010). Sometimes you need a reminder: The effects of prompting self-regulation on regulatory processes, learning, and attrition. Journal of Applied Psychology, 95(1), 132–144. https://doi.org/10.1037/a0018080

Stark, R., & Krause, U.-M. (2009). Effects of reflection prompts on learning outcomes and learning behavior in statistics education. Learning Environments Research, 12(3), 209–223. https://doi.org/10.1007/s10984-009-9063-x

StataCorp. (2021). Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC.

Stroet, K., Opdenakker, M.-C., & Minnaert, A. (2013). Effects of need supportive teaching on early adolescents' motivation and engagement: A review of the literature. Educational Research Review, 9, 65–87. https://doi.org/10.1016/j.edurev.2012.11.003

Tan, J. P.-L., Yang, S., Koh, E., & Jonathan, C. (2016). Fostering 21st century literacies through a collaborative critical reading and learning analytics environment. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16. the Sixth International Conference (pp. 377–381). ACM Press. https://doi.org/10.1145/2883851.2883965

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving Decisions About Health, Wealth, and Happiness. New York, NY: Penguin.

Valle, N., Antonenko, P., Valle, D. et al. Predict or describe? How learning analytics dashboard design influences motivation and statistics anxiety in an online statistics course. Education Tech Research Dev 69, 1405–1431 (2021). https://doi.org/10.1007/s11423-021-09998-z

Vytasek, J. M., Patzak, A., & Winne, P. H. (2019). Analytics for Student Engagement. In Machine Learning Paradigms (pp. 23–48). Springer International Publishing. https://doi.org/10.1007/978-3-030-13743-4_3

Wang, D., & Han, H. (2020). Applying learning analytics dashboards based on process-oriented feedback to improve students' learning effectiveness. Journal of Computer Assisted Learning, 37(2), 487–499. https://doi.org/10.1111/jcal.12502

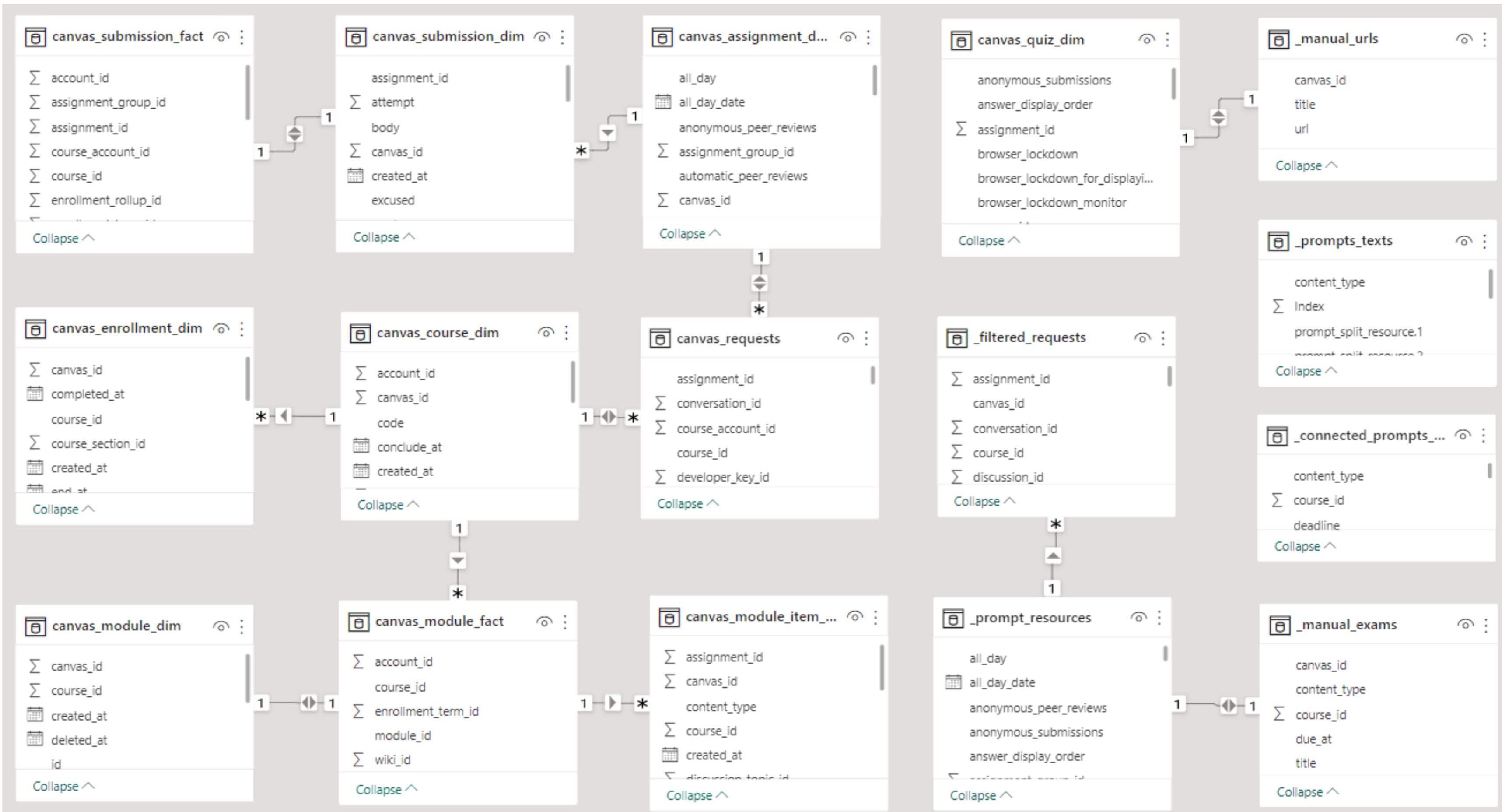
Warr, P., & Downing, J. (2000). Learning strategies, learning anxiety and knowledge acquisition. British Journal of Psychology, 91(3), 311-333. https://doi.org/10.1348/000712600161853

Williams, G. C., Freedman, Z. R., & Deci, E. L. (1998). Supporting Autonomy to Motivate Patients With Diabetes for Glucose Control. Diabetes Care, 21(10), 1644–1651. https://doi.org/10.2337/diacare.21.10.1644

Wirth, J. (2009). Promoting self-regulated learning through prompts. Zeitschrift für Pädagogische Psychologie, 23(2), 91–94. Hogrefe Publishing Group. https://doi.org/10.1024/1010-0652.23.2.91

Appendix A: Dashboard Model and Tables

Canvas Tables, Microsoft Power BI Aggregated Tables, and Connections:



List of Tables in Microsoft PowerBI:

- canvas_assignment_dim
- canvas_course_dim
- canvas_enrollment_dim
- canvas_external_tool_activation_dim
- canvas_module_dim
- canvas_quiz_submission_historical_fact
- canvas_module_fact
- canvas_module_item_dim
- canvas_quiz_dim
- canvas_quiz_fact
- canvas_quiz_submission_historical_dim
- canvas_requests
- canvas_submission_dim
- canvas_submission_fact
- canvas_wiki_page_dim
- canvas_wiki_page_fact
- osiris_la_v_student_cursus_toets
- osiris_ost_beoordeling
- osiris_ost_cursus_toets
- osiris_student_cursus_resultaat
- _prompt_resources
- _filtered_requests
- _manual_urls
- _prompts_texts
- _manual_exams

Appendix B: Information Sheet and Informed Consent

Information sheet for research project "Student Facing Dashboard 3.0"

1. Introduction

You have been invited to take part in research project StudentFacingDashboard 3.0, because you are enrolled in on the following courses: 0SAB0-EDF (USE Basic Theme: Ethics of Digital Futures and AI) or 0HV60 (Thinking and Deciding).

Participation in this research project is voluntary: the decision to take part is up to you and will not have any consequences on your grades or study progress. The teachers of the course in which you are enrolled do not have access to any of the datasets used in this research project. They are not informed of which students consented to participation in the research project, and they do also not who receives which dashboard.

Before you decide to participate we would like to ask you to read the following information, so that you know what the research project is about, what we expect from you and how we go about processing your personal data. Based on this information you can indicate by way of the consent declaration whether you consent to taking part in this research project and in the processing of your personal data.

You may of course always contact the researcher via c.s.j.m.vleeshouwers@student.tue.nl, if you have any questions, or you can discuss this information with people you know.

2. Purpose of the research

This research project will be managed by Uwe Matzat.

The overall goal of this study is to understand how a new online learning dashboard for Canvas could support and motivate students with their learning. In the project, a newly designed dashboard will be tested and its effects analyzed.

The newly designed dashboard will be based on previously designed dashboard (Project: 'Student Facing Dashboard'). It will be tested and its effects will be analyzed in a randomized field experiment by a Master Student at TU/e, hereafter referred to as 'researcher'. The research is part of the Human-Technology Interaction Group at TU/e.

The research project will lead to two main outcomes:

- the design of a "live" learning analytics dashboard with data refreshed once per day;
- evaluation of success of dashboard, done via surveys.

During the development of your course, you will have access to a dashboard in which your learning behaviour will be displayed, based on your Canvas data. Simultaneously, you will be asked to complete three surveys: one at the beginning of the project, one during the development of the project and one at the end, via Limesurvey. The three surveys will contain questions about learning behaviour and motivation, and about the student number. Only the first survey will contain questions about student number and email address (for the processing activities and purposes described in the following sections). The third survey will contain also questions about your experiences on using the dashboard during the course. During the last phase of the project, your Osiris data will also be analyzed to determine whether the use of the dashboard had an impact on your academic behaviour.

The research project will only process and analyze pseudonymized data. The researchers will not be able to identify you directly, because your student number will be replaced by a hashed value and your email address will not be included in the research database. Your email address is required only to create the account by which you will be able to access your dashboard and to send you the information regarding the payment of the compensation. Your email address will not be used to link your Canvas, Osiris and Limesurvey data.

3. Controller in the sense of the GDPR

TU/e is responsible for processing your personal data within the scope of the research. The contact data of TU/e are:

Technische Universiteit Eindhoven
De Groene Loper 3
5612 AE Eindhoven

4. What will taking part in the research project involve?

You will be taking part in a research project in which we will gather information by:

- asking you to fill out a survey on three [3] different moments, about your learning behaviour and study motivation;
- accessing your study data in Canvas and Osiris, in order to provide you with a personalized dashboard related to your learning behaviour;
- analyzing your answers to the survey in combination with your Canvas and Osiris data.

For your participation in this research project you will receive a compensation of 10 euros as a sign of our appreciation.

5. What personal data from you do we gather and process?

Within the framework of the research project we process the folllowing personal data:

Processing activity	Personal data
Registration research participants	• Student number
Performing and archiving research questionnaire	• Student number • Email address (only in survey No. 1) • Survey answers on self-regulated learning behavior and motivation, as well as experience of the dashboard.
Set-up and display of Dashboard to the student	• Student number • User ID • Course information (including course code, when course is given, dates of tests, exams, lectures) related to all courses as mentioned above • Course setup (including information on modules, (video) lectures, discussion forums,

Processing activity	Personal data
	wikis, assignments, such as type of test/exam, correct answers), by course • Student answers to tests and assignments, and performance on tests/exams/assignments, by course • Clickstream data (every click within a specific course with time stamps) by course (Canvas)
Creation of accounts for the students to access their individual Dashboard	• Student number • Email address
Register study progress	• Exam results (by course) (Osiris) • Course results (all results of a course) • Student number
Select, aggregate and pseudonymize data in a research dataset	All of the above
Analysis of merged data	All of the above (except student number and email address)
Correspondence and payment	• Email address

Your student number will be pseudonymized and your email address will only be used for the purposes of creating your dashboard account and to contact you for payment purposes. Your data from Canvas and Osiris and the surveys will not be directly traceable to you.

The teachers of the course in which you are enrolled do not have access to any of the datasets used in this research project. They are not informed of which students consented to participation in the research project, and they do also not know who receives which dashboard.

6. Withdrawing your consent and contact data

Participation in this research project is entirely voluntary. You do not have to answer questions you do not wish to answer. You may end your participation in the research project at any moment, or withdraw your consent to using your data for the research, without specifying any reason. Ending your participation will have no disadvantageous consequences for you or for any compensation you may already have received]
If you decide to end your participation during the research, the data which you already provided up to the moment of withdrawal of your consent will be used in the research.
Do you wish to end the research, or do you have any questions and/or complaints? Then please contact the researcher via c.s.j.m.vleeshouwers@student.tue.nl. In deviation from what is stated hereabove on page 1, the researcher will be able to directly identify you by your e-mail address if you e-mail him. He will however not be able to link your research data to your e-mail address. If necessary for executing your request, for example to carry out a withdrawal, the reseacher will request the authorized employee involved to take care of the request.
If you have specific questions about the handling of personal data you can direct these to the data protection officer of TU/e by sending a mail to functionarisgegevensbescherming@tue.nl. Furthermore, you have the right to file complaints with the Dutch data protection authority: the Autoriteit Persoonsgegevens.
Finally, you have the right to request access, rectification, erasure or adaptation of your data. Submit your request via privacy@tue.nl.

7. Legal ground for processing your personal data

To be permitted to process your personal data, the processing must be based on one of the legal bases from the GDPR. For this research project StudentFacingDashboard that is explicit consent.

8. Who has access to your personal data?

Access to personal data within TU/e

All relevant employees who are involved in the research project have access to your pseudonymized personal data, but only as far as is necessary to fulfil their respective tasks. These employees are:

- the research team: consisting of three researchers;
- the Analytics Product Owner;
- the Manager of Innovation in Education.

Beside these employees, only authorized persons in the relevant sections of TU/e like the Analytics Data engineer will have access to your data, but only as far as is necessary to fulfil their respective tasks.

Access to personal data by other parties

Within the framework of the research project, your personal data will be shared with the following third parties:

- storage solution: Microsoft;
- survey tool: LimeSurvey;
- data analysis tool: Databricks.

These third parties are processors: they processes your personal data on our instructions. We concluded an agreement with them concerning the processing of your personal data. This agreement stipulates that certain obligations for protection of your personal data are respected, to ensure that the data are processed in such a way that the requirements and standards of TU/e are met.

TU/e will process your personal data only within the European Economic Area (EEA) by storing the data on a server inside the EEA.

9. How are your personal data protected?

TU/e has implemented appropriate technical and organizational measures for protection of personal data against unintended or unlawful destruction, unintended damage, loss, alteration and unauthorized publication or access, and against all other forms of unlawful processing (including, but not limited to unnecessary gathering of data) or further processing. These appropriate technical and organizational measures include limitation of access to data through authorization and authentication, guidelines within the organization concerning the processing of personal data and storage on protected locations that are offered by the ICT service of TU/e.

10. How long will your personal data be retained?

Your personal data will be retained in accordance with the GDPR. The data are retained no longer than is necessary to achieve the goals for which the data were gathered and are deleted as soon as you withdraw your consent and there is no other ground to process your data lawfully. The research data will be retained for a period of 10 years, in line with regulatory requirements regarding retention periods for research data. At the latest after expiration of this time period, the dataset(s) will be deleted. We are legally obliged to retain your financial data for 7 years.

11. Confidentiality of data

We will do everything we can to protect your privacy as best as possible. The research results that are published will in no way contain confidential information or personal data from or about you through which anyone can recognize you, unless you have by way of our consent form explicitly consented to mentioning your name, for example in a quote. The research data will if necessary (for example for a check on scientific integrity) and only in anonymized form be made available to people outside the research group.

Finally, this research has been assessed and approved by the ethical committee of Eindhoven University of Technology.

Consent form

By signing this consent form I acknowledge the following:

1. I am sufficiently informed about the research project through a separate information sheet. I have read the information sheet and have had the opportunity to ask questions. These questions have been answered satisfactorily.
2. I take part in this research project voluntarily. There is no explicit or implicit pressure for me to take part in this research project. I am clear that I can end participation in this research project at any moment, without giving any reason. I do not have to answer a question if I do not wish to do so.

Furthermore, I consent to the following parts of the research project

3. I consent to processing my personal data gathered during the research in the way described in the information sheet.
4. I consent to using my answers for quotes in the research publications – without my name being published in these.

Beside the above, you can below give optional permission for further use of your research data. You can withhold your permission and still participate in this study.

YES/NO I give permission to store the pseudonymized research data collected from me (i.e. Canvas- and dashboard-interaction data and survey responses) for use in future research on learning motivation at the Human-Technology Interaction-group or the Learning Analytics-department of Information Management Services at TU/e, with due regard for recognized ethical standards for scientific research, and for education purposes.

Appendix C: Annex Informed Consent

Annex 1 to the Information sheet for research project “Student Facing Dashboard 3.0”

This consent is not mandatory and the additional data will not be used if you opt out.

1. Introduction

You have been invited to take part in the research project StudentFacingDashboard 3.0, because you are enrolled in on the following courses: Thinking and Deciding (0HV60) or USE Basic Theme: Ethics of Digital Futures and AI (0SAB0-EDF). You consented to this study and therefore became a participant of the research.

Initially, you have consented to a specific list of categories of personal data. However, we’d like to ask you four additional questions to improve the research we are conducting. Those questions cover the following: what is your **study program, study year**, **age**, and **gender**.

These questions will be included in the second survey of the study. This additional data will be used to analyze the overall results. No individual analysis will be performed.

The researcher only has access to pseudonymized data. Therefore, the chances of you being identifiable are minimal.
Participation in this research project is voluntary, as well as the participation in this additional data asked via surveys: the decision to take part is up to you and will not have any consequences on your grades or study progress. If you do not consent to this additional processing, you will simply not receive a survey containing those questions, instead you will receive the survey(s) without the additional data in it.
Consenting or not consenting to this additional data processing has no impact on the compensation you will receive for taking part in the study.
The teachers of the course in which you are enrolled do not have access to any of the datasets used in this research project. They are not informed of which students consented to participation in the research project, and they do also not who receives which dashboard.

Before you decide to participate, we would like to ask you to read the following information, so that you know what the new processing of data is about, what we expect from you and how we go about processing your personal data. Based on this information you can indicate by way of the consent declaration whether you consent to taking part in the processing of your personal data.

You may of course always contact the researcher via c.s.j.m.vleeshouwers@student.tue.nl, if you have any questions, or you can discuss this information with people you know.

2. Purpose of the additional information

By analyzing these variables, we aim to gain a better understanding of their potential impact on dashboard usage. We will not use your study program, study year, gender nor age for any other purposes other than analysis on the overall results of the study.

3. Controller in the sense of the GDPR

TU/e is responsible for processing your personal data within the scope of the research. The contact data of TU/e are:

Technische Universiteit Eindhoven
De Groene Loper 3
5612 AE Eindhoven

4. **What will taking part in this new processing of data involve?**

You will be receiving two surveys in which, in addition to the data you initially consented to, we will ask you:

- What is your study program?
- How many years have you been studying in higher education?
- What is your age?
- What is your gender?

The data you initially consented to:

- Email address
- Student number
- Canvas and Osiris data
- Survey answers on self-regulated learning behavior and motivation, as well as experience of the dashboard

5. **Withdrawing your consent and contact data**

Participation in this research project is entirely voluntary. You do not have to answer questions you do not wish to answer. You may end your participation in the research project at any moment, or withdraw your consent to using your data for the research, without specifying any reason. Ending your participation will have no disadvantageous consequences for you or for any compensation you may already have received]
If you decide to end your participation during the research, the data which you already provided up to the moment of withdrawal of your consent will be used in the research.
Do you wish to end the research, or do you have any questions and/or complaints? Then please contact the researcher via c.s.j.m.vleeshouwers@student.tue.nl. In deviation from what is stated hereabove on page 1, the researcher will be able to directly identify you by your e-mailaddress if you e-mail him. He will however not be able to link your research-data to your e-mailaddress. If necessary for executing your request, for example to carry out a withdrawal, the reseacher will request the authorized employee involved to take care of the request.
If you have specific questions about the handling of personal data, you can direct these to the data protection officer of TU/e by sending a mail to functionarisgegevensbescherming@tue.nl. Furthermore, you have the right to file complaints with the Dutch data protection authority: the Autoriteit Persoonsgegevens.
Finally, you have the right to request access, rectification, erasure, or adaptation of your data. Submit your request via privacy@tue.nl.

6. **Legal ground for processing your personal data**

To be permitted to process your personal data, the processing must be based on one of the legal bases from the GDPR. For this research project StudentFacingDashboard that is explicit consent.

7. **Who has access to your personal data?**

Access to personal data within TU/e

All relevant employees who are involved in the research project have access to your pseudonymized personal data, but only as far as is necessary to fulfil their respective tasks. These employees are:

- the research team: consisting of three researchers;
- the Analytics Product Owner;
- the Manager of Innovation in Education.

Beside these employees, only authorized persons in the relevant sections of TU/e like the Analytics Data engineer will have access to your data, but only as far as is necessary to fulfil their respective tasks.

Access to personal data by other parties

Within the framework of the research project, your personal data will be shared with the following third parties:

- storage solution: Microsoft;
- survey tool: LimeSurvey;
- data analysis tool: Databricks.

These third parties are processors: they process your personal data on our instructions. We concluded an agreement with them concerning the processing of your personal data. This agreement stipulates that certain obligations for protection of your personal data are respected, to ensure that the data are processed in such a way that the requirements and standards of TU/e are met.

TU/e will process your personal data only within the European Economic Area (EEA) by storing the data on a server inside the EEA.

8. How are your personal data protected?

TU/e has implemented appropriate technical and organizational measures for protection of personal data against unintended or unlawful destruction, unintended damage, loss, alteration and unauthorized publication or access, and against all other forms of unlawful processing (including, but not limited to unnecessary gathering of data) or further processing. These appropriate technical and organizational measures include limitation of access to data through authorization and authentication, guidelines within the organization concerning the processing of personal data and storage on protected locations that are offered by the ICT service of TU/e.

9. How long will your personal data be retained?

Your personal data will be retained in accordance with the GDPR. The data are retained no longer than is necessary to achieve the goals for which the data were gathered and are deleted as soon as you withdraw your consent and there is no other ground to process your data lawfully. The research data will be retained for a period of 10 years, in line with regulatory requirements regarding retention periods for research data. At the latest after expiration of this time period, the dataset(s) will be deleted. We are legally obliged to retain your financial data for 7 years.

10. Confidentiality of data

We will do everything we can to protect your privacy as best as possible. The research results that are published will in no way contain confidential information or personal data from or about you through which anyone can recognize you, unless you have by way of our consent form explicitly consented to mention your name, for example in a quote. The research data will if necessary (for example for a check on scientific integrity) and only in anonymized form be made available to people outside the research group.

Finally, this research has been assessed and approved [research manager fills in] by the ethical committee of Eindhoven University of Technology.

By signing this consent form I acknowledge the following:

1. *I am sufficiently informed about the additional processing of personal data for the study I'm participating in, through a separate information sheet. I have read the information sheet and have had the opportunity to ask questions. These questions have been answered satisfactorily.*

2. *I take part in this research project voluntarily. There is no explicit or implicit pressure for me to take part in this research project. I am clear that I can end participation in this research project at any moment, without giving any reason. I do not have to answer a question if I do not wish to do so.*

   Furthermore, I consent to the following parts of the research project

3. *I consent to the processing of the additional personal data gathered during the research in the way described in the information sheet.*

YES / NO

Appendix D: Survey Measurements

Motivation (12 items)

Intrinsic motivation (4 items)

Why are you currently engaged in this course?

- Because I think that this course is interesting
- Because I think that the course activities are pleasant
- Because this course is fun
- Because I feel good when doing the activities in the course

Intrinsic goal orientation (4 items)

- In a class like this, I prefer course material that really challenges me so I can learn new things.
- In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.
- The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.
- When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.

Extrinsic goal orientation (4 items)

- Getting a good grade in this class is the most satisfying thing for me right now.
- The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.
- If I can, I want to get better grades in this class than most of the other students.
- I want to do well in this class because it is important to show my ability to my family, friends, employer, or others.

Engagement (10 items)

To what extent do the following behaviors, thoughts, and feelings describe you, in this course?

Skills Engagement (3 items)

- Staying on top of the readings
- Looking over class notes between classes to make sure I understand the material
- Listening carefully in class

Emotional Engagement (3 items)

- Finding ways to make the course material relevant to my life
- Thinking about the course between class meetings
- Really desiring to learn the material

Behavioral Engagement (4 items)

- I work hard to complete the course.
- I study hard and prepared well for every course test.
- When course work is difficult, I give up or only study the easy parts.
- In order to get full understanding on the course content, I went over the lecture materials more than once.

Learning Strategies (10 items)

Active Reflection (5 items)

- When I study the readings for this course, I outline the material to help me organize my thoughts.
- When I study for this course, I go over my class notes and make an outline of important concepts.
- When reading for this class, I try to relate the material to what I already know.
- I try to understand the material in this class by making connections between the readings and the concepts from the lectures.
- I try to apply ideas from course readings in other class activities such as lectures and discussions.

Written Help-Seeking (5 items)

- I tried to understand something better by locating and studying a relevant document.
- I filled in gaps in my knowledge by getting hold of some written material.
- I tried to find written information about something to help me learn.
- I checked something I did not understand by looking it up in a document.
- I sought out relevant documents to help me learn.

Autonomy (4 items)

- I have been able to freely decide my own pace of learning while using the learning dashboard.
- I have been able to freely choose the tasks to be done while using the learning dashboard.
- The learning dashboard has allowed me to work independently.
- I felt I was capable of deciding how to learn and work with this learning dashboard.

Usability (8 items)

- I think that I would like to use this learning dashboard frequently.
- I thought this learning dashboard was easy to use.
- I found the various functions in this learning dashboard were well integrated.
- I thought there was too much inconsistency in this learning dashboard.
- I felt very confident using the system.
- I needed to learn a lot of things before I could get going with this learning dashboard.

Perceived usefulness (4 overall items 4 prompts items)

Dashboard Overall

- The learning dashboard enriched my learning activity.
- The learning dashboard was helpful to me in acquiring new knowledge.
- The learning dashboard helped me obtain useful information when needed.
- The learning dashboard helped me learn better.

Prompts

- The prompts enriched my learning activity.
- The prompts were helpful to me in acquiring new knowledge.
- The prompts helped me obtain useful information when needed.
- The prompts helped me learn better.

Open questions (3 items)

- What do you like most about the dashboard?
- What do you like the least (or dislike) about the dashboard?
- What could be improved about the dashboard?

Estimated Interactions (2 overall items, 6 prompts items)

- How often did you take a look at the dashboard?
- Approximately how many minutes have you spent using the dashboard?
- How often did you interact with the prompts?
  This includes both thinking about and executing what it stated.
- How difficult was it to understand the prompts?
- How much did you trust the guidance of the prompts?

Appendix E: Prompt texts

Reflection Prompts

- Did you set any goals and/or make a plan to ensure you have a thorough understanding of the course material?
- If you set any goals and/or made a plan, did you reach them? Do you need to adjust anything to still reach them before the final exam/assignment?
- How is the course material personally relevant for you at present or in the future outside of university? (Making these connections may help you remember the content better)
- How effective are your current study strategies (e.g., planning, summarizing, watching videos, etc.) to help you prepare for the final exam/assignment?
- If there are any, what are the topics you might find difficult to remember or understand for the final exam/assignment? What can you do to improve your proficiency in these topics?
- Did you forget any of the terms or topics introduced in previous course material? If so, what are they and do you need to revise them for the final exam/assignment?
- What links can you create between the contents of the videos on [*video material*] and your own life? (Making these connections may help you remember the content better)
- What questions (if any) do you have about the information presented and/or is there anything that you did not understand in the videos about [*video material*]?
- Do you need to go back to any of the videos on [*video material*] and fill any gaps in understanding?
- Which questions, in your opinion, were not sufficiently clarified by the videos on [*video material*]? What can you do to gain more sufficient knowledge?
- Which examples can you think of that illustrate, confirm, or conflict with what you have learned about [*topic*]?
- Which main points about [*topic*] do you already understand, and which do you not understand yet? What can you do to improve your knowledge in these points?
- How can you explain [*topic*] in your own words?
- How effective were your study strategies in learning about [*topic*]? How can you improve this strategy to study the upcoming topics (even) more effectively?
- What links can you create between what you have learned in [*reading material*] and your own life? (Making these connections may help you remember the content better)
- What main points did you learn so far while reading [*reading material*]?
- What are the connections you can think of between [*reading material*] and the previous reading material?

Resource-related Prompts

- To prepare yourself in time for the upcoming topics and the final exam/assignment, you can start watching [*video material*] to familiarize yourself with the content.
- It is important to watch the video material for this week to keep up with the lectures. Start watching [*video material*].

- This week it will be important to watch [*video material*].
- This week it will be important to read [*reading material*].
- If you have finished this week's course material. You can start working ahead by watching [*video material].*
- You can now find a video recording of the lecture in case you missed it or to help you revise. See: [*lecture recording*].
- To prepare yourself for the upcoming lecture, you can already check out the lecture slides. See: [*lecture slides*].
- It could be helpful to revise previous topics to prepare yourself better for the final exam/assignment. You could begin by looking through [*lecture slides*].
- Turning in assignments late can result in lower or missing grades. Start with [*assignment*] soon, to make sure you have enough time to put in the effort.
- Starting more than one day before the due date could result in better grades. Give yourself enough time to properly finish [*assignment*].
- This week you have to hand in [*assignment*], you can start by reading the description.
- There is an additional practice quiz, [*practice quiz*] to help you prepare for the quiz and exam questions on this topic.
- There are additional resources on Canvas in [*wiki page*] you can use to deepen your knowledge on the topics of this week.
- To create a better understanding of the course material, you can use the additional material: [*wiki page*].
- If you haven't read [*reading material*] yet. Make sure to start in time to keep up with the coursework.
- If you have finished this week's course material. You can start working ahead by reading [*reading material*].
- It is important to allocate time this week to read [*reading material*] to prepare yourself for the upcoming deadline.

Appendix F: Descriptive Tables and Figures

Descriptive Statistics Survey 2 (T1):

		Range	M	Mdn	SD	Var.	Skew.	Kurt.
Motivation	DA	1.67 – 4.92	3.62	3.79	.88	.78	-.82	3.6
	DB	2.67 – 5.08	3.96	4	.72	.52	-.32	2.6
	DC	2.92 – 6.33	4.41	4.25	1.08	1.17	.24	2.12
Engagement	DA	1.89 – 5	3.7	3.78	.89	.75	-.71	3.18
	DB	1.78 – 4.67	3.75	4	.87	.76	-1.31	3.96
	DC	3.11 – 5	3.98	3.9	.68	.46	.2	1.53
Active Reflection	DA	3.8 – 5.2	4.66	4.68	.42	.18	-.61	2.67
	DB	3.4 – 5.6	4.53	4.8	.84	.7	-.12	1.4
	DC	3.4 – 7	5.1	4.8	1	1	.5	2.69
Written Help-Seeking	DA	2.2 – 4.4	3.14	3.1	.74	.54	.31	1.9
	DB	2.4 – 4.2	3.66	4	.59	.35	-1.04	3.11
	DC	2 – 5	3.42	3.6	.88	.78	-.08	2.37
Autonomy	DA	1 – 4	2.63	2.5	.80	.64	-.25	3.35
	DB	1.5 – 3.5	2.69	2.75	.62	.39	-.4	2.75
	DC	1.5 – 4	2.88	2.75	.67	.45	-.21	2.81

Descriptive Statistics Survey 3 (T2):

		Range	M	Mdn	SD	Var.	Skew.	Kurt.
Motivation	DA	1.67 – 4.92	3.81	3.83	.96	.92	-.95	3.6
	DB	3.33 – 5.67	4.2	4.17	.72	.52	.78	3
	DC	3.08 – 6.83	4.69	4.5	1.18	1.4	.24	2.06
Engagement	DA	1.11 – 3.22	2.22	2.17	.68	.47	-.16	2.04
	DB	.78 – 3	2.16	2.78	.92	.84	-.63	1.74
	DC	1.11 – 4	2.43	2.33	.93	.87	.28	2.1
Active Reflection	DA	4 – 6	4.86	4.8	.72	.52	.31	1.65
	DB	3.6 – 7	4.84	4.4	1.16	1.35	.78	2.27
	DC	3.8 – 6.8	5.48	5.7	.99	.98	-.38	1.79
Written Help-Seeking	DA	2.4 – 4.4	3.36	3.3	.74	.54	.1	1.68
	DB	3 – 4	3.44	3.4	.41	.17	.05	1.32
	DC	1 – 4.6	3.17	3.7	1.41	1.19	-.57	2.21
Autonomy	DA	1.5 – 3.5	2.7	2.75	.61	.37	-.53	2.8
	DB	1.25 – 3.75	2.69	2.75	.76	.57	-.49	2.67
	DC	1.5 – 4	2.88	3	.84	.7	-.49	2.14
Usability	DA	1.17 – 4.17	3.02	3.42	1.01	1.02	-.8	2.34
	DB	2.67 – 4.67	3.65	3.83	.68	.46	-.1	1.76
	DC	1.33 – 4.83	3.26	3.67	1.14	1.3	-.38	1.87
Perceived Usefulness Dashboard	DA	2 – 5	3.3	3.5	.98	.97	.02	2.08
	DB	1.5 – 5.25	3.56	3.5	1.04	1.09	-.45	3.17
	DC	1.75 – 5.5	3.85	4.25	1.33	1.78	-.45	1.66

Perceived Usefulness Prompts	DB DC	1.25 – 4.75 2 – 5.25	3.31 3.78	3.5 3.88	1.16 1.05	1.36 1.11	-.48 -.42	2.12 2.06

Participant Characteristics Tables:

Course:

C00	dashboardgroup 0	1	2	Total
0HV60	6	5	8	19
0SAB0-EDF	4	4	4	12
Total	10	9	12	31

Gender:

SI03	dashboardgroup 0	1	2	Total
male	3	1	4	8
female	6	7	8	21
nonbinary	1	0	0	1
Total	10	8	12	30

Amount of years studying in higher education:

SI05	dashboardgroup 0	1	2	Total
1	3	3	4	10
2	6	1	4	11
3	1	1	3	5
4	0	1	1	2
5	0	1	0	1
6	0	1	0	1
Total	10	8	12	30

Amount of dashboard interactions:

D01	dashboardgroup 0	1	2	Total
Once	1	1	2	4
Twice	2	2	3	7
Three times	6	5	4	15
More than three times	1	1	3	5
Total	10	9	12	31

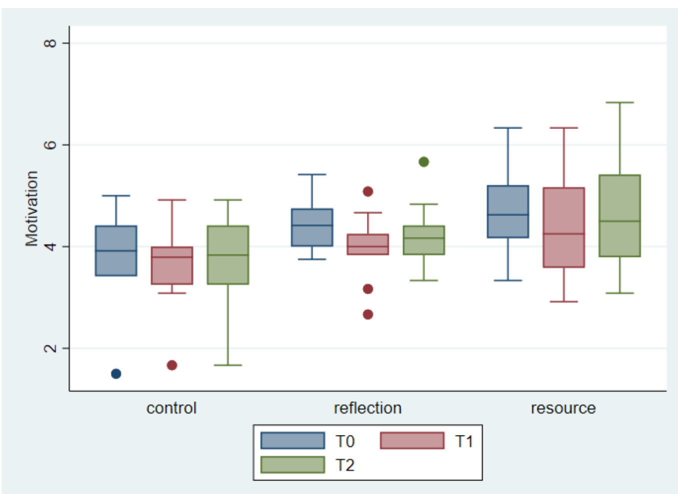
Amount of prompt interactions:

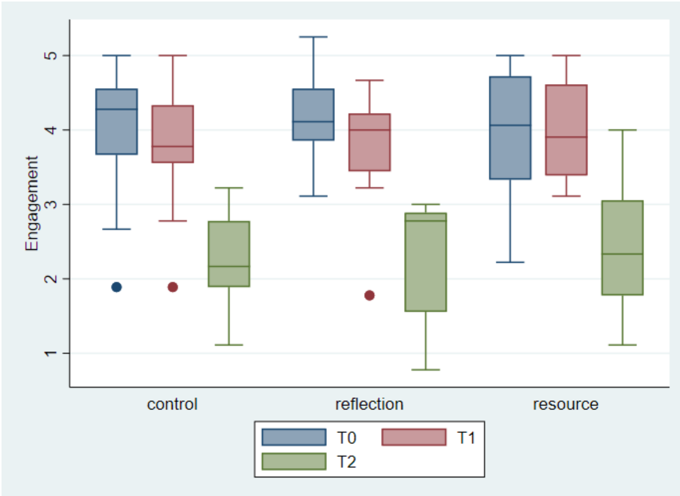
POMPTIN	dashboardgroup 1	2	Total
Not at all	0	2	2
Once	2	3	5
Twice	1	6	7
Three times	3	1	4
Every seen prompt	3	0	3
Total	9	12	21

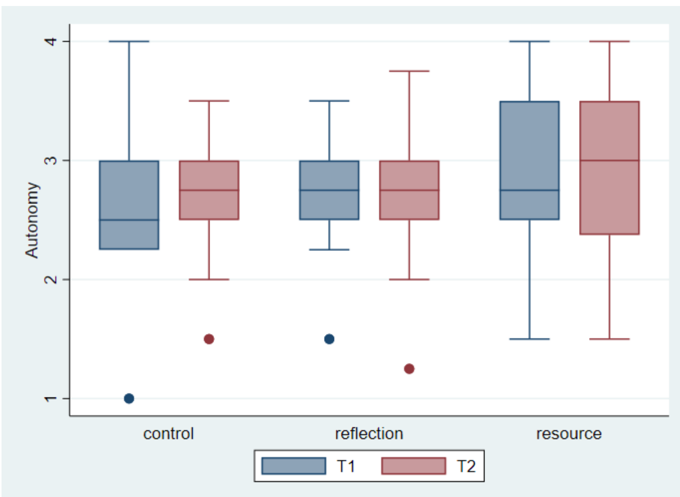
Dashboard interaction in minutes:

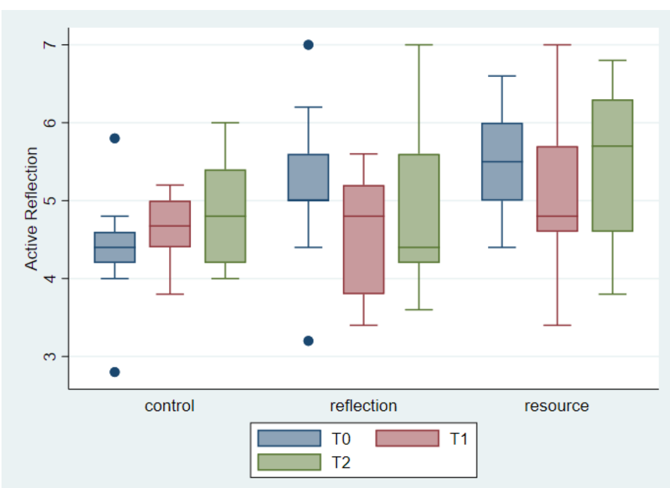
D02	dashboardgroup 0	1	2	Total
3	0	1	0	1
4	0	0	1	1
5	1	0	2	3
6	0	1	1	2
7	0	1	0	1
8	1	0	0	1
10	3	1	3	7
15	1	2	2	5
20	3	2	2	7
25	0	1	0	1
30	1	0	1	2
Total	10	9	12	31

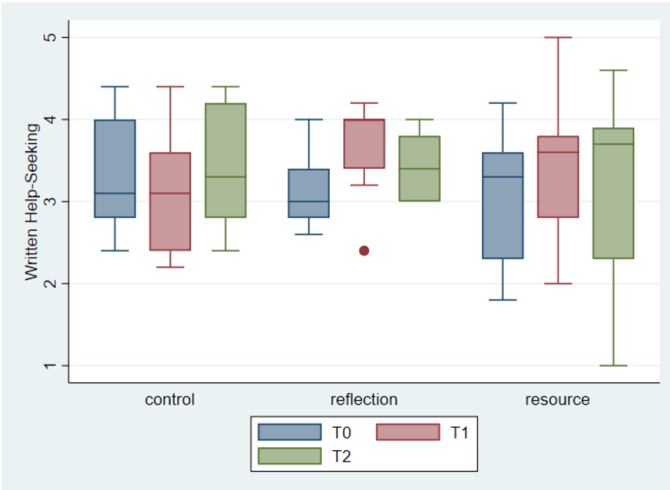
Box Plots of Measured Variables:

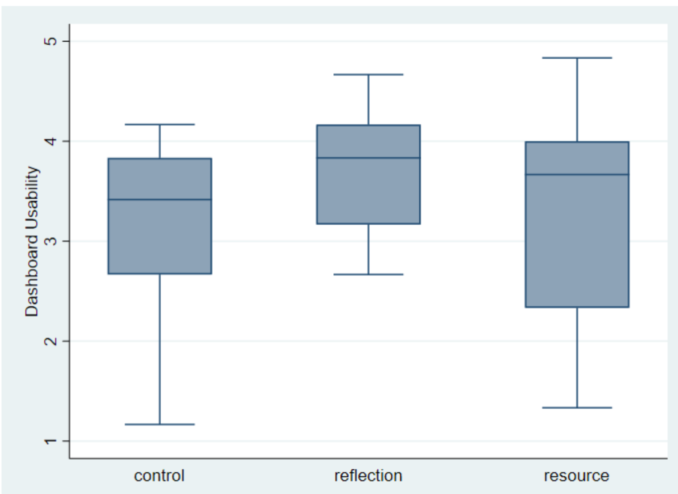


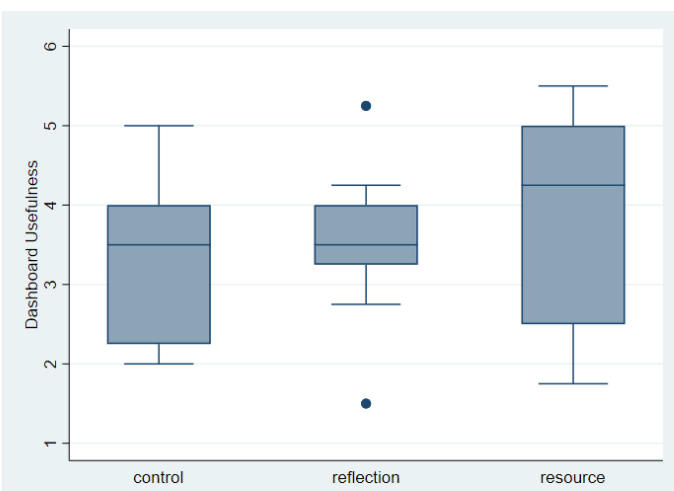

Engagement
1
2
3
4
5
control
reflection
resource
T0
T1
T2

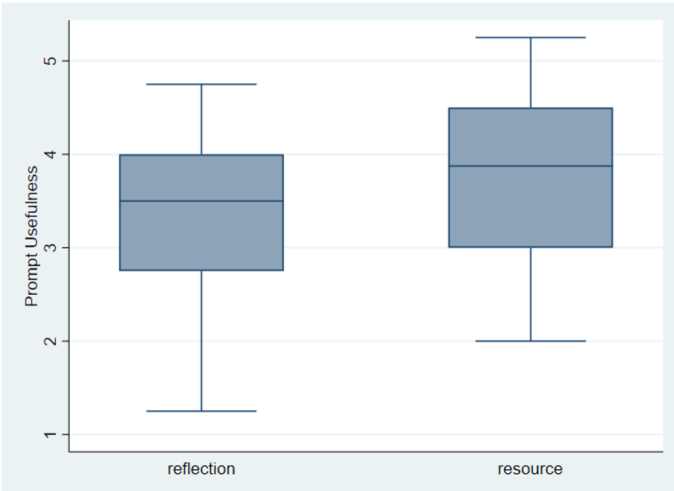

Autonomy
1
2
3
4
control
reflection
resource
T1
T2


Active Reflection
3
4
5
6
7
control
reflection
resource
T0
T1
T2


Written Help-Seeking
1
2
3
4
5
control
reflection
resource
T0
T1
T2

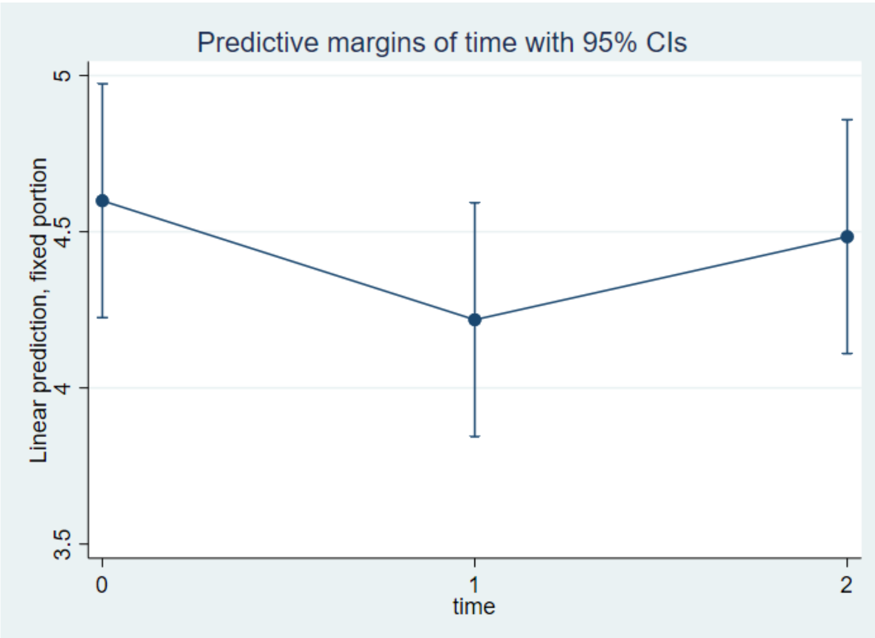

Dashboard Usability
1
2
3
4
5
control
reflection
resource


Dashboard Usefulness
1
2
3
4
5
6
control
reflection
resource

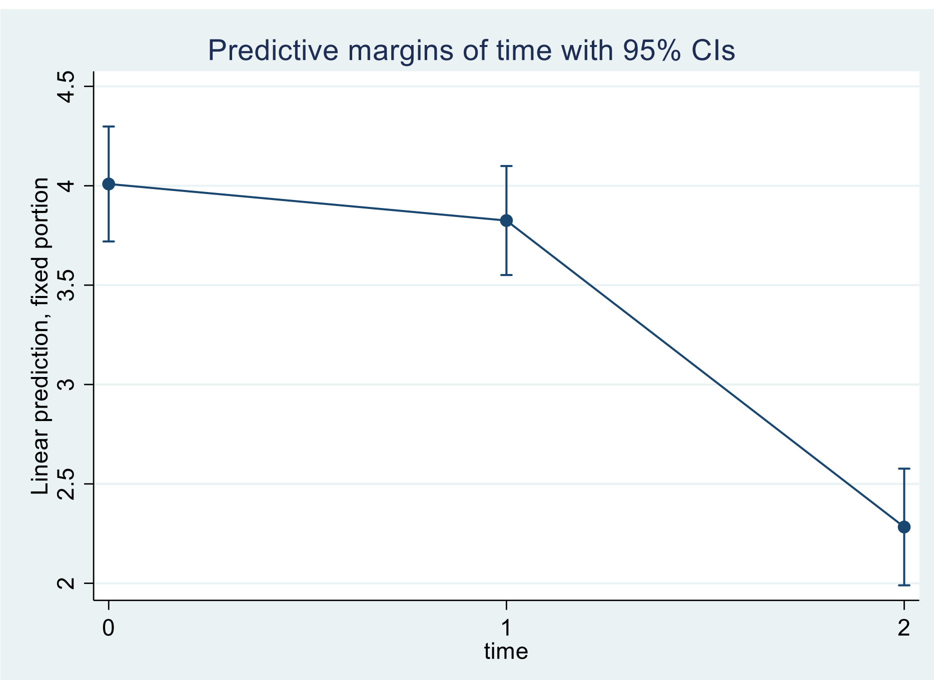

Prompt Usefulness
1
2
3
4
5
reflection
resource

Appendix G: Analysis Outcomes

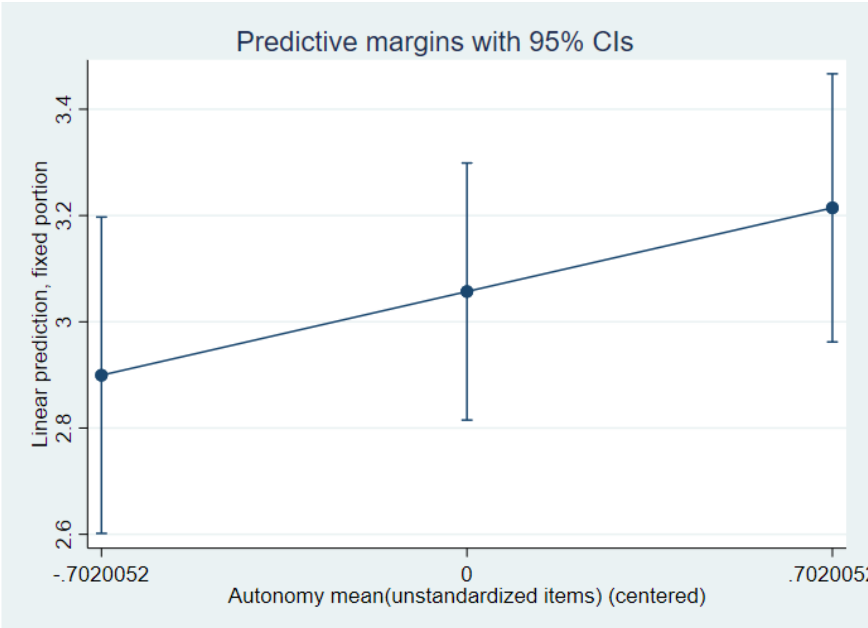
Motivation over time:



Engagement over time



Autonomy and engagement main effect



Learning Styles and Motivation Results

Pre-survey Active Reflection on Motivation

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -21.916295
Iteration 1:   log likelihood = -21.916293

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         27
Group variable: studentnr                       Number of groups  =          9
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =      10.73
Log likelihood = -21.916293                     Prob > chi2       =     0.0570
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.preLSARhigh	.2416667	.3861835	0.63	0.531	-.5152391	.9985724
time						
1	-.7333333	.293631	-2.50	0.013	-1.308839	-.1578272
2	-.4833334	.293631	-1.65	0.100	-1.05884	.0921727
preLSARhigh#time						
1 1	.4625001	.4404464	1.05	0.294	-.4007591	1.325759
1 2	.4416668	.4404464	1.00	0.316	-.4215924	1.304926
_cons	4.383333	.2574557	17.03	0.000	3.878729	4.887937

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.1158693	.0916751	.0245755	.5463031
var(Residual)	.2155479	.0718493	.1121527	.4142644

```
LR test vs. linear model: chibar2(01) = 2.97          Prob >= chibar2 = 0.0424
```

Overall Mean Active Reflection on Motivation

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -21.916295
Iteration 1:   log likelihood = -21.916293

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         27
Group variable: studentnr                       Number of groups  =          9
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =      10.73
Log likelihood = -21.916293                     Prob > chi2       =     0.0570
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.overallLSARhigh	.2416667	.3861835	0.63	0.531	-.5152391	.9985724
time						
1	-.7333333	.293631	-2.50	0.013	-1.308839	-.1578272
2	-.4833334	.293631	-1.65	0.100	-1.05884	.0921727
overallLSARhigh#time						
1 1	.4625001	.4404464	1.05	0.294	-.4007591	1.325759
1 2	.4416668	.4404464	1.00	0.316	-.4215924	1.304926
_cons	4.383333	.2574557	17.03	0.000	3.878729	4.887937

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.1158693	.0916751	.0245755	.5463031
var(Residual)	.2155479	.0718493	.1121527	.4142644

```
LR test vs. linear model: chibar2(01) = 2.97          Prob >= chibar2 = 0.0424
```

Pre-survey Written help-seeking on Motivation

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -28.667856
Iteration 1:   log likelihood = -28.667856

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         36
Group variable: studentnr                       Number of groups  =         12
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =      11.82
Log likelihood = -28.667856                     Prob > chi2       =     0.0374
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.preLSWHShigh	.8238096	.5170962	1.59	0.111	-.1896804	1.8373
time						
1	-.3666667	.2058021	-1.78	0.075	-.7700313	.036698
2	-.2	.2058021	-0.97	0.331	-.6033646	.2033647
preLSWHShigh#time						
1 1	.1642858	.2694582	0.61	0.542	-.3638426	.6924141
1 2	.3666665	.2694582	1.36	0.174	-.1614618	.8947948
_cons	4.2	.3949388	10.63	0.000	3.425934	4.974066

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.6739969	.2897466	.2902233	1.565249
var(Residual)	.1058862	.0305667	.0601338	.1864491

```
LR test vs. linear model: chibar2(01) = 35.88          Prob >= chibar2 = 0.0000
```

Overall Mean Written help-seeking on Motivation

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -29.435288
Iteration 1:   log likelihood = -29.435288

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         36
Group variable: studentnr                       Number of groups  =         12
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =       9.84
Log likelihood = -29.435288                     Prob > chi2       =     0.0799
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.overallLSWHShigh	.9166667	.5142745	1.78	0.075	-.0912929	1.924626
time						
1	-.3472222	.193339	-1.80	0.073	-.7261597	.0317153
2	.0138889	.193339	0.07	0.943	-.3650486	.3928263
overallLSWHShigh#time						
1 1	.1527778	.2734226	0.56	0.576	-.3831207	.6886763
1 2	-3.97e-08	.2734226	-0.00	1.000	-.5358986	.5358985
_cons	4.222222	.363647	11.61	0.000	3.509487	4.934957

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.681295	.2935962	.2927654	1.585443
var(Residual)	.1121399	.032372	.0636853	.1974608

LR test vs. linear model: chibar2(01) = 34.96   Prob >= chibar2 = 0.0000

Learning Styles and Engagement Results

Pre-Survey Active Reflection on Engagement

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -29.299239
Iteration 1:   log pseudolikelihood = -29.244931
Iteration 2:   log pseudolikelihood = -29.244739
Iteration 3:   log pseudolikelihood = -29.244739

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         27
Group variable: studentnr                       Number of groups  =          9
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =      50.06
Log pseudolikelihood = -29.244739               Prob > chi2       =     0.0000

                                   (Std. err. adjusted for 9 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
1.preLSARhigh	.4299603	.3876001	1.11	0.267	-.3297219	1.189642
time						
1	-.5936507	.5243633	-1.13	0.258	-1.621384	.4340825
2	-1.993651	.478627	-4.17	0.000	-2.931743	-1.055559
preLSARhigh#time						
1 1	.3644841	.5419047	0.67	0.501	-.6976297	1.426598
1 2	-.0688492	.8896109	-0.08	0.938	-1.812454	1.674756
_cons	3.993651	.2545548	15.69	0.000	3.494732	4.492569

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.0102194	.0923826	2.06e-10	506093.9
var(Residual)	.5008728	.1992274	.2296958	1.092199

Overall Mean Active Reflection on Engagement

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -29.299239
Iteration 1:   log pseudolikelihood = -29.244931
Iteration 2:   log pseudolikelihood = -29.244739
Iteration 3:   log pseudolikelihood = -29.244739

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         27
Group variable: studentnr                       Number of groups  =          9
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =      50.06
Log pseudolikelihood = -29.244739               Prob > chi2       =     0.0000

                                  (Std. err. adjusted for 9 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
1.overallLSARhigh	.4299603	.3876001	1.11	0.267	-.3297219	1.189642
time						
1	-.5936507	.5243633	-1.13	0.258	-1.621384	.4340825
2	-1.993651	.478627	-4.17	0.000	-2.931743	-1.055559
overallLSARhigh#time						
1 1	.3644841	.5419047	0.67	0.501	-.6976297	1.426598
1 2	-.0688492	.8896109	-0.08	0.938	-1.812454	1.674756
_cons	3.993651	.2545548	15.69	0.000	3.494732	4.492569

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.0102194	.0923826	2.06e-10	506093.9
var(Residual)	.5008728	.1992274	.2296958	1.092199

Pre-Survey Written help-seeking on Engagement

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -25.996606
Iteration 1:   log pseudolikelihood = -25.996606

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         36
Group variable: studentnr                       Number of groups  =         12
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =     556.57
Log pseudolikelihood = -25.996606               Prob > chi2       =     0.0000

                            (Std. err. adjusted for 12 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
1.preLSWHShigh	1.148016	.4208525	2.73	0.006	.3231601	1.972872
time						
1	.0888889	.3155242	0.28	0.778	-.5295272	.707305
2	-1.555556	.2152439	-7.23	0.000	-1.977426	-1.133685
preLSWHShigh#time						
1 1	-.072449	.3857751	-0.19	0.851	-.8285543	.6836563
1 2	.0773809	.292573	0.26	0.791	-.4960517	.6508135
_cons	3.266667	.3808196	8.58	0.000	2.520274	4.013059

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.1695691	.0618941	.0829185	.3467704
var(Residual)	.1520907	.0374669	.0938453	.2464863

Pairwise comparisons of predictive margins   Number of obs = **36**
Model VCE: **Robust**

Expression: **Linear prediction, fixed portion, predict()**

	Contrast	Delta-method std. err.	Unadjusted z	Unadjusted P>|z|	Unadjusted [95% conf.	interval]
preLSWHShigh						
1 vs 0	**1.14966**	**.2882071**	**3.99**	**0.000**	**.5847843**	**1.714535**
time						
1 vs 0	**.046627**	**.184522**	**0.25**	**0.801**	**-.3150295**	**.4082835**
2 vs 0	**-1.510417**	**.1463071**	**-10.32**	**0.000**	**-1.797173**	**-1.22366**
2 vs 1	**-1.557044**	**.1658445**	**-9.39**	**0.000**	**-1.882093**	**-1.231994**

Overall Meanr Written help-seeking on Engagement

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -25.106435
Iteration 1:   log pseudolikelihood = -25.106435

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         36
Group variable: studentnr                       Number of groups  =         12
                                                Obs per group:
                                                              min =          3
                                                              avg =        3.0
                                                              max =          3
                                                Wald chi2(5)      =     427.01
Log pseudolikelihood = -25.106435               Prob > chi2       =     0.0000

                             (Std. err. adjusted for 12 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
1.overallLSWHShigh	1.206018	.3586815	3.36	0.001	.5030156	1.909021
time						
1	.1534392	.2700439	0.57	0.570	-.3758372	.6827155
2	-1.555556	.17937	-8.67	0.000	-1.907114	-1.203997
overallLSWHShigh#time						
1 1	-.2136243	.3640175	-0.59	0.557	-.9270856	.499837
1 2	.0902778	.2922523	0.31	0.757	-.4825262	.6630817
_cons	3.333333	.3236529	10.30	0.000	2.698985	3.967681

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.1531451	.0472968	.0836028	.2805339
var(Residual)	.147366	.040634	.0858403	.2529902

Pairwise comparisons of predictive margins Number of obs = **36**
Model VCE: **Robust**

Expression: **Linear prediction, fixed portion, predict()**

	Contrast	Delta-method std. err.	Unadjusted z	Unadjusted P>|z|	Unadjusted [95% conf.	interval]
overallLSWHShigh						
1 vs 0	**1.164903**	**.2712041**	**4.30**	**0.000**	**.6333526**	**1.696453**
time						
1 vs 0	**.046627**	**.1820088**	**0.26**	**0.798**	**-.3101036**	**.4033576**
2 vs 0	**-1.510417**	**.1461261**	**-10.34**	**0.000**	**-1.796819**	**-1.224015**
2 vs 1	**-1.557044**	**.1609392**	**-9.67**	**0.000**	**-1.872479**	**-1.241609**

Autonomy and motivation

Comparing the experimental groups in autonomy, time, and dashboard group on motivation with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log likelihood =  -38.86694
Iteration 1:   log likelihood =  -38.86694

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         42
Group variable: studentnr                       Number of groups  =         21
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(6)      =      17.67
Log likelihood =  -38.86694                     Prob > chi2       =     0.0071
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
resource	.4217746	.419624	1.01	0.315	-.4006734	1.244223
2.time	.2193339	.134143	1.64	0.102	-.0435816	.4822494
cent_autonomy	-.0048037	.2010738	-0.02	0.981	-.3989012	.3892937
dashboardgroup#time						
resource#2	.1088454	.1792964	0.61	0.544	-.242569	.4602598
dashboardgroup#c.cent_autonomy						
resource	.2137103	.2148211	0.99	0.320	-.2073313	.634752
time#c.cent_autonomy						
2	-.3592463	.1578035	-2.28	0.023	-.6685355	-.0499571
_cons	3.962677	.3168196	12.51	0.000	3.341722	4.583632

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.8215031	.2693393	.4320488	1.562016
var(Residual)	.0805767	.025131	.0437249	.1484874

```
LR test vs. linear model: chibar2(01) = 33.49         Prob >= chibar2 = 0.0000
```

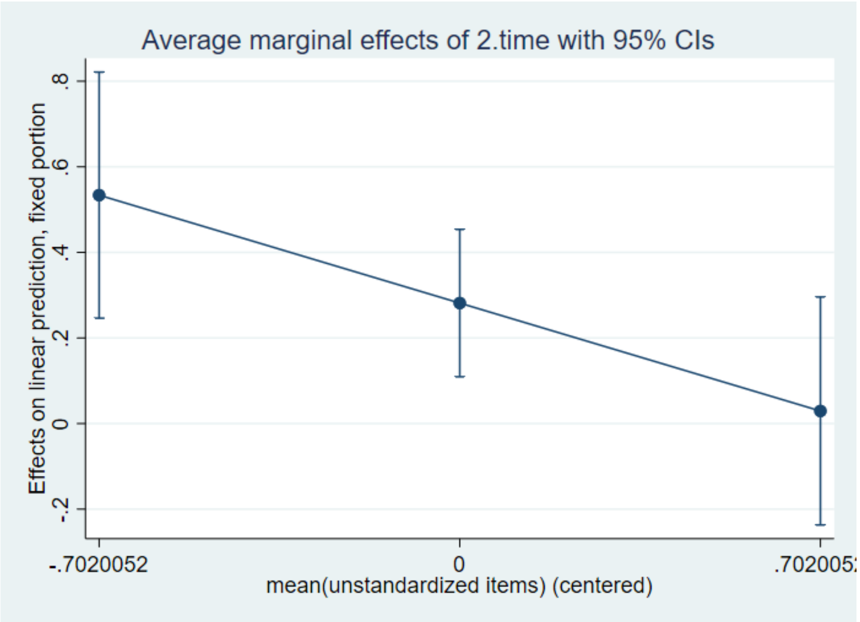
Predictions for interaction effect of time and autonomy:

```
Average marginal effects                                  Number of obs = 42

Expression: Linear prediction, fixed portion, predict()
dy/dx wrt:  2.time
1._at: cent_autonomy = -.7020052
2._at: cent_autonomy =         0
3._at: cent_autonomy =  .7020052
```

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
1.time	(base outcome)					
2.time						
_at						
1	.533724	.1466872	3.64	0.000	.2462223	.8212257
2	.2815313	.0878708	3.20	0.001	.1093077	.4537549
3	.0293385	.1359019	0.22	0.829	-.2370244	.2957014

Note: dy/dx for factor levels is the discrete change from the base level.



Autonomy and engagement

Comparing the three groups in autonomy, time, and dashboard group on engagement with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -61.963815
Iteration 1:   log pseudolikelihood = -61.963814

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         62
Group variable: studentnr                       Number of groups  =         31
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(9)      =     386.74
Log pseudolikelihood = -61.963814               Prob > chi2       =     0.0000

                                 (Std. err. adjusted for 31 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
reflection	.028725	.3531599	0.08	0.935	-.6634556	.7209056
resource	.1976839	.2938749	0.67	0.501	-.3783004	.7736681
2.time	-1.517449	.1478269	-10.27	0.000	-1.807184	-1.227713
cent_autonomy	.3547721	.1688901	2.10	0.036	.0237535	.6857907
dashboardgroup#time						
reflection#2	-.0895501	.3250375	-0.28	0.783	-.7266119	.5475117
resource#2	-.0103493	.2199553	-0.05	0.962	-.4414536	.4207551
dashboardgroup#c.cent_autonomy						
reflection	.0046237	.2935921	0.02	0.987	-.5708063	.5800536
resource	-.0281674	.2152866	-0.13	0.896	-.4501213	.3937865
time#c.cent_autonomy						
2	-.2417639	.2001738	-1.21	0.227	-.6340975	.1505696
_cons	3.745777	.2380255	15.74	0.000	3.279256	4.212299

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.3770093	.1433683	.1789201	.7944108
var(Residual)	.1964596	.0724873	.095325	.4048921

Usability and motivation

Comparing the experimental groups in usability, time, and dashboard group on motivation with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -39.366067
Iteration 1:   log likelihood = -39.366067

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         42
Group variable: studentnr                       Number of groups  =         21
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(6)      =      13.84
Log likelihood = -39.366067                     Prob > chi2       =     0.0315

------------------------------------------------------------------------------------------------------
                              motivation | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------------------------------+------------------------------------------------------------
                          dashboardgroup |
                               resource  |   .4255126   .4099377     1.04   0.299    -.3779505    1.228976
                                  2.time |   .2841354   .1578867     1.80   0.072    -.0253169    .5935878
                     cent_dashusability  |   -.10399    .4356176    -0.24   0.811    -.9577847    .7498047
                                         |
                     dashboardgroup#time |
                             resource#2  |  -.0033299     .20689    -0.02   0.987    -.4088268    .4021671
                                         |
dashboardgroup#c.cent_dashusability      |
                               resource  |   .5882569   .4849964     1.21   0.225    -.3623187    1.538832
                                         |
               time#c.cent_dashusability |
                                      2  |  -.1231236   .1085024    -1.13   0.256    -.3357844    .0895372
                                         |
                                   _cons |   3.999614   .3256732    12.28   0.000     3.361307    4.637922
------------------------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
studentnr: Identity          |
                  var(_cons) |   .6368193   .2134434      .3301552    1.228328
-----------------------------+------------------------------------------------
               var(Residual) |   .1055961   .0325877      .0576715    .1933457
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 27.95         Prob >= chibar2 = 0.0000
```

Usability and engagement

Comparing the three groups in usability, time, and dashboard group on engagement with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood =  -60.78709
Iteration 1:   log pseudolikelihood = -60.787089

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         62
Group variable: studentnr                       Number of groups  =         31
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(9)      =     633.38
Log pseudolikelihood = -60.787089               Prob > chi2       =     0.0000

                                    (Std. err. adjusted for 31 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
reflection	-.0179235	.2744577	-0.07	0.948	-.5558507	.5200038
resource	.1418505	.2582082	0.55	0.583	-.3642282	.6479293
2.time	-1.472559	.1118044	-13.17	0.000	-1.691692	-1.253427
cent_dashusability	.5222296	.1556891	3.35	0.001	.2170846	.8273746
dashboardgroup#time						
reflection#2	-.1266249	.3489147	-0.36	0.717	-.8104851	.5572353
resource#2	-.0838894	.1912522	-0.44	0.661	-.4587368	.2909579
dashboardgroup#c.cent_dashusability						
reflection	-.7342004	.3322881	-2.21	0.027	-1.385473	-.0829278
resource	-.3776243	.2308612	-1.64	0.102	-.8301039	.0748554
time#c.cent_dashusability						
2	.0187021	.1126375	0.17	0.868	-.2020633	.2394675
_cons	3.845719	.1770115	21.73	0.000	3.498783	4.192655

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.3119879	.1227363	.1443026	.67453
var(Residual)	.2080271	.0844658	.0938651	.4610369

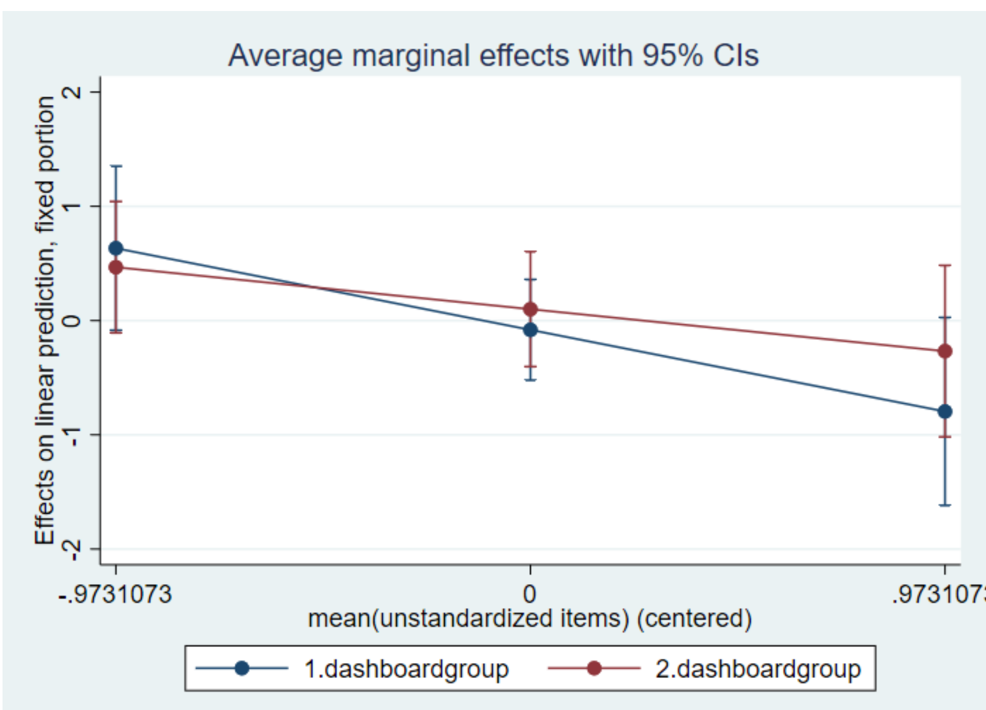
Prediction of interaction effect dashboard group and usability.

```
Average marginal effects                              Number of obs = 62
Model VCE: Robust

Expression: Linear prediction, fixed portion, predict()
dy/dx wrt:  1.dashboardgroup 2.dashboardgroup
1._at: cent_dashusabi~y = -.9731073
2._at: cent_dashusabi~y =         0
3._at: cent_dashusabi~y =  .9731073
```

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
0.dashboardgroup	(base outcome)					
1.dashboardgroup						
_at						
1	.6332199	.3663069	1.73	0.084	-.0847285	1.351168
2	-.0812359	.2249445	-0.36	0.718	-.5221191	.3596473
3	-.7956917	.4196812	-1.90	0.058	-1.618252	.0268682
2.dashboardgroup						
_at						
1	.4673748	.2932906	1.59	0.111	-.1074643	1.042214
2	.0999058	.2566294	0.39	0.697	-.4030786	.6028903
3	-.2675631	.3829303	-0.70	0.485	-1.018093	.4829665

Note: dy/dx for factor levels is the discrete change from the base level.



Dashboard Usefulness and motivation

Comparing the experimental groups in dashboard usefulness, time, and dashboard group on motivation with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -35.511789
Iteration 1:   log likelihood = -35.511789

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         42
Group variable: studentnr                       Number of groups  =         21
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(6)      =      25.36
Log likelihood = -35.511789                     Prob > chi2       =     0.0003

------------------------------------------------------------------------------------------------------
                              motivation | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------------------------------+------------------------------------------------------------
                          dashboardgroup |
                               resource  |   .2766143   .3279689     0.84   0.399    -.3661929    .9194216
                                  2.time |   .2368117   .1510343     1.57   0.117      -.05921    .5328335
                     cent_dashusefulness |   .4664979    .241201     1.93   0.053    -.0062474    .9392433
                                         |
                     dashboardgroup#time |
                             resource#2  |   .0793685   .2013778     0.39   0.693    -.3153248    .4740618
                                         |
dashboardgroup#c.cent_dashusefulness     |
                               resource  |   .1161902   .2854836     0.41   0.684    -.4433474    .6757277
                                         |
              time#c.cent_dashusefulness |
                                      2  |  -.1185053   .0851893    -1.39   0.164    -.2854732    .0484626
                                         |
                                   _cons |   3.978429   .2457414    16.19   0.000     3.496785    4.460073
------------------------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
studentnr: Identity          |
                  var(_cons) |   .4403086    .1525401      .2232892    .8682536
-----------------------------+------------------------------------------------
               var(Residual) |   .1026152    .0316677      .0560435    .1878876
------------------------------------------------------------------------------
LR test vs. linear model: chibar2(01) = 22.51         Prob >= chibar2 = 0.0000
```

Dashboard Usefulness and engagement

Comparing the three groups in dashboard usefulness, time, and dashboard group on engagement with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -60.271325
Iteration 1:   log pseudolikelihood = -60.271324

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         62
Group variable: studentnr                       Number of groups  =         31
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(9)      =     404.94
Log pseudolikelihood = -60.271324               Prob > chi2       =     0.0000

                                    (Std. err. adjusted for 31 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
reflection	-.0800418	.346666	-0.23	0.817	-.7594945	.599411
resource	.0576339	.2809497	0.21	0.837	-.4930175	.6082852
2.time	-1.510233	.1019294	-14.82	0.000	-1.710011	-1.310455
cent_dashusefulness	.4691336	.272261	1.72	0.085	-.0644882	1.002755
dashboardgroup#time						
reflection#2	-.0860865	.299304	-0.29	0.774	-.6727116	.5005387
resource#2	-.016969	.2116513	-0.08	0.936	-.4317979	.39786
dashboardgroup#c.cent_dashusefulness						
reflection	-.3993024	.3101589	-1.29	0.198	-1.007203	.208598
resource	-.1305014	.2856535	-0.46	0.648	-.690372	.4293692
time#c.cent_dashusefulness						
2	-.1124155	.1294754	-0.87	0.385	-.3661825	.1413516
_cons	3.835443	.2217415	17.30	0.000	3.400838	4.270049

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.3168877	.1130322	.1575021	.6375651
var(Residual)	.2006376	.0713168	.099966	.4026915

Prompt Usefulness and motivation

Comparing the experimental groups in dashboard usefulness, time, and dashboard group on motivation with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log likelihood = -37.183542
Iteration 1:   log likelihood = -37.183542

Computing standard errors ...

Mixed-effects ML regression                     Number of obs     =         42
Group variable: studentnr                       Number of groups  =         21
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(6)      =      19.91
Log likelihood = -37.183542                     Prob > chi2       =     0.0029
```

motivation	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
resource	.2207884	.3562212	0.62	0.535	-.4773923	.9189692
2.time	.2082239	.1540121	1.35	0.176	-.0936343	.5100821
cent_promptusefulness	.3655683	.234003	1.56	0.118	-.0930691	.8242057
dashboardgroup#time						
resource#2	.1008858	.2057825	0.49	0.624	-.3024405	.5042121
dashboardgroup#c.cent_promptusefulness						
resource	.2802342	.3150408	0.89	0.374	-.3372345	.8977028
time#c.cent_promptusefulness						
2	-.1223018	.0949765	-1.29	0.198	-.3084524	.0638488
_cons	4.060158	.2700359	15.04	0.000	3.530897	4.589418

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.5175689	.1764819	.2652915	1.009748
var(Residual)	.1038694	.0320548	.0567285	.190184

```
LR test vs. linear model: chibar2(01) = 24.84         Prob >= chibar2 = 0.0000
```

Prompt Usefulness and engagement

Comparing the three groups in prompt usefulness, time, and dashboard group on engagement with interactions.

```
Performing gradient-based optimization:
Iteration 0:   log pseudolikelihood = -45.196913
Iteration 1:   log pseudolikelihood = -45.196908
Iteration 2:   log pseudolikelihood = -45.196908

Computing standard errors ...

Mixed-effects regression                        Number of obs     =         42
Group variable: studentnr                       Number of groups  =         21
                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2
                                                Wald chi2(6)      =     182.71
Log pseudolikelihood = -45.196908               Prob > chi2       =     0.0000

                                  (Std. err. adjusted for 21 clusters in studentnr)
```

engagement	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
dashboardgroup						
resource	.1485175	.3404641	0.44	0.663	-.5187799	.8158149
2.time	-1.61263	.3448825	-4.68	0.000	-2.288587	-.9366724
cent_promptusefulness	.0524773	.1564672	0.34	0.737	-.2541927	.3591474
dashboardgroup#time						
resource#2	.0706137	.4008324	0.18	0.860	-.7150033	.8562308
dashboardgroup#c.cent_promptusefulness						
resource	.2855954	.1931146	1.48	0.139	-.0929023	.664093
time#c.cent_promptusefulness						
2	-.075363	.17927	-0.42	0.674	-.4267257	.2759997
_cons	3.767039	.290372	12.97	0.000	3.19792	4.336157

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
studentnr: Identity				
var(_cons)	.3231281	.1663756	.1177875	.8864419
var(Residual)	.2753633	.1102705	.1256142	.6036338

Prompt difficulty on usability

```
                    Number of obs =         21    R-squared     =  0.3904
                    Root MSE      =    .774561    Adj R-squared =  0.3583
```

Source	Partial SS	df	MS	F	Prob>F
Model	7.2994728	1	7.2994728	12.17	0.0025
promptdif~y	7.2994728	1	7.2994728	12.17	0.0025
Residual	11.398939	19	.59994417		
Total	18.698412	20	.9349206		

```
. estat esize

Effect sizes for linear models
```

Source	Eta-squared	df	[95% conf.	interval]
Model	.3903793	1	.0646348	.6075287
promptdifficulty	.3903793	1	.0646348	.6075287

Prompt trust on usability

```
. anova dashusability c.prompttrust if time == 2 & dashboardgroup > 0

                    Number of obs =         21    R-squared     =  0.2362
                    Root MSE      =    .866997    Adj R-squared =  0.1960
```

Source	Partial SS	df	MS	F	Prob>F
Model	4.4164204	1	4.4164204	5.88	0.0255
prompttrust	4.4164204	1	4.4164204	5.88	0.0255
Residual	14.281992	19	.75168377		
Total	18.698412	20	.9349206		

```
. estat esize

Effect sizes for linear models
```

Source	Eta-squared	df	[95% conf.	interval]
Model	.2361923	1	.	.4909625
prompttrust	.2361923	1	.	.4909625

Prompt difficulty on dashboard usefulness

```
. anova dashusefulness c.promptdifficulty if time == 2 & dashboardgroup > 0

                         Number of obs =         21    R-squared     =  0.3376
                         Root MSE      =    1.00097    Adj R-squared =  0.3027

                  Source | Partial SS         df         MS        F    Prob>F
                         +
                   Model |   9.701192          1    9.701192      9.68  0.0057
                         |
             promptdif~y |   9.701192          1    9.701192      9.68  0.0057
                         |
                Residual |  19.036903         19   1.0019423
                         +
                   Total |  28.738095         20   1.4369048

. estat esize

Effect sizes for linear models

                  Source | Eta-squared     df     [95% conf. interval]
                         +
                   Model |   .3375725       1     .0358038     .5695697
                         |
        promptdifficulty |   .3375725       1     .0358038     .5695697
```

Prompt trust on dashboard usefulness

```
. anova dashusefulness c.prompttrust if time == 2 & dashboardgroup > 0

                         Number of obs =         21    R-squared     =  0.2178
                         Root MSE      =    1.08769    Adj R-squared =  0.1767

                  Source | Partial SS         df         MS        F    Prob>F
                         +
                   Model |  6.2598625          1   6.2598625      5.29  0.0329
                         |
             prompttrust |  6.2598625          1   6.2598625      5.29  0.0329
                         |
                Residual |  22.478233         19   1.1830649
                         +
                   Total |  28.738095         20   1.4369048

. estat esize

Effect sizes for linear models

                  Source | Eta-squared     df     [95% conf. interval]
                         +
                   Model |   .2178245       1            .     .4755844
                         |
             prompttrust |   .2178245       1            .     .4755844
```

Prompt trust on prompt usefulness

```
. anova promptusefulness c.prompttrust if time == 2 & dashboardgroup > 0

                         Number of obs =         21    R-squared     =  0.3064
                         Root MSE      =    .938797    Adj R-squared =  0.2699

                  Source | Partial SS         df         MS        F    Prob>F
             ------------+----------------------------------------------------
                   Model |   7.397383          1    7.397383      8.39  0.0092
                         |
             prompttrust |   7.397383          1    7.397383      8.39  0.0092
                         |
                Residual |  16.745474         19   .88134074
             ------------+----------------------------------------------------
                   Total |  24.142857         20   1.2071429

. estat esize

Effect sizes for linear models

-------------------------------------------------------------------
             Source | Eta-squared     df     [95% conf. interval]
--------------------+----------------------------------------------
              Model |   .3064005       1     .0222659    .5463338
                    |
        prompttrust |   .3064005       1     .0222659    .5463338
-------------------------------------------------------------------
```