

1. Research team [1500-200 words/ 8 – 10 pages]

Name PhD candidate: **Nithila Ramesh**

Education	Institute	Study program	Graduation date
Master	Tilburg University	ReMa: Individual Differences and Assessment	13/08/2024
Bachelor	Maastricht University	BSc: Maastricht Science Programme	30/06/2022

Starting date as PhD candidate: 1st September 2024

Size of appointment in FTEs: 1.0

Composition of the supervisory team:

Name, title(s)	Role	Discipline	Supervision frequency	Hours per week
Prof. Dr. Chris Snijders	Promotor	IE & IS; HTI Group	Once per month	0.5
Dr. Uwe Matzat	Daily Supervisor	IE & IS; HTI Group	Once per week	1.5
Dr. ir. Rianne Conijn	Daily Supervisor	IE & IS; HTI Group	Once per week	1.5

2. Title of the research project:

Let the data inspire students: Design, testing, and implementation of student-facing dashboards on a larger scale

3. Relevance for the Department Industrial Engineering & Innovation Sciences

This project takes place within the Human-Technology Interaction (HTI) Group and contributed to the IE&IS research theme of Humans and Technology. HTI focuses on translating social scientific knowledge to design effective, sustainable and responsible human-centred technology that aims to impact individual, organisational and societal behaviour. Along those lines, this project aims to apply psychological theories to design personalised student-facing dashboards that present students with their learning data in an informative manner to nudge them to self-regulate, learn and perform more successfully in their university studies. This project is also in line with the pipeline for student-facing learning analytics developed within the TU/e as part of the DRIVE program and with the primary goal of LA use at TU/e (2023, December 4).

4. Brief summary of the main research issue (max. 200 words)

Blended learning has become a significant component of the modern higher education landscape. However, not all students thrive in this learning environment that requires more self-regulation of learning. Since blended learning often implies substantial amounts of isolated learning, students need to regulate their learning by setting up their own learning goals, self-managing their motivation, self-monitoring their learning activities, etc. In recent research, dashboards that display students' learning data obtained from Canvas (learning environment) or self-reports have been used to support this added cognitive load by attempting to build students' self-regulation skills. However, these dashboards are often not designed based on educational theories, not accurately evaluated, and have very low effects on self-regulated learning behaviour and performance. In this PhD project, I attempt to

understand what elements of dashboards are working, and why, and to design dashboards that support specific learning outcomes in a theory-driven manner. Further, I note that not all learners require the same amount/kind of support, and over-scaffolding already self-regulated learners can hamper motivation. Through this project, I aim to understand which individual differences impact dashboard preferences and effectiveness and how personalised support should be provided such that all students can benefit from the dashboard.

5. Duration of the project

Period (in years): 4 years

Starting date: 01/09/2024

6. Any other appointment besides PhD

No

7. How is the project financed?

Fully funded by 4TU.Centre for Engineering Education (4TU.CEE) and BOOST! Programme

8. Description of the project (max. 4 pages of which max. 1-page references)

8.1 Specification of the main research problem (i.e., key research problems and aims)

In recent years, blended learning (a combination of face-to-face interactions and online learning) has become a significant component of the higher educational landscape as it allows for flexibility and personalisation (Kaur, 2013). However, not all students benefit equally. As educators and scholars note, a considerable amount of self-regulation is required from students to be successful in this learning environment. (Montgomery et al., 2019). Self-regulated learning (SRL) consists of thoughts, feelings, actions and adaptations systematically generated to attain a self-set goal in the process of learning (Zimmerman, 2000). Feedback from prior performances plays an important role in SRL by allowing students to reflect and make adjustments in their goal-oriented actions (Zimmerman, 2000). However, in traditional online learning environments, very few cues are available for students to make judgments on their learning and performance, placing a higher cognitive burden on students than face-to-face learning environments (Viberg et al., 2020). Thus, a goal of researchers in blended learning environments is to develop a tool to intervene and support students with low SRL skills.

In this PhD project, I will design and test theory and evidence-based, student-facing learning analytics-based dashboards (LADs) for university students. LADs are potentially interactive, personalised, and analytical monitoring displays that present a student's learning data (e.g., log data from learning management systems) in a way that provides insight into their learning patterns and performance (Park & Jo, 2015). Overcoming the lack of feedback in online learning environments, LADs can provide students with external feedback, allowing them to monitor their learning behaviour and performance (Viberg et al., 2020).

However, LADs have been found to have low or negligible effects on learning outcomes (Kaliisa et al., 2024). One reason for this is the paucity in theory-driven designs (Jivet et al., 2017) and accurate evaluation of LADs (Valle et al., 2021). In terms of theory, in our study, I will focus on SRL theories. SRL skills have been a strong focus of prior LAD research due to their importance in supporting blended learning (Jivet et al., 2017; Matcha et al., 2020). Through different studies in this project, I aim to identify which elements within an LAD work to support the four phases of SRL and why: [1] Task definition, [2] Goal-setting and

planning, [3] Enactment and [4] Adaptation/Reflection (Winne & Hadwin, 1998). I will then evaluate the educational value of the LADs by assessing their influence on four learning outcomes (Jivet et al., 2018): [1] Intrinsic motivation (emotional), [2] SRL Development (metacognitive), [3] SRL Application of SRL (behavioural) and [4] Performance (cognitive; i.e., grades, subjective performance), focusing on different aspects across studies.

A second reason for the low effectiveness of dashboards is the lack of personalisation. LADs often present the same type of information to all students, ignoring individual differences in terms of traits and needs of the student (Divjak et al., 2023; Tsai et al., 2020). When creating an educational tool, as with all interventions, it is important to consider that students require different support based on their individual differences (e.g., SRL skills, goal orientation, course motivation) and needs from education. Thus, in this project, I attempt to understand how to personalise support to improve the efficacy of LADs.

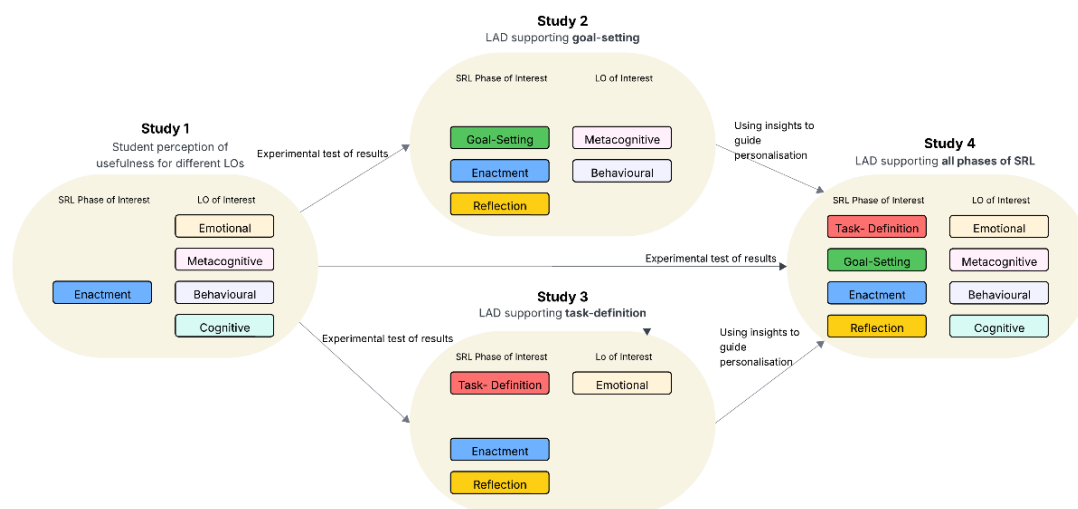
In this project, I ultimately aim to understand how to design and test a personalised and scalable theory-driven LAD to increase emotional, metacognitive, cognitive and behavioural learning outcomes. To achieve this project goal, I will conduct four studies (see Figure 1).

8.2 Scientific importance and relevance of the project (i.e., innovative aspects, added-value, theoretical background, embedding in the existing literature, etc.)

This project aims to design and test LADs in a theory and evidence-guided manner, advancing our understanding of how to design and test the efficacy of educational support tools. While previous LADs have aimed to foster SRL, they have often had low efficacy (Kaliisa et al., 2024). Through our four studies, we aim to understand how LADS can be used to support SRL in a theory-grounded manner (i.e., what information is important and how it should be presented), and if personalisation is key. On a theoretical level, the most innovative aspect of this project is the understanding when personalisation is required and how to develop LADs that support learning outcomes in a personalised manner. In this way, the results of this project are relevant not only for learning analytics research, but also for fields such as educational and personality psychology and education technology.

8.3 Research methodology (e.g., research procedure, research design, models, sample, measures, statistics)

Figure 1: Connections Between Studies within the PhD Project. LO = Learning Outcomes.



In **Phase 1**, I focus on student preferences for LAD elements.

Study 1: One Size Does Not Fit All: What Affects Learning Analytics-Based Dashboard Preferences?

Through this user-centred study, I aim to uncover which elements supporting the enactment phase (from those previously used in LAD studies) students prefer. Despite the enactment phase being the most represented phase in LADs (Matcha et al., 2020), it is not yet understood which LAD elements work and why. Through this study, I attempt to understand whether and why users prefer certain LAD elements and comparison frames with the following RQs: [1a] “What dashboard elements and modes of comparison are preferred by students in general?”, [1b] “What individual differences impact these preferences?”. I will focus on the following individual differences: self-regulated learning skills, course motivation, goal-orientation, social comparison orientation and past performance. In a survey study, I will present students with a subset of theoretically informative combinations of nine elements $\times$ six modes of comparison. Students will then rate their preference for these combinations in terms of goal orientation, learning motivation, behaviour change and performance improvement (Yoo et al., 2015). From this study, I will gain insight into what users prefer in dashboards, which acts as a starting step to design LADs from a user-centred perspective and assess whether this matches with design from a theory-centred perspective.

In **Phase 2**, I test the match between user-rated preferences and empirical evidence, and design LADs to support the learning outcomes: [1] development and use of SRL through goal-setting in study 2, and [2] intrinsic motivation through task-definition in study 3.

Study 2: Nudging Academic Goal Setting in a Personalised Manner

Using insights from study 1, study 2, will test if the preference ratings are reflected in the effectiveness of different elements on SRL skills and behaviour in real courses. In this study, we will nudge SRL through **goal-setting** (SRL Phase 2). While previous work has tackled goal-setting (Jivet et al., 2021; van Jaarsveld et al., 2025), personalised support based on goal orientation has not been designed in a scalable manner. This study aims to design an LAD to support goal-setting in a personalised manner. The dashboard will also contain elements from the enactment (from Study 1) and adaptation phase to prompt students to monitor, evaluate and adapt their learning activities based on the set goal, allowing for a more holistic evaluation of the efficacy of the dashboard to support SRL development and application (metacognitive and behavioural learning outcomes). The LAD will be evaluated by answering the following RQ: [2] “Does encouraging goal-setting within an LAD in a personalised manner increase the development and use of SRL strategies within a course?”. To test the efficacy of the dashboard in supporting the development and use of SRL skills, within a single course, an experimental group will be given access to the personalised goal-setting dashboard, an active control group—a non-personalised goal-setting dashboard, and a passive control group—no dashboard. Through this study, I will gain a better understanding of what elements work to support the phase of goal-setting, and how and whether they should be personalised.

Study 3: Building Academic Self-Efficacy and Task-Value in a Personalised Manner

In study 3, I will test if the preferences rated in study 1, match with which elements effectively support intrinsic motivation in real courses. In this study, I will increase intrinsic motivation by focusing on supporting **task definition** (producing optimal standards or definitions of the task; SRL Phase 1; Winne & Hadwin, 1998). Few studies have used elements in LADs attempting to support task-definition, however, only by displaying information about the task (Villagrán et al., 2024). In this study, I aim to design a theory-driven dashboard to build up students’ task value (value placed on learning tasks within a

course) and self-efficacy (self-confidence in academic ability) based on theories such as the socio-cognitive theory (Bandura, 1977). I will evaluate if this dashboard is effective in increasing the intrinsic motivation of students for this course (emotional learning outcome) with the RQ: [3] “Does building task-value and self-efficacy via an LAD in a personalised manner lead to an increase in intrinsic motivation within a course?”. Similar to study 2, the dashboard’s effectiveness in increasing intrinsic motivation will be experimentally evaluated within a course, with an active and a passive control group. From this study, I aim to understand how the phase of task-definition can be best supported through an LAD, and how and whether personalisation will increase the effectiveness of the dashboard in raising intrinsic motivation.

In **Phase 3**, I bring together insights from previous studies and design an LAD to support individual learning paths across all phases of SRL in a scalable manner.

Study 4: Supporting All Phases of SRL in a Personalised Manner

In this study, I will incorporate insights from the three previous studies and previous personalised dashboards to design an LAD that can support all four stages of SRL (Winne & Hadwin, 1998); see Figure 1). The designed dashboard will keep in mind the cyclical and recursive natures of the four phases and work to support all phases in different timelines for each student as required, thus supporting individual learning paths. Once again, the efficacy of dashboard in increasing learning outcomes will be tested in an experimental set-up with an active and passive control group with the RQ [4] “Does an LAD designed to support students through the different phases of SRL in a personalised manner increase affective, cognitive and behavioural learning outcomes?”. However, for this study I will employ the dashboard within different courses, thereby testing the scalability of the dashboard and testing under what contexts it is effective. This study offers insights into how to design a dashboard to support individual learning paths, how and whether personalisation should be applied, and whether the built dashboard is scalable and can be applied in different contexts.

8.4 Fit of research team (i.e., why are you and your research team suitable candidates to conduct this research)

The research team has previously designed, implemented and tested LADs: attempting to support SRL within courses (Peters, 2023), with reflective and resource-directed prompts (Vleeshouwers, 2023) and with metacognitive prompts (van Dijk, 2024). They have also tested and solved technical issues, e.g., prior tests revealed that it was not possible for users to input information and to track user behaviour on Power BI, thus, this project will shift to using R Shiny to host the LAD. This project will build on this foundation and prior work done by the research team to test and implement *personalised* dashboards on a larger scale than previously done, and evaluate their educational value

8.5 Overview of research project

	Aim	Data	Method	Expected outcome
Study 1	To test student preferences for “enactment” elements for different learning outcomes	Observational data collected through a survey study	Mixed effects models	Dashboard items preferred on average, and impactful individual differences for these preferences.
Study 2	(1) To design and test a personalised LAD to support “goal-setting”	Experimental data collected through an	Mixed effects models (with repeated	Understanding how to improve SRL behaviour through nudging goal-setting;

	(2) To test the match between student preferences (study 1) and empirical tests of “enactment” elements increasing development and use of SRL	LAD experiment situated within a single course	measures of outcome)	and if preference matches true outcomes
Study 3	(1) To design and test a personalised LAD to support “task definition” (2) To test the match between student preferences (study 1) and empirical tests of “enactment” elements increasing intrinsic motivation	Experimental data situated within a single course	Mixed effects models (with repeated measures of outcome)	Understanding how to improve intrinsic motivation through supporting students’ task-definition; and if preference matches true outcomes
Study 4	(1) To design and test a personalised LAD to support all four phases of SRL (2) To test the match between student preferences (study 1) and empirical tests of “enactment” elements increasing the four chosen learning outcomes	Experimental data situated within multiple different courses, across different disciplines	Mixed effects models (with repeated measures of outcome)	Understanding how to improve intrinsic motivation, SRL skills and behaviour, and performance by supporting all phases of SRL; and if preference matches true outcomes

8.6 Applicability and/or societal relevance of the project (max. ½ A4 page)

This project aims to understand which individual differences influence learning goals and paths, and how these differences should be considered when designing an educational support tool (i.e., LAD). The results of this project not only contribute to scientific literature, but also have a strong societal relevance as they contribute to improving engineering education and creating equitable education. Finally, considering the setting of the study: Dutch universities consist of diverse students with various backgrounds and specific educational needs. TU/e embraces this diversity and its educational plan aims to support personalised learning paths (TU/e, 2018). Thus, the project will help reach the goals of TU/e. The findings of this study can further be applied to any situation with online learners; for example, massive open online courses (MOOCs), corporate trainings, etc.

8.7 Relevant literature for the project, with separate citation of relevant literature of the research group and data sources

References and Relevant Literature

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df](https://research.tue.nl/files/306950459/Master_Thesis_Report_Cahelle_Vleeshouwers.pdf)

9. Project embedding

This project will work in close collaboration with 4TU.CEE, and other research teams in the Netherlands building student-facing LADs, for example: IguideME from UvA, Joshi and colleagues from UU. This project will also work very closely with TU/e's student-facing learning analytics vision led by Dr. Suzanne Groothuijsen from Education and Student Affairs at TU/e.

10. Time plan and planned publications

10.1 Detailed description of the research plan for the first twelve months – including status of the research at the moment of submitting the research proposal.

Month	Sept	Oct	Nov	Dec	Jan	Feb	March	April	May	June	July	August
Research												
<i>Overview of Literature</i>												
Literature Review												
Conceptualisation and Proposal												
<i>Familiarisation with Click-Stream Data and Dashboard Design</i>												
Introduction to Click-Stream Data Handling												
Familiarisation with R Shiny												
Introduction to Databricks												
Running Built Mock Dashboard												
Improving Mock Dashboard												
Changing Dashboard Information Based on Real-Time Data												
<i>Study 1 Tasks</i>												
Conceptualisation												
Literature Review												
Experimental Set-Up												
RQ and Hypotheses for Study 1												
Designing LAD Elements for Study 1												
Writing ERB Proposal												
Setting up and Conducting Study 1												
Data Analysis of Study 1												
Writing up Study 1												

Dissemination												
Preparing for LAK Presentation												
LAK25 Presentation at Workshop												
Teaching/Supervising Tasks												
Grading TA: [0HV30, 0HV130, 0HV150]												
Traineeship: Bachelor End Projects [0BEPP0]												
TA: Applied Data Skills [0HV130]												

10.2 Framework of the research plan for the rest of the project's duration

Year	Year 1								Year 2								Year 3								Year 4											
Month	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
Research tasks																																				
Literature Review																																				
Conceptualising Project																																				
Familiarisation with LAD Design																																				
Formulating Study 1																																				
Conducting and Analysing Study 1																																				
Writing Article 1																																				
Formulating Study 2																																				
Designing Dashboard 2																																				
Conducting and Analysing Study 2																																				
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Designing Dashboard 4																																				
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10.3 Publications planned

Study 1: Journal of Learning Analytics or LAK Conference Proceedings

Study 2: Educational Technology Research and Development

Study 3: tbd.

Study 4: tbd.

10.4 Status of the project and education plan at the time of submitting the proposal

See section 10.1 for what has been completed and status of project at nine months.

At the time of submitting this proposal, the following course have been completed.

Course name	Organizing institute	Level (PhD / Master)	Workload in hrs	Timing
Compulsory courses				
Scientific Integrity for PhD Candidates	PROOF-program TU/e	PhD General Skills	7	20-03-2025
Writing and Assessing PhD Research Proposals (WARP)	GP-IE&IS – TU/e	PhD General Skills	84	17-10-2024 and 09/04/2025
Supervising (<i>P&E PhD candidates can replace this with an alternative general skills course</i>)	PROOF-program TU/e	PhD General Skills	12	19-11-2024 and 3-12-2024
In-Depth PhD Courses				
Open Qualitative Research	Paul Meehl Graduate School	PhD Course	15	11-04-2025
Online Courses				
Coursera course on R Shiny: Publishing Visualizations in R with Shiny and flexdashboard	John Hopkins University	Intermediate	10	06-01-2025 to 10-01-2025
Training PROOF Courses				
Information Literacy and Reference Management	PROOF-program TU/e	PhD General Skills	5	7-10-2025 and 14-10-2025
Foundations	PROOF-program TU/e	PhD General Skills	4.5	15-10-2025
<i>Total</i>			<i>137.5 hours</i>	

PhD candidate: Nithila Ramesh

Date: 28/04/2025

Signature



Supervisor 1: Prof. Dr. Chris Snijders

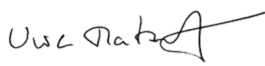
Date: 28/04/2025

Signature



Daily Supervisor 1: Dr. Uwe Matzat

Date: 28/04/2025

Signature 

Daily supervisor 2: Dr. ir. Rianne Conijn

Date: 28/04/2025

Signature 