Designing and Evaluating Student-facing Learning Dashboards: Lessons Learnt

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Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Engineering Science (PhD): Computer Science

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Acknowledgements

Twenty years ago, I figured, let’s do Physics. I loved all things space and dinosaur related, and had an awesome Physics teacher. However, that same teacher told me studying Physics would most likely land me in Finance. So, I followed my other passion, Computer Science.

But after completing my degree and spending years in the private sector, I wondered if I had made the right decision. While I had a passion for programming, the lack of creativity that comes with a software engineering job (beyond the code) was killing me. Moving to Nottingham to pursue a career in games did not improve the situation either: a developer just develops, it seems. Side projects (indie game development and art academy) were an attempt to bring some creativity back into my life, but I needed a serious change where I spent most of my time: the day job.

The PhD was an unexpected opportunity that presented itself in my mailbox. Two weeks it sat there until I finally decided to reply. What followed was life changing. Research meant I could explore the unknown, build things no one had before, and join the user in their experience with our new creations. I got paid to create visualisations, play with new technology, and spend time thinking of all the crazy things we could accomplish with it. Both the nerd and the artist in me were satisfied. This might just be where I belong. It only took me 36 years to figure it out...

Thirty-six years is a long time. I owe where I am today to a lot of amazing people: for the opportunities, the support, the patience, and the listening.

I would like to thank Erik. In 2013, I somehow convinced him I would be the right guy for the job. When times got tough, he would keep convincing me I was. “I wasn’t that smart either and look where I am now”, a pep talk I will never forget. From all the “bosses” I’ve had, he was one of the few who genuinely cared about his people, at a personal, family, and career level. Thanks for letting me get to know you and your amazing family. Your awesome ideas
ACKNOWLEDGEMENTS

will live on in our work, we will all make sure of that.

If it wasn’t for Bert, I would have never even considered a PhD. But it was his better half, Katrien, who got me in the room with Erik. I owe a lot to her. She stepped in just as I was close to jumping ship. She was the motivating force I needed, and pushed me across the finish line. Thanks to both Katrien and Tinne, this last year and a half of the PhD has been amazing. We’ve published great papers, made a name in the community, and put our stamp on student advice at the university.

Joris. What was it Jose said, thanks for the coffee? I’ll do one better: bourbon at Harvard, such an amazing trip! He never once doubted me, and I will never forget his endless “het komt goed” (it will be all right). And who’d have thought, it did! (I guess this calls for another round of drinks in Boston!).

I would also like to thank Andrew, Bieke, Yolande, and Martin, for taking the time to read my dissertation, providing valuable feedback, and a memorable private defence.

But my biggest thanks goes to Elke. I could not have achieved this without the love of my life (15 years this year, 10 as my gorgeous wife). Always supporting my crazy decisions. She quit a promising career to follow me abroad and let me pursue my game developer dream back in 2008. And in 2013 she supported me again in my biggest career change, when I gave up a well-paid, secure job to become a student once again. We were not expecting the PhD to be such a roller-coaster. I experienced moments of joy and despair, feelings that would affect her as much as it did me. But she always had my back, endured the after-work rants, and supported me in every way possible. Without her, I would never have managed.

Hazel joined us (in the womb) at the start of the PhD. Kids do not make things easier. But they do give you a reason to keep going. During dark periods of the PhD, she was always there to put a smile on my face (or add to the misery with sleepless nights. She’s a little monster like that). Hazel, if you read this when you are older, we love you and we will make sure you get to follow your dreams just as we could.

My parents, Marinette and Guy: they have always been there for me, supported me, and believed in me (and also provided me with all the nerdy hardware a kid needs to keep his technology interest going). And my grandparents, Meke, Vake, Peter Wieke, and Bobonne. Meke is not here to see this, but if someone believed I could pull this off, it was her.

My parents-in-law, Monique and Daniel, and the “Moekes”, for treating me like one of their own. Monique, the things you have missed out on, it is not fair.
We miss you, words cannot describe.

Kurt, thanks for showing up at the defence (if you didn’t, this is going to be awkward). You’ve been that one true best friend. Always there in time of needs. And always making me look good at the board game table.

Franky, the bastard who pulled me out of the Flemish, secure mindset, and lured me to England. I ended up working long unpaid hours in Nottingham and lived amongst criminals and drunks. But I regret nothing!

José, for his unique perspectives on things, telling it like it is, and your attempt at keeping me sane through the PhD (it did not work).

Thomas for the babysitting and being Hazel’s coolest uncle. And “Tantan”, for taking care of Hazel all those Mondays, and for all the things you have done for Elke.

Kris, for bringing that new addiction into my life. The Nets won’t run themselves! Lies, for being Hazel’s awesome godmother. Jim, thanks for letting me win sometimes. Wait, no.

Sean, Jenna, Greg, and Johnny. One day Rad Lab Games will rise again!

Francois and Denis, we will make that dinner happen and bathe in Brasschaat’s sushi! Until then we will just shoot people online.

NorthgateArinso: Fred, Schtroumpf, Maarten, Karo, and Tom. My first and fourth job (thanks Samir), and also my last job before I ran off to academia (I am not implying anything!).

Everyone at Monumental Games and iChoosr, even though the stops were short, they were life changing.

My current, former, and visiting colleagues at the coolest lab of the Computer Science department: Yucheng, Karsten, Francisco, Gonzalo, Robin, Tom, Sam, Bruno, Victor, Gayane, Chen, Sten, Till, Frans, Samara, and Oana. And all the amazing people of the weSPOT, eCloud, and ABLE projects.

The Blade Runner soundtrack, for getting me through numerous paper deadlines.

And Bert. For getting me into this mess in the first place.

“Dude, sucking at something is the first step towards being sorta good at something.”
– Jake the Dog, Adventure Time

“I love you, Pumpkin.”
– Honey Bunny, Pulp Fiction
Abstract

Through the rise of on-line education, an abundance of learner data is generated and gathered. While Educational Data Mining provides insights algorithmically to better understand students, Learning Analytics (LA) attempts to leverage these traces to empower learners by increasing motivation, autonomy, effectiveness, and efficiency. One method to achieve this empowerment is that of Learning Dashboards, a personal informatics or Quantified Self approach, helping learners self-reflect and gain self-knowledge through the visualisation of these traces.

Learning Dashboards are a welcome and much needed topic that shifts the research focus towards, and actively involves, teachers, advisers, and students, providing them with insights into behaviour of learners at both individual (a student) and group level (peer activities in courses, study programs, institutions). Investigating the potential impact of visualising these traces is important, but such research demands long-term deployments in realistic settings. Such an endeavour is challenging, as it requires commitment from institutions, teachers, and learners of (usually) unproven technology during sensitive, life-impacting situations, as well as running the risk of discovering problems with the dashboard designs after commitment, which raises ethical issues. Our research attempts to provide some leverage for such deployments by i) providing evidence of the perceived benefits and ii) providing design guidelines required to create useful and meaningful dashboards. To explore the required design choices, we take an iterative, design-based research approach, in close collaboration with experts, teachers, and students.

The work starts by tackling following research questions: “How should we visualise learner data to support students to explore the path from effort to outcomes? (RQ1),” and “How can we promote students, inside and outside the classroom, to actively explore this effort to outcomes path? (RQ2).” To explore these questions, we have designed, deployed, and evaluated five learning dashboards in blended learning environments. This research resulted in several
guidelines on how to visualise the LA data and how to promote exploration of students’ efforts to outcomes. These lessons cover topics such as abstraction to deal with the abundance of data, facilitating easy access to learner artefacts and feedback, and integrating Learning Dashboards into the work-flow for better user acceptance.

From our research, we noticed potential in the design of collaborative Learning Dashboards, and further explored possible scenarios that could benefit from this approach in two case studies: live dashboards to orchestrate feedback activities in the classroom, and support of the dialogue during advising sessions with students.

The first case study focuses on the following questions: “What are the design challenges for ambient Learning Dashboards to promote balanced group participation in classrooms, and how can they be met? (RQ3)”, and “Are ambient Learning Dashboards effective means for creating balanced group participation in classroom settings? (RQ4)”. Exploring these questions resulted in a Learning Dashboard that raises activity awareness, activates students, and assists with classroom orchestration. We learn that it is important to visualise the data in a neutral way, toning down over-participators to leave room for under-participators.

The second case study explores how a collaborative Learning Dashboard can assist both student and study adviser during advising session, and addresses the following research questions: “What are the design challenges for creating a Learning Dashboard to support study advice sessions, and how can they be met? (RQ5)”, and “How does such a Learning Dashboard contribute to the role of the adviser, student, and dialogue? (RQ6)”. Our design and evaluation process reveal that a passive, supportive dashboard can assist in guiding the student-study adviser conversation, provide further insights and new perspectives, and help convince students of taking specific actions.
Beknopte samenvatting

Door de opkomst van online educatie wordt er een grote hoeveelheid activiteit data van studenten gegenereerd en verzameld. Datamining bezorgt inzichten via algoritmes om studenten beter te leren begrijpen, terwijl Learning Analytics (LA) gebruik maakt van deze data om studenten te in staat te stellen zichzelf te verbeteren op gebied van motivatie, efficiëntie en effectiviteit. Dit kan bereikt worden door middel van Learning Dashboards: visualisaties van de data die studenten kunnen help met zelfreflectie en zelfkennis over hun leerproces.

Learning Dashboards zijn een noodzakelijk onderwerp waarbij de focus verplaatst naar docenten, begeleiders en studenten. Het bezorgt hen inzichten in het gedrag van individuen (een student) en groepen (vergelijkingen met collega-studenten, tijdens lessen, studieprogramma’s, institutie). Het is belangrijk om de potentiele impact van deze visualisaties te onderzoeken, maar dit vereist dat de Learning Dashboards uitgerold worden tijdens lange duur in realistische omgevingen. Dit is geen makkelijke opdracht: het vereist engagement van instituties, docenten en studenten voor het gebruik van (meestal) nog niet bewezen technologie, en dit tijdens gevoelige, levensveranderende situaties. Een negatieve impact door specifieke Learning Dashboard ontwerpkeuzes kunnen pas laat naar boven komen, wat kan resulteren in etische problemen. Ons onderzoek probeert te zorgen voor de nodige onderbouw vooraleer Learning Dashboards kunnen uitgerold worden op grote schaal door i) bewijs te bezorgen over de voordelen die Learning Dashboards bieden en door ii) ontwerprichtlijnen te bezorgen om nuttige en betekenisvolle dashboards te maken. Om de nodige ontwerpkeuzes te exploren, nemen we een iteratieve, ontwerp gebaseerd onderzoek aanpak, in samenwerking met experts, docenten en studenten.

We starten met de volgende onderzoeksvragen: “Hoe moet data van studenten activiteiten gewezen word om studenten te helpen met het exploreren van hun pad van inspanning naar uitkomst”, en “Hoe kunnen we studenten aanmoedigen, in de klas en daarbuiten, om dit pad actief te exploreren?”. Om deze vragen de beantwoorden, hebben we vijf Learning Dashboards ontworpen,
uitgerold en geëvalueerd in “blended learning” omgevingen (een combinatie van online leren en contactonderwijs). Dit onderzoek resulteerde in verschillende richtlijnen voor het visualiseren van LA data en het aanmoedigen van de exploratie ervan door studenten. Deze richtlijnen bevatten punten zoals het abstraheren van de data om de grote hoeveelheid data overzichtelijk te maken voor de student, toegang geven tot artefacten en feedback gegenereerd door studenten en docenten, en het integreren van dashboards in de workflow voor betere acceptatie.

Uit ons onderzoek leren we dat het ontwerpen van collaboratieve Learning Dashboards potentieel heeft. De voordelen hiervan werden verder onderzocht in twee casestudies: live Learning Dashboards om feedbackactiviteiten te ondersteunen in de klas, en Learning Dashboards die ondersteuning bieden voor de dialoog tussen studietraject begeleider en student tijdens advies sessies.

De eerste casestudy focust op de volgende onderzoeksvragen: “Wat zijn de ontwerpuitdagingen voor Ambient Learning Dashboards om balans te creëren in groep participatie in de klas, en hoe kunnen dashboards daaraan voldoen?”, en “Zijn Ambient Learning Dashboards een effectieve aanpak om balans in groep participatie in de klas te creëren”. Het onderzoek resulteerde in het ontwerp en ontwikkeling van een Learning Dashboard dat studenten beter bewust maakt van hun activiteiten en die van medestudenten, dat studenten activeert, en dat helpt bij het “orkestreren” van de klas. Het is belangrijk om de data op een neutrale en abstracte manier te visualiseren, om over-participatie tegen te gaan, om zo ook ruimte te laten voor minder participerende studenten.

De tweede casestudy onderzoekt hoe een collaboratieve Learning Dashboard student en studietraject begeleider kan helpen tijdens een advies sessie. We stellen de volgende onderzoeksvragen: “Wat zijn de ontwerpuitdagingen voor het maken van een Learning Dashboard om ondersteuning te bieden tijdens studieadvies sessies?”, en “Wat is de meerwaarde van dergelijk Learning Dashboard voor de rol van de begeleider, student, en dialoog?”. Het resultaat van ons ontwerp en evaluatieproces toont aan dat een passief, ondersteunend dashboard kan assisteren in het begeleiden van de student-begeleider conversatie, participanten verdere inzichten en nieuwe perspectieven kan bezorgen, en studenten kan helpen overtuigen om specifieke acties te ondernemen.
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AE</td>
<td>aesthetic emphasis.</td>
</tr>
<tr>
<td>AIV</td>
<td>Ambient Information Visualisation.</td>
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<tr>
<td>DBR</td>
<td>Design-based Research.</td>
</tr>
<tr>
<td>DG</td>
<td>Design Goal.</td>
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<tr>
<td>EDM</td>
<td>Educational Data Mining.</td>
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<tr>
<td>IC</td>
<td>Information Capacity.</td>
</tr>
<tr>
<td>IV</td>
<td>Information Visualisation.</td>
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<td>LA</td>
<td>Learning Analytics.</td>
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<tr>
<td>LAR Ae</td>
<td>Learning Analytics Reflection &amp; Awareness environment.</td>
</tr>
<tr>
<td>LAR Ae.TT</td>
<td>Learning Analytics Reflection &amp; Awareness environment - Tabletop.</td>
</tr>
<tr>
<td>LD</td>
<td>Learning Dashboards.</td>
</tr>
<tr>
<td>LISSA</td>
<td>Learning dashboard for Insights and Support during Study Advice.</td>
</tr>
<tr>
<td>LMS</td>
<td>Learning Management System.</td>
</tr>
<tr>
<td>MOOC</td>
<td>Massive Open Online Course.</td>
</tr>
<tr>
<td>NL</td>
<td>Notification Level.</td>
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<tr>
<td>PLE</td>
<td>Personal Learning Environment.</td>
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<tr>
<td>QS</td>
<td>Quantified Self.</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>RF</td>
<td>Representational Fidelity.</td>
</tr>
<tr>
<td>RSS</td>
<td>Rich Site Summary.</td>
</tr>
<tr>
<td>SA</td>
<td>Study Adviser.</td>
</tr>
<tr>
<td>TEL</td>
<td>Technology Enhanced Learning.</td>
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<td>1.1</td>
<td>Overview of the chapters, the learning setting and environment on which they focus, the target audience of the dashboards, the data visualised by the dashboards, the technique used in the dashboards, the level, sub-level and cycle to which they apply.</td>
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Chapter 1

Introduction

Through the rise of on-line education, learner activities such as course material access, quiz results, and social behaviour can be gathered from Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and Personal Learning Environments (PLE) [123]. Due to the large number of activities and, in some cases, huge number of learners, this results in an abundance of interesting and useful learner data. The field of Educational Data Mining (EDM) [158] processes these traces algorithmically to better understand students, and the settings which they learn in [134]. A slightly younger field is that of “Learning Analytics” (LA). While both fields work with the traces left behind by learners, LA takes a less automated approach and attempts to empower learners to be “better learners” [50]. Its objectives include increasing motivation, autonomy, effectiveness, and efficiency of learners and teachers [133]. Siemens & Baker [135] define LA as

“The measurement, collection, analysis, and reporting of data about learners and their contexts, for purpose of understanding and optimising learning and the environments in which it occurs.”

The fields of EDM and LA are not mutually exclusive: LA can use data mining techniques and statistics to discover warning signs, recommending courses or activities, improve retention, etc. Social network analysis provides insights on social behaviours and detection of outliers [39]. A key focus of research in the learning analytics community is to put this information in the hands of human experts to support decision making. The objective is to inform and to empower
instructors and learners of issues that are identified and to leverage human judgement [134].

One way to help people “collect personally relevant information for the purpose of self-reflection and gaining self-knowledge” [80], is through personal informatics systems. A more popular term is Quantified Self 1 (QS), best known for its applications in health, with companies such as Nike and Apple jumping on the bandwagon successfully. In LA, these personal informatics systems are dubbed “Learning Dashboards” (LD) [146]. LDs depend on visualisation techniques of learner traces. These visualisations can play a supportive role for teachers [87, 113] and provide students with ways of self- and peer-monitoring [125]. This awareness of learner activities can promote reflection and insights, and in turn impact learner behaviour [147].

Assessing real learning impact is difficult. While longitudinal studies can provide further evidence, isolating the effect of the intervention is not straightforward [50]. Another hurdle is LD acceptance [49]: if teachers and learners do not understand the benefits LDs can provide, we cannot expect them to use them, let alone result in any impact.

This work therefore focuses on the different steps needed towards achieving impact [146]: awareness, reflection, and sense-making (see Figure 1.1). We explore the design requirements to create useful and meaningful dashboards: what learning activities can be tracked, how we should visualise these data in such a way that it helps raise awareness of relevant activities, and how we can motivate students to explore their learning path and paths of their peers. To this end, we designed, deployed, and evaluated a total of seven dashboards. We

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1http://quantifiedself.com
summarise several lessons learnt that can guide future LD research based on our results in three types of authentic learning settings:

- Blended Learning courses [6], combining traditional classroom methods with digital activities,
- Live Classroom Orchestration [43], making the educational work-flow visible and tangible in real-time to help students self-regulate classroom activities, and
- Advising Sessions, supporting the dialogue between study adviser and students through LDs.

The remainder of this chapter first elaborates on the context and background of this work (Section 1.1). Section 1.2 explains our research methodology. Section 1.3 lists the research questions and contributions of this thesis. Section 1.4 provides an overview of publications related to each chapter.

1.1 Context and Background

Based on the LA framework presented by Greller and Drachsler [63], this section elaborates on the different dimensions relevant to our work: stakeholders, data, objectives, and instruments. The stakeholders are presented in Section 1.1.1, which explains the different levels of “data-clients” and “data-subjects” in LA, but also the time intervals at which LA can be applied. Section 1.1.2 elaborates on the different types of learner data captured and used in LA. We discuss the final two dimensions, objectives and instruments, in Section 1.1.3.

1.1.1 Stakeholders & Timing

LA covers a broad spectrum of applicable areas. Shum et al. [133] define three “strategic” levels of analysis in LA:

- **Macro**: enabling analytics across institutions at a regional, national or international basis, building upon data gathered at meso/micro level.
- **Meso**: enabling analytics on institutions’ data warehouses, enabling LA applications that can be used institution-wide on available data such as student grades and retention, providing insights on an institutional level.
Figure 1.2: Three “strategic” levels of analysis in LA [133, 119]

Figure 1.3: LA can focus on the individual, group, or class. By providing the data of a higher sub-level to lower sub-levels, peer data can be used for comparison.

- **Micro**: tracking the data at a more personal, individual/group level, providing a feedback loop regarding the finest details possible.

The micro level can be further subdivided according to different data-subject focused sub-levels (see Figure 1.3)
Figure 1.4: Data can be captured and fed back during different cycles: during a session, between sessions, at course level, across a year or even an entire degree.

- **Individuals:** providing information regarding personal, individual performance.

- **Small groups:** providing information regarding group performance.

- **Classroom:** providing information regarding classroom performance.

The information on these data-subjects can be oriented towards different actors of the learning process, including students, teachers, intelligent agents, administrators, study advisers [31]. Leitner et al. [79] groups these in Learners, Teachers, and Researchers/Administrators. Note that in case of learners, the information can be fed back to the same micro-levels: individual learners, groups of learners, and entire classrooms.

For each sub-level, LA can be applied on different time intervals. These “cycles” (see Figure 1.4) include [84]:

- **A (classroom) session:** data can be gathered during the session. This is valuable for e.g. real-time/timely feedback during and across sessions.

- **A complete course:** data can be gathered across an entire course/semester, which in turn can be used for e.g. final evaluation purposes.

- **A year:** data can be gathered across multiple courses/semesters for peer comparison, trends.

- **A complete course:** data can be gathered across the entirety of a degree for e.g. drop-out prediction purposes.

Our work focuses on the micro-level and all its sub-levels, across the different time intervals presented. This will be detailed more in Section 1.3.
1.1.2 LA Data

Many learner traces can be easily tracked as they occur in digital environments such as PLEs and MOOCs. Every interaction with such platforms can be logged, e.g. the time and amount of access to lecture slides, quiz results, interactions with videos, and activity on fora. Even physical spaces can be digitally augmented: “smart classrooms” [131] integrate technology into the classroom, through for instance interactive surfaces [86], motion-capturing devices [86], brain wave sensors [141], and gaze detection [114]. This live data provides teachers with means for better classroom orchestration and information on students’ attention and focus.

Digital tools, such as LMS, wikis, blogs [121], can also complement and support regular, off-line courses. Even activities outside the classroom can be logged using mobile devices through e.g. self-reporting and location tracking [119]. In addition, student grades are stored in central data warehouses by most institutions and are therefore readily available for LA research.

While Santos et al. [119] focus on the capturing and storing of these traces, this thesis focuses on the visualisation of the learner data. The data used and presented in this thesis ranges from student grades, to live feedback during classroom sessions, and activity in on-line environments.

1.1.3 LA Techniques

EDM [158] uses the captured data to e.g. identify students at risk and send warnings to both teachers and students. It tries to help students by making decisions on their behalf [16, 123]. As such, they automatically use students’ efforts to produce information regarding outcomes. For example, they show students that they have a calculated chance on passing the course, or they show which paper to read next. This black box nature can lead to trust issues [104].

Klerkx et. al [76] raise another issue: "If learners are always told what to do next, then how can we expect them to possess the typical 21st century skills of collaboration, communication, critical thinking and creativity? Or, at a more fundamental level, can we expect students who are always told what to do next to become citizens equipped with the knowledge, skills and attitude to participate fully in society?".

LA can be used for a multitude of objectives: monitoring, prediction, tutoring, assessment, adaption, recommendations, and reflection. Chatti et al. [31] divide the techniques used to achieve these objectives into three categories:
statistics (simple reporting tools) [18], data mining (e.g. prediction, text mining, clustering) [160, 47], and information visualisation [146].

As technology can also support the student to play a more active role in the LA reflection process [43], we wish to empower students rather than automating the learning process. To provide students and instructors with insights and improve reflection, we therefore focus on information visualisation. With the abundance of captured learner traces, it is challenging to present this data back to the learner. The next section digs deeper into information visualisation of learner traces.

1.1.4 LA Dashboards

Stephen Few [55] defines a dashboard as “a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance.” By visualising the data in a concise form, dashboards can relay messages in short amounts of time, requiring less effort and expertise knowledge from their users. Similarly, LDs visualise learner traces [139] to present large amounts of data in a meaningful way so that this information can be digested by both teachers and learners [147], or as Schwendimann et al. [126] define:

“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 visualisations.”

LD research is gaining a lot of popularity recently [126]. Where LA research usually focuses on researchers and administrators [79], LDs are a welcome and much needed topic that shifts the research focus towards, and actively involves, an important group of stakeholders: teachers and students [125].

At this micro-level (see Figure 1.3), the data involved is more granulated, as LDs try to leverage traces at an individual level [146, 147]. The data, captured in authentic educational situations, are often activity logs and artefacts generated by learners [125]. Common examples of indicators generated by these data are engagement (e.g. time spent [61, 122], social activity [39]), performance (e.g. grades [109]), goals met [15, 69]), and interaction (e.g. interaction with course content [1]). These indicators are valuable to both teachers and students, and are used usually for self-monitoring and monitoring of others [125]. Typical examples help teachers detect isolated or at risk students and assist in finding
students requiring attention [87, 113]. Meanwhile LDs help students to stay aware of their progress and that of peers [147].

LDs can present learner traces in many ways [136], and to this day, the most common approaches still are bar charts, line graphs, tables, pie charts, and scatter plots [126]. A few examples step outside the box. Course Signals [3], for example, uses a traffic light visualisation to indicate how students perform. People Garden [159] visualises message board participation using a flower and garden metaphor. These LDs can raise teachers’ and students’ awareness of their activities and performance, and trigger further reflection. This in turn can impact behaviour [146] and improve retention and grades [3].

Little research has been done on actual learning impact, as most research does not focus on long term studies [125]. But without proper acceptance [49] of dashboards by students, such research is difficult to pull off. It is therefore important to focus on convenience and perceived benefit. An extensive literature review identified several shortcomings of current research on LDs [11], including a lack of needs assessment, a lack of articulation of information selection and visual design choices, and usability testing. As argued by Bodily and Verbert [11], these aspects “can affect how students perceive and use a reporting system, so to better understand how students use these systems, more rigorous usability tests should be conducted.”

This thesis explores the design choices required to help improve perception of the usefulness and meaningfulness of LDs through a participatory, iterative approach across multiple learning settings. The next section provides details on the methodology.

1.2 Methodology

This works uses the design-based research (DBR) methodology, which has demonstrated its potential as a methodology suitable to both research and design of TEL [152]. This methodology relies on i) early focus on users, ii) empirical measurement via prototypes that are designed and implemented and iii) iterative design. It differentiates itself from more traditional approaches through [152]:

- **Multiple dependent variables**: the methodology deals with real world situations that contain limitations, complexities, and dynamics, requiring a flexible approach [35].
- **Rapid-prototyping**: iteration through design, implementation, and interventions. Outcomes from previously conducted designs provide expectations that become the focus of investigation during the next cycle [34].

- **External input**: the researcher is not the sole decision maker. External input is often solicited through collaboration with participants with different expertise, which in turn affects the decisions during the research process [36].

- **Inform**: it is important to document and connect outcomes with development process, and provide contextual information to develop knowledge that other designers can put into practice [152].

We first evaluate our solutions relying on paper prototypes to gather initial feedback on early ideas and then gradually develop more functional digital prototypes in rapid iteration cycles. We build our prototypes on top of data gathered from authentic learning environments and deploy them in such environments. Participants range from expert users (i.e. researchers in the field of Learning Analytics, Information Visualisation, and Human-Computer Interaction) to the intended target users (teachers, study advisers, and students). Initial input and feedback is gathered through interviews, questionnaires, brain storm sessions, and observations. Evaluations consist of usage tracking and observation, think-aloud, interviews, and questionnaires.

### 1.3 Contributions

This section articulates the contributions of this thesis: through the visualisation of LA traces, we designed, deployed, and evaluated seven LDs. The results shed light on the design approaches required to improve student, teacher, and study adviser’s perceived usefulness of dashboards. We first explain the settings in which our dashboards were deployed. Then we list the contributions per chapter. Each chapter focuses on a specific type of dashboard: Chapter 2 researches LDs in blended learning settings, Chapter 3 researches LDs to support group work, and Chapter 4 researches LDs to support study advisers. Table 1.1 positions each chapter into the different dimensions discussed in Section 1.1 and the learning settings that we used. These learning settings are discussed in the next Section.
Table 1.1: Overview of the chapters, the learning setting and environment on which they focus, the target audience of the dashboards, the data visualised by the dashboards, the technique used in the dashboards, the level, sub-level and cycle to which they apply.

<table>
<thead>
<tr>
<th>Chapter 2</th>
<th>Setting</th>
<th>Environment</th>
<th>Target</th>
<th>Data</th>
<th>Technique</th>
<th>Level</th>
<th>Sub-Level</th>
<th>Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blog-supported</td>
<td>blended learning</td>
<td>blog-supported/</td>
<td>student/</td>
<td>digital activities</td>
<td>data visualisation</td>
<td>micro</td>
<td>individual/groupers</td>
<td>course</td>
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</tr>
<tr>
<td>Chapter 3</td>
<td>group work</td>
<td>design-critique sessions</td>
<td>student/</td>
<td>real world activities</td>
<td>data visualisation</td>
<td>micro</td>
<td>individual/groupers</td>
<td>session</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>teacher</td>
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</tr>
<tr>
<td>Chapter 4</td>
<td>study advice</td>
<td>advising sessions</td>
<td>student/</td>
<td>institution data</td>
<td>data visualisation</td>
<td>micro</td>
<td>individual/class</td>
<td>semester/year</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>study advisor</td>
<td>warehouse (e.g., grade)</td>
<td></td>
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</tr>
</tbody>
</table>

**Blended Learning**

In blended learning, where students combine both physical and digital activities, LDs can provide an overview of learner traces, their performance, and predict learning outcomes [146]. Chapter 2 elaborates on the dashboards designed for, and deployed in, two such blended environments: Blog-supported Courses and Inquiry-based Learning Courses.

**Blog-Supported Courses:** Blogging has become more popular in learning environments [153] as it facilitates assessment, reflection, interaction, and collaboration among students, and improves participation in learning activities [83]. It allows students to develop their ideas and receive contributions from peers through blog comments [75, 108]. During the face-to-face Master course “Human-Computer Interaction” of 2013 and 2014 at KU Leuven, students used blogs to report progress, share opinions and knowledge [82], and provide feedback to peers through blog comments. Twitter was used as a communication channel for quick questions about the topic of the course or for sharing reading material. These on-line activities often generate an abundance of data. A typical course results in 140-300 blog posts, 600-1400 blog comments, and 300-500 tweets.

**Inquiry-based Learning Courses:** Contrary to a traditional passive role in a classroom, in Inquiry-Based Learning (IBL), learners assume an active role as explorer and scientist with a focus on learning “how to learn”. Teachers try to stimulate learners to ask questions and create hypotheses regarding a specific topic, perform independent investigations, gather data to confirm and discuss their findings, and generate conclusions. In the on-line weSPOT Inquiry Environment ², a teacher can set up an inquiry regarding a specific research topic. The students then use this on-line environment to create hypotheses, join discussions, generate mind-maps and conclusions. By taking pictures, recording

²http://inquiry.wespot.com
videos, and registering measurements through a mobile application integrated into the IBL environment, students collect data in the field to support their hypotheses [93, 112].

Group work

Awareness created by LDs can lead to specific learning impact [147]. These visualisations can provide enhance classroom orchestration and participation in learning activities of student teams by e.g. providing teachers with a private view on student group’s activities [43] or providing mutual awareness of progress among groups [85]. Chapter 3 elaborates on the dashboards designed for, and deployed in a group work focused environment: Design-Critique Sessions.

During the two Master courses “Information Visualisation” and “Fundamentals of Computer-Human Interaction” at KU Leuven, students work in group to design, implement, present and iterate on information visualisations and mobile games. The courses put a large emphasis on peer review, teaching students how to evaluate and discuss their designs and technical implementations, in a community of practice [156]. This process is supported using blogs that helps students report and share opinions and knowledge [83]. As communication and collaboration skills are key 21st century competences for lifelong learning [78], “design critique” face-to-face sessions are organised where students present their group’s progress to the class. A large emphasis is put on providing feedback to each other on their intermediate results during such presentations.

Study Advice

The effect of student counselling is a well-studied subject in social and behavioural sciences [130]. In recent years, automatic data analysis to support student counselling has gained increased interest [140]. Little work however has been done so far to use dashboards to support the live interaction between a study adviser and student. Chapter 4 focuses on our last setting: the study adviser session.

These sessions are advice sessions for first year students at KU Leuven, Belgium. Our work was evaluated with students of the Bachelor of Engineering Science and the Bachelor of Engineering Science: Architecture. After completing secondary school, every student can enrol in a program of the Faculty of Engineering Science. As a result, most programs have a relatively high number of students entering that are not necessarily optimally qualified for the program, resulting in an overall drop-out rate of around 40% [77]. In this setting, study advisers
are key-actors in advising students from the start of their program on their academic performance and the impact on their future study pathway.

1.3.1 LA Dashboards for Blended Learning

This section summarises the findings of Chapter 2 and focuses on the following two research questions:

<table>
<thead>
<tr>
<th>RQ1</th>
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<tbody>
<tr>
<td>How should we visualise learner data to support students to explore the path from effort to outcomes?</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>RQ2</th>
</tr>
</thead>
<tbody>
<tr>
<td>How can we promote students, inside and outside the classroom, to actively explore this effort to outcomes path?</td>
</tr>
</tbody>
</table>

Problem Statement

As elaborated in Section 1.1, LDs often visualise data such as artefacts produced, time spent, social interaction, resource use, and exercise and test results [147]. This can result in an abundance of data. RQ1 therefore investigates what data traces are relevant for both teachers and students and how to visualise these traces to enable exploration in a meaningful and efficient way, while not overwhelming them. While EDM already attempts to narrow these data to the essentials, we believe that it is highly important to empower students rather than fully automating decision-making and feedback. Indeed, technology can support the student to play a more active role in the LA reflection process role [43].

The captured data traces present indications of learning efforts. A collection of efforts is part of progress towards a larger goal, or a learning outcome, such as learning a language, passing an exam, etc. When LDs focus on effort alone, they can have a detrimental effect on motivation [121, 119]. Therefore, RQ1 explores whether we can help students and teachers gain insights into this learning process by creating a more elaborate picture of the learning process, i.e. by providing access to the different learning steps and their resulting outcomes.

Teachers usually perceive dashboards more useful than students [119]. While solving the problem of data abundance can make LDs less daunting to use, and extrinsic motivators such as notifications can draw students to the tools [57],
RQ2 researches alternative ways of improving student acceptance and perceived benefits of LDs through different visualisation techniques, taking into account the different contexts in which their learning occurs [68], and using different technologies.

**Approach**

Through multiple case studies during two years, five dashboards were designed, deployed and evaluated. Each dashboard builds upon the finding of the previous, considering the stakeholders and the specific learning context in which it will be deployed. The LD data used was gathered from authentic blended learning environments: Blog-supported Courses and Inquiry-Based Learning courses. This participatory design was supported by an iterative, rapid-prototyping approach, questionnaires, usage tracking, observation, interviews, and focus groups.

At KU Leuven, four dashboards were designed, deployed and evaluated with a total of 60 students and six people with teaching responsibilities during blog-supported courses. Deployment times ranged from single sessions to entire semesters. Evaluations typically consisted of questionnaires regarding usability, activity logging through Google Analytics, and further insights into perceived usefulness through semi-structured interviews.

Furthermore, one dashboard was deployed during inquiry-based learning pilot courses across multiple European schools. While evaluation results were limited to high level feedback from pilot teachers, a total of 461 students used the dashboard. Fifteen people with teaching responsibilities/pedagogical research experience participated in a focus group around the final dashboard.

**Outcomes**

Throughout our case studies, we have learnt that it is essential that students are continuously aware of the impact of their efforts towards these intended learning outcomes. To facilitate this process, we gathered several guidelines on how to visualise the LA data (RQ1) and how to help promote exploration of these efforts to outcomes (RQ2). These guidelines are further elaborated on in Chapter 2.

- **Abstract the LA data:** a good start for LDs is to abstract or aggregate the data. Providing an overview makes the data accessible to students and teachers, and sheds immediate light on important events and course
goals. Perceived motivation was rated higher than previous attempts that focused on raw data through lists and charts.

- **Provide access to the artefacts:** Abstracted data may be more accessible, but ends up sacrificing clarity and understanding. An overview can however serve as a gateway to facilitate further exploration of the data [132]. Teachers reported that this “overview-context” approach would be useful for evaluations and could help students with self-improvement.

- **Augment the abstracted data:** While the abstraction provides a good overview, exploration of the layers behind this data is necessary for further insights. It is therefore interesting to move some information back to the top, but without cluttering the abstracted data. By adding simple indicators which for instance highlight where to find highly rated artefacts, we can guide students and teachers quicker to relevant data.

- **Provide access to teacher and peer feedback:** As it is important to provide timely feedback to students [10, 110], integrating this into LDs is beneficial for both students and teachers. Students can learn from feedback on peer activities, feedback information can assist in augmenting the abstracted data to find relevant artefacts (e.g. good artefacts have good feedback), and teachers are aware of colleague activities to reduce redundant work (e.g. providing the same feedback as colleagues).

- **Visualise the learner path:** it is essential that students are continuously aware of the impact of their efforts towards these intended learning outcomes. Visualising the steps is important, but providing an overview of how each step is achieved provides further insights, and helps students/teachers understand the steps they or peers took to reach a certain end goal.

- **Integrate LA into the work-flow:** Low efforts and time requirements can have a positive effect on LD acceptance. By building LDs to support existing work-flows, we can introduce LA into students’ existing learning environments, supporting and augmenting their current process.

- **Facilitate collaborative exploration of the LA data:** new scenarios become possible when creating LDs that support multi-user interaction and collaboration. Leveraging technologies such as large interactive tabletops, we can design LDs with these features in mind. Discourse around LA happens naturally, is experienced as “fun”, and evaluation activities become richer experiences as both teacher and student can explore, reason, and provide evidence through LA data.
1.3.2 LA Dashboards for Group Work

This section summarises Chapter 3. It focuses on creating a better balance in feedback participation through ambient LDs, resulting in the following research questions:

<table>
<thead>
<tr>
<th>RQ3</th>
<th>What are the design challenges for ambient LDs to promote balanced group participation in classrooms, and how can they be met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>RQ4</td>
<td>Are ambient LDs effective means for creating balanced group participation in classroom settings?</td>
</tr>
</tbody>
</table>

**Problem Statement**

LA data is often used post-session/course to look back and reflect on the activities that have passed. Quantified Self facilitates reflection and insights after a run, sensors collect the data live, reporting back heart rate at the very same moment as the activity occurs. Similarly, we can leverage LA data gathering to provide live feedback as the learning process and activities occur.

Chapter 3 focuses on live interaction between student groups during presentation sessions (see Section 1.3). As over- and under-participation in collaborative learning settings can reduce motivation and lower learning outcomes [118], we wish to create a balanced participation through the means of LDs (RQ3). As ambient displays have been proven to positively affect participation distribution in meetings and small learner groups [138], we investigate how to design ambient LDs for larger classroom sessions, and whether they are effective (RQ4).

**Approach**

To tackle RQ3, we designed four prototypes. These designs were the result of discussions with twelve students involved in the Information Visualisation course, with the four design dimensions for ambient information systems by Pousman & Stasko’s taxonomy [111] as extra guideline. These LDs visualise the duration of speech by each group while providing feedback to the presenting group. The dashboard is visualised on a large display in the classroom, next to the students who are presenting. Through user evaluations with these twelve
students during an authentic course session, we explored what design choices worked and created a new iteration based on this input. Student questionnaires were used to evaluate our design choices regarding e.g. clarity, distraction, usefulness. Activities were recorded for post-analysis. Based on our findings, we designed the next iteration, which was deployed during a three-hour session of the Fundamentals of Computer-Human Interaction course. We evaluated the LD’s perceived usefulness and effect on balance distribution (RQ4) with 19 students by recording and analysing the feedback activity traces and through questionnaires to get further insights into the perceived usefulness.

**Outcomes**

Our first attempts at ambient LDs were perceived as useful by students and did promote activity in the classroom. However, achieving balance through visualisations was more difficult as over-participators experienced the LDs as rewarding, while under-participators interpreted it as punishing and demotivating.

Our final design attempts to overcome those problems. We list the findings here, which are more elaborated on in Chapter 3 (RQ3):

- **Visualise balance in an abstract and neutral way:** Abstracting the data into the essential message helps motivate students. By visualising “balance” in a broader sense by widening the representation of average participation, under-participators experience the visualisation less negatively, and have the feeling that catching up remains possible. Removing positive connotation for over-participation will tone down over-participation, resulting in a better overall balance.

- **Add the qualitative dimension to the visualisation:** while the final design focuses on quantity of feedback, earlier designs implemented a rating system. Qualitative attributes can improve the validity of the visual representation.

We further explore whether they are effective means for balanced participation (RQ4):

- **Ambient LDs raise awareness of the invisible:** LA can affect awareness, and through live capturing of learner activities, can have an immediate effect on reflection and impact. Students reported to be more aware of their own participation and that of peers.
- **Ambient feedback information can activate students:** While balance was achieved easier when the students were asked to do so, the presence of the ambient LD resulted in a quicker conversion towards balanced feedback. This constant awareness did thus have an impact on balance.

- **Ambient LDs as support for teacher/presenter:** raising awareness of activities is not only beneficial for students, but it can help teachers orchestrate the classroom, learn about outliers, and know when to intervene.

### 1.3.3 LA Dashboards for Study Advisers

This section summarises Chapter 4. It focuses on how to design a LD to support the dialogue between study adviser and student during study adviser sessions. We define following research questions:

<table>
<thead>
<tr>
<th>RQ5</th>
<th>What are the design challenges for creating a LD to support study advice sessions, and how can they be met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>RQ6</td>
<td>How does such a LD contribute to the role of the adviser, student, and dialogue?</td>
</tr>
</tbody>
</table>

**Problem Statement**

As mentioned in Section 1.3, study advisers are key-actors in advising students from the start of their program on their academic performance and the impact on their future study pathway. Study advisers receive information regarding the students through different sources: Excel files, central grade system, and elaborate textual and graphical information regarding study success. Combining and interpreting these multiple channels of information for each specific student requires effort and time, and is error-prone. In addition, data is often incomplete: grades across multiple exams of the same course are for instance often not available. SAs typically rely on experience to verbally provide information regarding course difficulty, exam success rate, or earlier success of decisions regarding study program.
The study adviser session is important to get a deeper understanding of the student’s problems and needs, as external factors often play an important role in the reason behind failed exams, de-motivation, and drop-out. We therefore look at LDs as a collaborative means to support the dialogue between adviser and student.

**Approach**

To support the needs and requirements for improving the study advising sessions, we took a participatory approach during a year, working together with study advisers. A total of 19 study advisers were involved through questionnaires, interviews, observations of advising sessions, and brainstorm sessions. Through an iterative rapid-prototyping design approach, we designed, developed, and deployed a dashboard in 97 advice sessions after the examination periods of June and September 2016. We evaluated the perceived usefulness and impact through student questionnaires, observations of fifteen sessions in which the dashboard was used, and adviser interviews.

**Outcomes**

Our iterative design process resulted in a well-received LD design by both students and study advisers (RQ5). The visualisation of their learner path had a motivating effect: students received a visual confirmation of their progress through the year. A more negative overview provided the adviser with extra leverage to convince a change in study program. The dashboard adds peer evidence to the conversation: instead of relying on experience, advisers have facts to back their arguments. These facts are visually present in the conversation, which again helps with convincing students. As all data is readily available, the dialogue becomes the focus. Previously, advisers would have to move back and forth between multiple sources of information.

The dashboard helped student reflect about their activities, linking changes in performance with specific events during the year. By adding peer information, grades receive a new meaning: a bad grade can still be relatively good if the rest of the class performed badly. The dashboard triggered factual, interpretative, and reflective insights. Chapter 4 elaborates on the different kinds of insights.

Our evaluations resulted in several lessons learnt (RQ6):

- **Data Confidence**: The LA data used is basic data available in every institution, yet provides many benefits when made available through
our LD. Without any pre-processing and data-mining, we present the data as-is, creating faith in the correctness of the data, and leave the interpretation to the student adviser and students.

- **Collaboration:** the LD can play a supportive, inactive role, leaving no one in “charge”, allowing both student and adviser to drive the conversation. This allows for reflection and sense-making in a collaborative way.

- **Adviser’s role:** even with objective data, interpretation depends on the user. Student advisers play an important role in guiding the student through this reflection process: overconfident students might interpret too positively. Personal opinions and tacit experience remain important. The dashboard’s supportive role assures that this remains possible.

- **Authorship:** The dashboard serves as a guide through the conversation. Its story driven nature allows for both student and adviser to take the role of author or reader, supporting the freedom of conversation flow.

- **Visual encoding:** visual encoding can add extra nuance, but can also create overhead. By keeping the visual encoding simple, we can leave the interpretation to the user, providing a quicker factual overview (e.g. this student failed 10 courses), but still allowing for deeper insights (e.g. but 3 of those were not too bad).

- **Ethics:** ethical issues arise with the use of such dashboards. During the deployment, some advisers chose not to show the dashboard, as it portrayed the student too negatively and would not contribute in a positive way to the conversation. Peer information could demotivate students when peers perform better. Fluctuations in general exam results across years could cause legal issues. Students request access to the dashboard without advisers, but advisers worry about misinterpretations.

### 1.4 Thesis Outline

This section provides an overview of the authored/co-authored publications that resulted from the work during the last four years. We present these publications per chapter.

**Chapter 2:** The chapter presents research that has been published in the following paper:

The paper has been expanded in this chapter with research results that have been published in the following papers:


Chapter 3: This chapter has been published in the International Journal Of Technology Enhanced Learning:


Chapter 4: This chapter has been accepted for publication in IEEE Transactions on Learning Technologies:

Chapter 2

Creating Effective Learning Analytics Dashboards: Lessons Learnt

2.1 Introduction

LDs visualise data such as artefacts produced, time spent, social interaction, resource use, and exercise and test results [147]. We believe that it is highly important to use technology to empower students [43] instead of fully automating decision-making and feedback through e.g. EDM [158]. To facilitate this empowerment, this chapter researches what data needs to be accessible to students and how this data should be visualised to result in effective usage. To discover knowledge relevant to the learning process of students, the empowerment should happen in their everyday lives, in and outside the classroom. We therefore also consider the different contexts in which their learning occurs [68], and how we can leverage these contexts to promote students to explore the path from effort to outcome. The research questions are:

<table>
<thead>
<tr>
<th>RQ1</th>
</tr>
</thead>
<tbody>
<tr>
<td>How should we visualise learner data to support students to explore the path from effort to outcomes?</td>
</tr>
</tbody>
</table>
RQ2

*How can we promote students, inside and outside the classroom, to actively explore this effort to outcomes path?*

Five dashboards were deployed and evaluated to answer these research questions. The deployments and the evaluation setups are described in Section 2.2. Section 2.4 discusses the lessons learnt based on the design, deployment, and evaluation of these dashboards. We then link our findings to the state of the art and discuss remaining challenges in Section 2.5. Conclusions are drawn in Section 2.6.

2.2 Deployments and Evaluations

We briefly discuss how the learning traces are collected, and present an overview of the dashboards and their evaluations. The context in which these dashboards were deployed are blog-supported courses and inquiry-based learning courses (see Section 1.3).

2.2.1 Learning Analytics Traces

To collect the learning traces from these learning environments, we use the architecture presented by Santos et al. [123]. For the blog-supported courses, trackers connect to the RSS feeds of the student blogs and utilise the Twitter API to track the activities related to the course hash-tag. The content of these activities, together with relevant meta-data (time of activity, student identification) is pushed to the Learning Record Store (LRS), which stores the data following a simplified xAPI format [123].

Through exposed REST services\(^1\) of the weSPOT Inquiry Environment, the trackers access the learner artefacts (e.g. hypothesis created, picture taken, mind-map created) and meta-data (e.g. time of the activity, user identification, peer and teacher rating), and store the data in the LRS.

The LRS exposes a set of REST services for data retrieval\(^2\), which the dashboards use to request the relevant learner traces to populate the LD visualisations.

\(^1\)http://goo.gl/37mr4D

\(^2\)https://github.com/weSPOT/wespot_datastore
2.3 Deployed Dashboards

Five dashboards were developed and deployed during two years. Each dashboard builds upon the finding of the previous, taking into account the stakeholders and the specific learning context in which it will be deployed. They are built as a low-fidelity prototype at first, with four high-fidelity dashboard prototypes deployed in authentic settings during pilot studies [88]. Table 2.1 provides an overview of the dashboards and their evaluations.

<table>
<thead>
<tr>
<th>Details</th>
<th>Navi Badgeboard (A)</th>
<th>Navi Surface (B)</th>
<th>Class View (C)</th>
<th>LARAe (D)</th>
<th>LARAe.TT (E)</th>
</tr>
</thead>
<tbody>
<tr>
<td>References</td>
<td>[7, 36]</td>
<td>[7]</td>
<td>[9]</td>
<td>[8]</td>
<td></td>
</tr>
<tr>
<td>Course setting</td>
<td>Master in Engineering Science course</td>
<td>Multiple IBL courses at European Secondary schools</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>142 blog posts 549 comments 648 tweets</td>
<td>254 blog posts 1326 comments 352 tweets</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activities accessible</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Artefacts accessible</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Learner path visualised</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
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<tr>
<td>Visualisation methods</td>
<td>Abstraction of course goals through badges</td>
<td>Abstraction of course goals through badges</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focus</td>
<td>Abstraction</td>
<td>Collaboration</td>
<td>Access to artefacts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Research questions</td>
<td>RQ1</td>
<td>RQ1, RQ2</td>
<td>RQ1</td>
<td>RQ1, RQ2</td>
<td>RQ1, RQ2</td>
</tr>
<tr>
<td>Evaluation</td>
<td>Navi Badgeboard (A)</td>
<td>Navi Surface (B)</td>
<td>Class View (C)</td>
<td>LARAe (D)</td>
<td>LARAe.TT (E)</td>
</tr>
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<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
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<tr>
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<td>x</td>
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<tr>
<td>Ethnographic Field Study</td>
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<td>x</td>
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<tr>
<td>Interviews</td>
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<td>Focus group</td>
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<tr>
<td>Prototype Evaluation</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pilot Run</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Participants</td>
<td>22 Master students</td>
<td>14 Master students</td>
<td>38 Master Students Secondary school students</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expert Participants</td>
<td>6 with teaching responsibilities</td>
<td>5 with teaching responsibilities Teachers at secondary schools</td>
<td>15 with teaching responsibilities and pedagogical research experience/interest</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.3.1 Dashboard A: Navi Badgeboard

During the blog-supported course, students were rewarded for their activity and achievements through the means of badges. These badges were designed in collaboration with the instructor of the course. Badges, which can represent abstractions of learning traces, bring with them many benefits, and uses: The creation process of the badges can influence the design of the course [65] and hence create clearer goals for both student and teacher. Badges can be used as feedback and are proven to directly impact behaviour and motivate students in off- and on-line courses [65, 91, 120].

These badges shed light on their progression and that of the class. These badge designs were based on the activities the teacher wished to promote in his class:

1. **Activity Badges**, rewarding a minimum number of activities, such as ten entries posted on Twitter.

2. **Quality Badges**, rewarding activities of value through the attention they receive, such as five “re-tweets” or ten comments on a blog post.

3. **Result Badges**, rewarding the achievement of specific milestones, such as handing in an assignment.

To keep the students actively engaged during the entire duration of the course, badges are awarded biweekly. There are badges that are awarded instantly (i.e. a student that tweets 5 times receives a badge). Other badges are awarded at the end of the two-week period (i.e. the most active student in class). To reward team effort, some badges can only be earned as a team. Lack of any activity during a two-week period is “awarded” by a negative badge.

These badges form the basis of reducing the abundance of data generated and turning it into a manageable source. The Navi dashboard was developed to provide an overview of the awarded badges to the students. This application was developed in Java and JavaScript, using D3.js and is deployed on Google App Engine.

Every definition of a badge is set up as follows:

- a badge icon with an easily identifiable image related to the meaning of the badge,
- a colour coding for categorising the badge by type,

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Figure 2.1: Navi Personal Badge Dashboard: achieved badges are coloured. The number next to the badges indicates the class progression for the badge.

Figure 2.2: Navi Class Progression: Each line represents class progression for a specific badge. The circle indicates when the student achieved the specific badge.
a bronze/silver/gold medal for badges indicates different steps of achievements, and

- a textual description on how this badge can be achieved.

A list of all achievable badges is available in the dashboard and helps students understand what activities and results are required to complete the course.

Figure 2.1 illustrates Navi’s Personal Dashboard which contains the achieved and remaining badges of one student. To support a better group awareness, Navi also displays the total number of awarded badges next to each badge. Hovering the mouse over a badge displays the names of the students who have acquired this badge. Not only can this make students more aware of the class activity, but it can also be used to compare their progress with that of their peers.

Drilling down on badges in Navi’s Personal Dashboard, the student obtains Navi’s Class Progression view, a visualisation of the awarded badges over time. An example of this view is shown in figure 2.2 for student A, where the X-axis represents time and the Y-axis the number of students that have been rewarded the badge. Each line thus represents the class progression for a specific badge. The circle indicates when student A was awarded this badge. With these views, Navi invites the students to reflect on their individual progress by giving them a tool to be aware of their activities, but also of that of their fellow students.

Navi’s Personal Dashboards are also available to teachers, providing them with an immediate overview of the class progression. The dashboards can help teachers figure out what activities the class or even specific students are struggling with.

**Evaluation Summary**

Twenty-two students participated in the evaluation of Navi Badgeboard. This dashboard provided an up-to-date visualisation of the students’ progress of the Fundamentals of Human-Computer Interaction course (2012-2013) of the Master in Engineering Science program during 16 weeks. They received a questionnaire regarding their perceived importance of the different features using a 5-level Likert scale (1 - Not at all important, 5 - Extremely important), and a questionnaire regarding the perceived impact (1- Strongly disagree, 5 - Strongly agree).

A System Usability Scale (SUS) [14] questionnaire resulted in a score of 65 (SD = 12). Students rated the list of achievable badges as most important (M =
DEPLOYED DASHBOARDS

3.5, SD = 1.0), as it provided them with an overview of course goals. They did, however, not show much interest in peer information (“Badges achieved by peers”, M = 2.9, SD = 1.1, and “Class Progression view”, M = 2.6, SD = 1.3). This class overview information was, on the other hand, perceived as very valuable by the teacher and teacher assistant. **Dashboard C** (see Section 2.3.3) will further explore this aspect.

Students indicated that Navi Badgeboard promotes commenting (M = 3.7, SD = 0.8), reading peer blogs (M = 3.8, SD = 0.6) and use of Twitter (M = 3.9, SD = 0.5), i.e. the activities these badges were designed to impact. Students were moderately positive about motivation improvements (M = 3.2, SD = 1.1). In our previous work on learning dashboards showing raw activity data through lists, tables, and charts, students had a more negative perception about potential motivation improvements [122].

Through usage tracking (Google Analytics), we learnt students were most active on Navi Badgeboard just before and after the course. We explore improving the usage and interaction with LA dashboards further through **Dashboard B** (see Section 2.3.2) and **Dashboard D** (see Section 2.3.4).

Further information and details on the dashboard and its evaluations can be found in [27].

### 2.3.2 Dashboard B: Navi Surface

In previous work, actual use of the dashboard was more limited [122] and therefore had little effect on student behaviour. To further promote students’ interaction with our dashboards, Navi Surface attempts to provide a more active, social space to explore the LA data. Adding collaboration to the process creates opportunities for a more active discourse around the data. A prototype of a multi-user multi-touch tabletop display application was developed using HTML5, JavaScript and Paper.js4. Few cases are specifically designed for tablets [86] or large displays. To the best of our knowledge, no examples exist of learning dashboards deployed on devices such as interactive tabletops and whiteboards.

Similar to Navi Badgeboard, Navi Surface includes a view that presents an overview of earned badges. This view is represented in the bottom left part of Figure 2.3. Next to this view a list of students is represented. The upper part represents an interactive “Playfield” to explore badges, students, and their interrelationships. All badges and students can be dragged onto the Playfield. The badges in the Playfield light up the names of students that have been

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4[http://paperjs.org](http://paperjs.org)
CREATING EFFECTIVE LEARNING ANALYTICS DASHBOARDS: LESSONS LEARNT

Figure 2.3: Navi Surface: The bottom left shows the list of badges of a specific period. The bottom right contains the students’ names. The items in the Playfield (top) are touched and held to display the relationships between them.

Figure 2.4: Navi Surface: Students actively using the tabletop display application during our evaluation session.

awarded these badges. Student names light up the badges that have been awarded to the respective students. Dropping badges onto the Playfield also displays their detailed information.

Touching and holding an item will activate the relationship visualisation: lines will connect the item to all its related items on the Playfield e.g. a student name will be connected to all its awarded badges. As the application supports multi-touch, multiple items can be moved and touched simultaneously, creating more interesting visual relationships (see Figure 2.3) and enabling collaborative interaction with the data.
Evaluation Summary

Navi Surface was deployed in the classroom during the final session of the Fundamentals of Human-Computer Interaction (2012-2013) course of the Master in Engineering Science program. The dashboard ran on a large 42" custom-built interactive tabletop with multi-touch capabilities. Fourteen students (two groups of two students, two groups of three, and four individuals) walked up to the tabletop and could freely explore the data that was tracked during the semester. Participants were asked to follow the think-aloud protocol [99]. Their activities were video-recorded. After each session, students were asked to fill in a questionnaire (5-Likert scale, Completely Disagree-Completely Agree) regarding perceived usefulness.

A SUS questionnaire resulted in a score of 71 (SD = 16). From observation, we learnt that participants facing the tabletop alone were more hesitant and needed input from the observer to continue using the tool, while participants in group spontaneously started discussions around the data: they reflected on why and how certain badges were achieved, or not achieved. They also experienced this collaboration to be more fun. Participants had a preference of using the tool in group and showed interest in using Navi Surface in collaboration with a teacher (“I would like to use this tool together with the teacher to evaluate my progress”, M = 3.4, SD = 0.8) and peers (“I would like to use this tool together with other students to compare our progress”, M = 3.7, SD = 0.8). Students were moderately positive about how Navi Badgeboard provided insights into the meaning of the badges (M = 3.5, SD = 0.9). This was reflected during observations: students would not always remember why they for instance received a badge for lack of activity in specific periods. Dashboard C and D explore how to solve this problem.

Further information and details on the dashboard and its evaluations can be found in [27].

2.3.3 Dashboard C: Class View

As mentioned in Section 2.3.1, teachers show interest in progression data. The Class View dashboard was designed with visualising progress of individual students, groups, and the entire classroom in mind.

The dashboard is designed to be presented on a large display, an interactive whiteboard, or a touch display. It is a web application developed using HTML5,
Figure 2.5: Overview of information areas of the Class View dashboard.

Figure 2.6: Zooming in on the Student-Badge Matrix, Activities Over Time and Badge Overview graphs.
JavaScript, D3.js and crossfilter.js\(^5\). The backend is created with Node.js\(^6\) and MongoDB\(^7\).

It consists of six main information areas (see Figures 2.5 and 2.6):

1. **Student-Badge Matrix:** With student names on the horizontal axis and badges on the vertical axis, the matrix gives an overview of how many times a specific student has been awarded a specific badge. Larger circles denote that a badge has been awarded more often to a particular student.

2. **Activities/Badges Over Time:** This view consists of five graphs. The first graph displays the total activity of all students over time by day. These activities are split up in the next three graphs: blog posts, blog comments, and tweets. The last graph shows the number of badges awarded each day. The bars of these bar charts are interactive. Clicking or touching a bar will update the Activity List.

3. **Activity List:** This list contains the activities done or badges awarded on the selected day of the bar chart. These items are selectable and will update the Activity Details Field.

4. **Activity Details Field:** This fields shows the content that is linked to an activity. In the case of blog activity, it will provide the user with the content of the blog post or comment. A tweet activity will display the related tweet. The field can also present more information on badges, such as the name and description.

5. **Badge Overview:** The Badge Overview is another visualisation of the awarded badges and facilitates student or group comparison (see Figure 2.6 for details). T represents the total number of badges awarded to the class. S1 and S2 stand for Set 1 and Set 2 and display the number of badges awarded to the sets of selected students (see Filter Area). Clicking on a badge provides the user with a description of the badge.

6. **Filter Area:** Several filtering options are available in the Filter Area. Students can be selected from the list and can be assigned to Set 1 (blue) and Set 2 (red). All other areas will be updated with the cumulative data of the selected students in each set, in the corresponding set colour (see Figure 2.6): The Student-Badge matrix will highlight the selected student, the Activities Over Time will show the subset of data as an overlay on top of the total data, the Badge Overview will show the total number of

\(^5\)http://square.github.io/crossfilter/
\(^6\)http://nodejs.org/
\(^7\)http://www.mongodb.org
badges awarded in Set 1 and Set 2, and the Activity List will highlight activities done by the selected students. The time slider allows the user to modify the time range of the data displayed on the dashboard.

**Evaluation Summary**

Class View was populated with the activity data of the entire semester of the Fundamentals of Human-Computer Interaction course (2012-2013) of the Master in Engineering Science program at KU Leuven and presented to six instructors. Three participants were involved in this course. Through a questionnaire (5-Likert scale, Completely Disagree-Completely Agree) and semi-structured interviews, we gathered insights into perceived clarity, usefulness, and effectiveness. To confirm their perceptions, we observed the participants’ usage and thought process through a think-aloud study. This study provided insights into how every information area was used and which conclusions participants made based on the different areas.

A SUS questionnaire resulted in a score of 76 (SD = 7). Participants considered the Class View’s information areas as clear (“The data the widgets portrays is clear”, M = 4.0, SD = 0.9). The comparison feature was regarded very useful and was used as a starting point to dig deeper into the data, for instance to compare groups (“Comparison feature helps me understand the data better”, M = 4.2, SD = 0.8). Participants indicated that the data was visualised in a clear way (“The visualisation provides a good overview of the activities”, M = 4.2, SD = 0.8, and “The visualisation provides a good overview of the badges awarded”, M = 4.2, SD = 0.8), helping them achieve a better awareness of the class activities and progress (“The visualisation improves my general awareness of the activities”, M = 4.0, SD = 0.6, and “The visualisation improves my general awareness of the badges awarded”, M = 4.2, SD = 0.4). Activity Over Time was perceived as useful to analyse and recognise inactive periods (“The visualisation helps me determine the least active time periods”, M = 4.0, SD = 0.6).

Through the Activity Details Field, participants obtained insights into the amount of activity, the rewards, and the actual contribution of each student (group). By combining these multiple data, participants mentioned that they can gain insights into the overall quality of the participation of the students. They agreed it would therefore be beneficial to use in discussions and evaluations of course outcomes among teaching staff (“I would like to use this tool together with colleagues”, M = 4.0, SD = 0.9) and with students (“I would like to use this tool to perform evaluations with students”, M = 4.0, SD = 0.9).
Further information and details on the dashboard and its evaluations can be found in [28].

2.3.4 Dashboard D: LARAe

LARAe (Learning Analytics Reflection & Awareness environment) was developed with specific audiences in mind: a dashboard for the blog-supported courses, and a dashboard for inquiry-based learning courses. LARAe is a web application developed using HTML5, JavaScript and D3.js running on a Node.js web service and MongoDB database. It supports both the proprietary API and Tin Can APP8. It can easily be extended to support other APIs. The dashboard is designed to run on large displays, desktop computers and tablets.

8http://tincanapi.com/
During the first three weeks of a blog-supported course, we organised three evaluation sessions where we observed and interviewed teacher assistants and students regarding the way they keep track of and their awareness of blog activities. We learnt that students split up work to keep track of the large amount of blog posts and comments (148 blogs post, 1046 comments, and 193 tweets were generated by week 3). Eleven students used RSS\(^9\) readers to keep track of the activities, while 27 would manually visit the blog sites. Students would often limit this activity to once per week, not revisiting previous discussions they contributed to. Similarly, only two teacher assistants used an RSS reader, while three would visit the blogs directly. For participants without RSS readers, their entire process was long and tedious.

LARAe \([29]\) visualises traces gathered from 38 engineering students and teachers. Students worked in groups of three and reported weekly through blog posts, comments, and Twitter.

Based on our findings, LARAe was designed to replicate RSS reader functionality, but augmenting it with further LA data (see Figure 2.7). Every activity is represented by a circle (see Figure 2.7.B). Like Dashboard C (see Section 2.3.3), clicking on an activity loads the related content (e.g. blog post, comment, tweet, retweet) on the right. Activities are sorted chronologically, from top left to bottom right. Gradient colour values (see Figure 2.7.A) help recognise the age of an activity. A table (see Figure 2.7.B) structures the activities by student group and type. Every column represents an activity type, every row a student group. The user can sort the data by any activity type.

To provide more context, activity content is visualised in a thread view (see Figure 2.7.C) with its surrounding activities (e.g. a comment with its surrounding discussion and original post). This “focus+context” \([60]\) solution is further supported by highlighting the related events in the visual representation of the activities, and indicating with numbers how large the related thread is (Figure 2.7.B).

The dashboard has also been deployed in an inquiry-based learning setting, visualising the learner traces gathered from the weSPOT Inquiry system\(^{10}\) \([93]\).

**Evaluation**

LARAe was deployed during the Fundamentals of Human-Computer Interaction (2013-2014) course of the Master in Engineering Science program at KU Leuven during a period of five weeks. Five teacher assistants and 38 students were

\(^9\)https://en.wikipedia.org/wiki/RSS
\(^{10}\)http://portal.ou.nl/documents/7822028/f475d712-5467-40ea-968c-5aa00d951400
Teacher assistants gave LARAe a SUS score of 93 (SD = 4). All teacher assistants agreed that the overview LARAe helps them detect problematic (inactive) groups of students that require their attention ("Knowing what groups are active", M = 5, SD = 0, "Knowing what groups are inactive", M = 4.6, SD = 0.9). The thread size indicators pointed teacher assistants to threads that required feedback (high activity could mean a very interesting discussions, or a problem that requires help) ("Knowing what groups require attention/feedback", M = 3.4, SD = 0.5,"Finding interesting discussions on blogs", M = 4.0, SD = 0.7). As the visual overview provided information regarding peer teacher assistant activity, teacher assistants agreed that this extra awareness could help redundancy in work and feedback ("Knowing who my colleagues already provided feedback to", M = 3.8, SD = 0.4). The interface also helped them navigate the data quicker ("Quickly and efficiently go through the blog posts of the students", M = 4.6, SD = 0.5, “Quickly and efficiently go through the comments of the students”, M = 4.8, SD = 0.4).

A part of the weekly requirement of the course is to comment on peer blog posts. Students gave LARAe a SUS score of 75 (SD = 10). Students reported the thread size indicator helped to find interesting discussions (M = 3.9, SD = 0.7) and posts to comment on (M = 4.0, SD = 0.5). Twenty-one students interpreted high numbers as interesting topics and discussions, while three students considered a short thread an indication of difficult topics. Three students interpreted it as an indication of quality, for self-assessment. ("It’s not a good sign that I have such few comments")

Twelve students found the easiness of finding teacher feedback (on peer and own work) very useful. Three students even considered this feature more useful than student comments.

The dashboard was deployed after the third week of the start of the course. This meant students already created a work-flow and chose specific tools (e.g. the RSS reader Feedly\(^{11}\)). Still, through Google Analytics, we know 21 students (55%) visited the visualisation for a total of 154 visits in the duration of five weeks. Twelve students (31%) visited the dashboard on a weekly basis. Students seemed to find LARAe beneficial enough to change work-flows permanently. Figure 2.8 shows the number of visits and the time spent in the dashboard. Students performed an average of 43 events (SD = 17) per visit, which includes sorting, clicking through the activities, and accessing the content source (blog post, comment, tweet, re-tweet).

\(^{11}\)feedly.com
CREATING EFFECTIVE LEARNING ANALYTICS DASHBOARDS: LESSONS LEARNT

Figure 2.8: Student visits (left) and time per visit on dashboard in minutes (right)

Figure 2.9: A prototype with five filter “drop zones”. Dropping a filter value into the blue (top-left) drop zone highlights data points matching the filter result by colouring the top-left part of the glyph.

2.3.5 Dashboard E: LARAe.TT

LARAe.TT (Learning Analytics Reflection & Awareness environment - Tabletop) [21] builds on the findings of Dashboard B to create a collaborative LA data exploration environment. Similar to Dashboard C and D, LARAe.TT provides access to the content of the activities. It follows the visual information-seeking mantra of “Overview first, zoom and filter, then details-on-demand” [132]: our tabletop visualisation presents users with a coordinated set of widgets which contain: (i) a complete overview of all activities (Figure 2.9.A), (ii) data filters (Figure 2.9.B) and (iii) the content view (Figure 2.9.C).
First, enabling multiple learners and teachers to explore the visualisation together for collaborative sense-making is achieved by developing personal (Figure 2.9.D) and public (Figure 2.9.C) drop zones to support the collection of interesting activities (see Figure 2.9). Visualising activities of contributors across personal spaces [71] can help participants remain aware of group activity and maintain a common ground.

The public drop-zone is located at the top end of the tabletop (see Figure 2.9.C). Like dashboard D, it enables the user to access the content of the activity. Dragging an activity from the main area (see Figure 2.9.A) to the public drop-zone expands the activity and presents its content. A line running from the content to the activity shows the user, but also the other participants around the tabletop, its relation.

The private drop-zone (see Figure 2.9.D) provide a personal interface for up to five participants. Each participant chooses a colour and can drag filter items into the drop-zone. Figure 2.9 shows one type of filter items: student names. Dragging a filter item onto the drop zone causes the visualisation to highlight activities in the colour of the user’s drop-zone.

To enable filter activities of multiple users on a shared display, without causing interference, we introduce an alternative to the more commonly used data-lens solution [151]. Glyphs [92] can represent both data and the position of participants around the tabletop and the filter status per individual user. Thus, when a user drags a filter item (student name) onto his drop-zone, only the part of the glyphs corresponding to the user will be highlighted. The colour provides an extra identification. A more detailed explanation of the glyphs, and how the Kinect\textsuperscript{12}-driven alternative helps with awareness of participant filtering can be found in [22].

The visualisation displays a time-line per activity thread. For instance, the creation of a hypothesis by a learner is followed by every comment on, rating on, and edit of the hypothesis. Activities within a single thread are located on the same horizontal line. This enables teachers and learners to see the evolution of an activity thread, the comments that may have impacted edits of e.g. the original hypothesis, and the rating trend.

Activities in other activity threads can enrich the context of a specific thread. A discussion in one thread might influence the creation of a new hypothesis, or an edit of an existing one. Therefore, every activity is positioned relative in time to all other activities displayed, allowing the users to backtrack through time across multiple threads at once.

\textsuperscript{12}https://en.wikipedia.org/wiki/Kinect
LARAe.TT is an early prototype developed with D3.js and Processing.js running on a Node.js back-end.

**Evaluation Summary**

At the “Leren en doceren met technologie” (Learning and teaching with technology) conference\(^{13}\), November 2014, Eindhoven, a workshop on “Visual Learning Analytics” was organised to introduce LARAe.TT and receive preliminary feedback and ideas. Fifteen participants (six people had teaching responsibilities, three participants were researchers in the field of education, all participants were active in the field of education) were split in three groups. Each group received an introduction of LARAe.TT, explored the data together, and discussed their impressions.

The evaluation served to collect ideas and feedback from participants. Participants came up with the following scenarios how the visualisations could assist both teacher and students:

1. **Argumentation and evaluation:** LARAe.TT can facilitate dialogue between students and teachers. Students can provide argumentation backed by the data, while teachers and students can use peer examples for comparison.

2. **Finding peers to help:** a student can explore peer activities to find good examples of how to solve specific problems. A student struggling in a certain area can find peers that might be able to assist the student.

3. **Distribution of work:** LARAe.TT can visualise data of groups of students, providing insights in the distribution of activities and results across members.

4. **Progress awareness:** adding deadlines/goals to the visualisation could help students remain aware of their progression towards these goals and deadlines.

Further information and details on the dashboard and its evaluations can be found in [26]. The topic of “Distribution of work” is further explored in Chapter 3. Chapter 4 builds further on “Argumentation and Evaluation”.

\(^{13}\)http://portal.ou.nl/web/conferentie-wi/introductie
Figure 2.10: Facilitating exploration of the abundance of learning traces and student learning paths through overview to details and facilitating learning path exploration.

## 2.4 Lessons Learnt

Facilitating the exploration of the “efforts to outcomes” path can empower the student. Previous work however has shown that dashboards are often perceived less useful by students [61, 122]. We investigate what data is useful for students to explore, and how it should be visualised to promote exploration. It is also important to tailor our dashboards depending on the context in which their learning occurs [68], in- and outside the classroom.

### 2.4.1 Presenting the Data

**Abstract the LA data:**

LA can be used to create explanatory systems, such as e-mail notifications generated by EDM systems, simplified, at-a-glance visualisations [3] or hybrid solutions. Aggregating or abstracting the information can help create progress awareness towards specific learning outcomes [27]. These “overview” presentations of the learner traces can serve as a first incentive to trigger students into further LA data exploration.

With dashboard A and B [122], the abstract overview using badges (see Figure 2.11.A) had more impact on student motivation than our previous aggregate version which visualised the data through tables and numbers [122]. The badges still sufficed for the teacher to intervene or start a discussion in the classroom by projecting dashboard A on the wall. An interactive tabletop dashboard B visualising the reward relationship between students and badges served as enough incentive for students to actively explore and discuss their achievements with peers [27].
Figure 2.11: **Dashboard A:** a student’s personal overview of the student’s course goals. Each badge represents a course goal. Greyed out badges were those not achieved by this student. The number next to the badge indicates how many students in the class did receive the badge. **Dashboard D:** overview of blog activity of the class. Each circle represents an artefact. The colour hue indicates age, the number is the amount of social activity on the artefact. Clicking on an artefact shows its contents (right). **Dashboard E Concept:** Visualising the learner path. Angela’s comment on Geoff’s hypothesis results in Geoff accessing her data collection and changing his hypothesis and conclusion.

**Provide access to the learner artefacts:**

By limiting dashboard visualisation to an abstracted overview, teachers and students need to access the original, external environment in which the activities occur to gain further insights (e.g. the on-line learning environment, the individual blog posts). By doing so, the user loses the advantages of the LA overview, and it becomes more difficult to link effort to learning outcome (e.g. which blog posts resulted in a badge). During dashboard B’s evaluation, students could still reflect on their personal progress through memory recall, but when trying to make sense of peer data, the lack of access to the blog posts inhibited further discussion. By adding artefacts directly to the LA dashboard, we can retain the connection between effort and outcome.
then details-on-demand” [132] is the basis used in dashboard C, D and E: the abstraction layer becomes a gateway to further exploration of the learning analytics data (see Figure 2.10). Teachers and students reported this functionality to be very valuable: further exploration in the learner artefacts makes the LA dashboards applicable for e.g. evaluations with the student, or finding relevant learner artefact examples of peers for self-improvement.

**Augment the abstracted data:**

Abstractions present the essentials, and thus lower the cognitive efforts required by students. Students could access peer’s personal overviews in dashboard A, but rarely did so. However, the simplified, abstracted personal overview left room for the integration of peer information: every badge rewarded in the class was included to the personal overview, including the number of times each badge was awarded in class (see Figure 2.11.A). This was regarded as a valuable asset for students: they reported the presence of peer data in the personal overview helped position themselves among their peers and played an important motivational role.

In a blog-course setting, dashboard D [29] provides an overview of each blog post generated, and augments each data point (blog post) with the age of the blog post and number of comments the blog post has received (see Figure 2.11.D). This helped teachers and students find learner artefacts worthy of their attention: 55% of students considered a high number and thus active thread as interesting, while 18% reported they would avoid such threads. Teachers reported inactive threads were a sign for need of intervention. 7% of students would use the numbers for self-assessment (e.g. low numbers on personal artefacts could indicate low quality). In the IBL setup, learner artefacts can be rated by teachers and peers. This information was visualised per artefact data point, providing a good overview of both the quantity and quality of learner outcomes per student, and helped peers in finding valuable (highly rated by peer or teacher) hypotheses, conclusions, discussions.

**Provide access to teacher and peer feedback:**

For teachers, it is important to remain up to date with student efforts and outcomes, but also to provide students with timely feedback [10, 110]. Providing public access to teacher feedback was well received by both students and teachers. As mentioned above, visualising ratings of the IBL learner artefacts provides teachers with a clear view of the quality of the student contributions. Students can use these ratings as guides to find quality example artefacts to learn from.
In the blog-supported courses, feedback is given through blog comments. Dashboard D helped students quickly access all teacher feedback across the entire course. Students reported that having access to teacher feedback given to peers helped them to “be ahead of the game”. While the important feedback is usually repeated in face-to-face sessions, students mentioned “by then it might be too late”. Teachers, when working with multiple colleagues on the same course, reported the feedback visualisation helps keep track of colleagues’ activities, resulting in a better feedback consistency, and preventing redundant feedback.

**Visualise the learner path:**

Until now, we have explored the vertical path of overview to details: abstraction as a way to facilitate teacher and student to drill down and explore the abundance of learner traces. A quality learner artefact does not necessarily indicate a good understanding of the matter, and only provides a narrow view of the student’s process [13]. We define the *learner path* as the sequence of student activities and artefacts: An artefact created and the activity that happens on an artefact (e.g. a rating, a comment) can impact the next one: a comment by a peer can influence the next blog post, the creation of a mind-map might result in a new hypothesis.

While the vertical path from overview to details can help navigate the LA data, this horizontal learner path (see Figure 2.10) can help provide deeper insights into students’ learning [56]. We have explored this concept in dashboard E [21], where we visualise the sequence of an entire class across multiple activity types (see Figure 2.11.E). Teachers reported that visualising this path can help students backtrack through their IBL process, reflect, and make sense of it. But it can also assist students in exploring peer paths, to discover different approaches and improve their own methods: when discovering an interesting inquiry conclusion posted by a peer, both teacher and student can access and reflect on every learner activity that helped arrive at that specific solution.

### 2.4.2 Contexts

**Integrate the dashboard into the work-flow:**

During dashboard A’s deployment, the Master in Engineering students reported that their high workload did not leave much room for LDs. Google Analytics logs showed that students would access the dashboard the evening before class. The successful dashboard features were those with low requirements on effort
and time: a quick glance was sufficient to raise student awareness of personal and class progress [27].

With dashboard D, we attempted to integrate the dashboard into the student work-flow. As reading and commenting on peer blogs is part of the course activities, dashboard D [29] provides direct access to the learner artefacts (blog posts), teacher and peer feedback, and augments the data with blog post age and activity to help students navigate. Simply put, the dashboard replicates RSS\(^{14}\) reader functionality, but leverages LA data to facilitate richer exploration to provide further insights. Dashboard D was used by 55% of the blog-supported course students on a weekly basis. During the IBL pilots, dashboard D was reported to be used in the classroom for weekly coaching tasks, while it also became part of the student’s time management tool set.

**Facilitate collaborative exploration of LA data:**

Dashboard A was developed as a desktop application, but was several times projected on a wall in the classroom when the teacher deemed intervention necessary. Problematic students would be highlighted, and the students would get the opportunity to explain their (lack of) activity. In this situation, the teacher drives the visualisation and students can contribute to the discussion. However, students cannot interact with the visualisation directly, only through the teacher.

Leveraging the affordances of large interactive tables, we can facilitate collaborative sense-making [70] as students and teachers can simultaneously interact with and explore the LA traces. To the best of our knowledge, no examples exist of LA data visualised on such devices.

Dashboard B limited the visualisation to badges. This abstract view of the data was sufficient to trigger exploration and discussion, but only happened when students grouped around the tabletop (see Figure 2.4). They would reflect on their own and peer achievements, and come up with arguments for their lack of achieving certain badges. However, students who approached the tabletop by themselves were not motivated to explore the LA data. Students interacting in group experienced the system as “fun”, and reported they would like to use it together with teachers.

Dashboard E visualises an overview of the class’ learner paths and learner artefacts. The collaborative aspect was well-received and resulted in many scenarios teachers considered interesting: a teacher can initiate a discussion and ask students around the tabletop to explain their reasoning. Teachers

\(^{14}\)https://en.wikipedia.org/wiki/RSS
can use other students’ examples to inspire struggling students. Participants also mentioned that it can help students self-support their learning activities without teacher intervention: a student can explore peer activities and find “peer experts” on specific topics the student struggles with.

2.5 Discussion

In the previous section, we have listed the findings of five dashboard deployments. We now discuss the lessons learnt, link back to the state of the art, and elaborate on the remaining challenges.

2.5.1 Data

Abstract the LA data:

LA can be visualised in multiple ways [136, 61], depending on the audience and desired message. LA prediction systems create notifications and visualisations to warn users and impact retention [3, 67], while structural and content analysis help teachers gain insights at higher levels [108]. The data can also be abstracted or aggregated, providing students with awareness of efforts [98] and outcomes [122]. It is clear that there are many ways of dealing with the abundance of LA data, so that both teachers and students can make sense of it. These overview approaches are a good basis for facilitating further and deeper exploration of the LA data.

Provide access to the artefacts:

Few examples of LDs provide access to the learner artefacts. Fulantelli et al. [59] support the LA visualisations with direct access to the artifacts, but use is limited to teachers. When artefacts are made available to students, the selection is usually made for them: Shum et al. [137] automatically filter the large amount of assets to provide students with relevant resources. Bull et al. [17] provide assessment feedback to the student which can be linked with artefacts as evidence.

To empower the student and promote exploration of the effort to outcome path, LDs should allow manual exploration of the artefacts. DDart [72] aims to improve learners’ meta-cognition and self-regulation awareness by letting
students explore their personal traces. Huang et al. [102] give students access to peer LA data to help learn from past peer experiences.

Many LA systems already store the learner artefacts [37, 59, 102], but limit its access to teachers [59]. We believe it is very important for future dashboards to make personal and peer artefacts also available to students. Larger evaluation studies should be carried out to confirm this.

**Augment the abstracted data:**

Extra meta-data regarding the LA traces can serve as indicators to guide the user to relevant information, without forcing a predefined decision. Huang et al. [102] use location, time, and peer information as a way for students to find relevant data. Doug & Makryannis [33] suggest reputation meta-data to support judgement on the quality of artefacts.

By leveraging meta-data to extend simple dashboards, students can be exposed to peer information without much user effort (e.g. the class badge rewards of dashboard A). Interpretable indicators (e.g. the social activity count in dashboard D) can help explore and find relevant artefacts. While abstraction can help tackle the abundance of learner traces, these augmentation approaches should be taken into account to help improve judgement of quality and exploration of the abundance of LA data.

**Provide access to teacher and peer feedback:**

LA-supported feedback is often related to EDM systems, where informative and explanatory notifications and visualisations attempt to change student behaviour [3, 67]. Clear evidence of dashboards that help teachers intervene when necessary, is provided in [28, 90]. Bull et al. [17] successfully use artefacts as evidence for assessment feedback. Our evaluation participants showed interest in using the dashboard to support evaluation. But as shown in [96], incorporating teacher feedback into the LA traces can play an important role as well.

Students value teacher feedback and are interested in accessing feedback given by peers [17, 29]. In the blog- and IBL-supported courses we presented, feedback activities (ratings of activities, teacher contributions to discussions or as blog comments) are already stored in and accessible through the LMS. But feedback also happens in the classroom, or in more personal ways such as one-on-one meetings and private messages and e-mails. The challenges related to tracking these types of feedback should be further explored, both from technical as well as ethical perspectives.
Visualise the learner path:

Tracing all learner activities helps visualise the learner paths, which is a valuable source of information for teachers to intervene and assess, and for students’ self- and peer-awareness and reflection. Most learning activities in environments such as LMS can be registered, and through new technologies, this also becomes feasible in the classroom: Martinez et al. [90] leverage interactive tabletops to log interactions on an individual level. Raca et al. [113] use video to record and analyse student attention in the classroom.

The rising ubiquity of sensors in our daily lives can help complete the map of student activities (inside and outside of the classroom) such as eye gaze [113] (attention) and location tracking [40] (attendance, library visits). LD design should try to integrate these resources and visualise them in meaningful ways.

2.5.2 Contexts

Integrate LA into the work-flow:

Kapros et al. [73] integrated LA visualisations into an LMS and empowered learning and development managers by providing context next to LA visualisations. But this LA contextualisation can also benefit students. For example, Course Signals’ traffic light representation of success chance was successfully integrated and accepted into the student’s course homepage [3]. Dashboard D leveraged LA to support students’ learning activities (e.g. finding, reading, and reacting to relevant posts, accessing feedback), improving not only their work-flow, but also exposing them to LA data more often.

It is important to tailor LDs depending on the context in which their learning occurs [68]. Therefore, while designing dashboards, keeping in mind the specific user needs, the course setting, and the target location and technologies available results in a better user acceptance, which in turn can help raise usage and improve impact.

Facilitate collaborative exploration of the LA data:

While many LDs visualise social and group interactions [116, 90], few dashboards are created with collaborative sense-making of the LA data in mind. Yet, dashboard B and E showed great potential for discussion, exploration, sense-making, and assessment. Even dashboard A triggered group discussions when projected in the classroom.
To support this collaborative exploration and sense-making, LD design can learn from the fields of Collaborative Visualisation [70] and Computer-Supported Cooperative Learning [142]. We also assume more (single user) dashboards have been used in a collaborative setting. It would therefore be beneficial for LA researchers to explicitly report on their findings regarding these experiences.

2.6 Conclusion

The intent of this chapter was to formulate the lessons learnt that the authors consider important for future development of learning analytics dashboards. We belief that it is highly important to empower students to reason about their efforts and outcomes. We therefore discussed how to create dashboards that support students in actively exploring their efforts and outcomes: by providing data beyond personal analytics, through visualisation techniques to make the abundance of data accessible, multi-user interaction to facilitate collaborative sense-making, and integration of the dashboards into student work-flow.

By linking these lessons learnt to the current state-of-art, we tried to identify potential areas of improvement. As such, we hope that this work will help to raise the effectiveness of future learning analytics dashboards.
Chapter 3

Towards Balanced Discussions in the Classroom Using Ambient Information Visualisations

3.1 Introduction

LA traces can reflect activities inside and outside the classroom [120] of both students and teachers, but can also be used to impact activities in a live classroom. It allows teachers to intervene or orchestrate [87], and students to become aware of their behaviour and progress on tasks [43].

This chapter focuses on visualising learning analytics live in “design critique” face-to-face sessions as explained in Section 1.3. Over- and under-participation in collaborative learning settings can reduce motivation and lower learning outcomes [118]. Literature has shown that ambient displays are an effective means to tone down over-participators and motivate under-participators [5]. As such, they can help achieve a better balance by raising awareness of participation distribution in meetings and small learner groups. This work goes a step further. By placing an ambient information visualisation (AIV) [138] that visualises participation distribution in a non-distracting way, we investigate if and how it can promote balanced feedback participation in larger learning groups during repeated face-to-face “design critique sessions” in the classroom. Two case
studies were carried out toward that goal.

The first case study explores and evaluates four visualisation designs to raise awareness of balanced discussion in the classroom. The second case study improves the first case study’s most promising design and investigates students’ perception of its impact in the classroom. The gathered analytics data of the two case studies are used to investigate the effect on feedback balance. More specifically, we aim to answer the following research questions:

<table>
<thead>
<tr>
<th>RQ3</th>
<th>What are the design challenges for AIVs to promote balanced group participation in classrooms, and how can they be met?</th>
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<tbody>
<tr>
<td>RQ4</td>
<td>Are visualisations on ambient displays effective means for creating balanced group participation in classroom settings?</td>
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</table>

We start by explaining the state of the art in Section 3.2, and how our work attempts to contribute to it. Section 3.3 explains the methodology and briefly discusses the technical implementation. Section 3.4 describes the design choices, elaborates on the different visualisations for our AIVs, and reports on the evaluation results of the first case study. Section 3.5 builds upon the findings of the first case study and reports on the evaluation results of the second case study, including students’ perception of having such an AIV in the classroom. Section 3.6 reports on the actual effects on discussion balance during both case studies. Section 3.7 and 3.8 discuss our general findings and reflect on opportunities for future work.

### 3.2 Related Work

Communication and collaboration skills are key 21st century competences for lifelong learning [78]. We focus specifically on the former in “design critique” sessions where on average four to seven teams of three students present their work to each other and receive in-depth feedback from their peers. The quality of the feedback students give to their peers correlates positively with the quality of their own work [81]. It is thus important to promote this activity in the classroom. Lack of balance in participation can however negatively impact collaborative learning [118]: Over-participation of a learner can affect others to “free-ride”, while the “free-riders” can affect the motivated learner to
reduce contributions. Over-participation can lead to a group dominating the conversation, giving other groups no chance to contribute.

Group mirrors [9] are systems that can shed light on the distribution and thus type (presentation, interview, meeting) of group discussion participation through real-time visualisations [127]. Pentland et al. [107] use personal devices to visualise discussion balance by showing discussion dominance in a “tug of war” fashion, resulting in improved cooperation for distributed groups. Occhialini et al. [101] designed halogen spots to shed light on time management in meetings. DiMicco et al. [45, 44] present discussion activities as bar charts, circle sizes and time-lines on walls and small tabletop devices, helping over-participators stay aware and tone down their activities. Schiavo et al. [124] explore ways of creating more subtle interventions to guide discussions through peripheral displays. A natural discussion setting, such as sitting around a table, can be augmented with participation distribution by visualising the data on the table’s surface [5, 7]. These examples show that peripheral visualisations of discussion activities can directly influence participation.

The previous examples focus on creating awareness of individuals’ participation. Visualisations can furthermore enhance classroom orchestration and participation in learning activities of student teams, by making the invisible factors in the classroom visible [43]. MTDashboard [85] provides teachers with a private view on group’s activities and progress, to facilitate intervention. Lantern (a multi-LED device) and Shelf (a classroom dashboard) visualise the group’s working and time waiting for teaching assistants (TA), informing TAs which groups to attend to first [43]. These public visualisations also create a mutual awareness of activities and progress between teams. Paulus & Dzindolet [105] found that knowledge about other group’s brainstorm performance could influence participation behaviour. Similarly, the awareness created by LDs can lead to specific learning impact [147].

This work attempts to leverage the use of ambient displays to create balance in participation of during discussion sessions in the class room. Wisneski et al. [157] defines ambient displays as a way of moving information into the environment, hereby allowing the user to switch between their main focus and peripheral information. Pousman & Stasko [111] pitched the term ambient information systems, adding that the information represented should be important but not critical, the display environmentally appropriate, subtle with updates and tangible. Some examples mentioned above fall into this category: Lanterns [43] for example help students become aware of surrounding peer progress. Occhialini et al. [101] augment the peripheral environment through halogen spots information with time management data.

Ambient displays are still best known for being physical in nature. The first
occurrence is assumed to be the Dangling String [155], notifying co-workers about network traffic through a moving string hung from the ceiling. More recent examples are Ambient Rabbits [95] that visualise weather forecast, AwareMirror [58] that provides personal information during morning bathroom activities, and Gleamy [19], a bedside lamp visualising daily activity. Skog et al. [138] argue that ambient displays should not necessarily be physical in nature. Both small displays such as mobile phones [145], as well as large displays [66] are suitable for ambient information systems, and can display artistic [138, 52, 94], informative [66] and more traditional visualisations [45, 44]. These AIVs [138] move information visualisation applications from the desktop computer screen into the environment or periphery of the user. Similarly, our work uses large displays and wall projections in the classroom, to display information visualisations of class participation. The focus of the design is thus not on the physical, but on the digital information on the screen. Whereas it does not match the tangible characteristic of Pousman & Stasko’s definition [111], it takes every other aspect into account: the display visualises information regarding participation balance (important but not critical information), it is projected/displayed on a screen and thus already part of the classroom structure (environmentally appropriate), next to the presenting students (in the periphery, see Figure 2), and we focus on keeping the distraction low (updates subtly).

To quantify oral participation, Pentland et al. [107] measured length and speed of talking, vowel and pause counting. Tausch et al. [143] manually measure the number of contributions. DiMicco et al. [45] used length of speaking time to effectively tone down over-participators. For the purpose of our evaluation study, we use length of speaking time as measure for the quantity of participation in the discussion. The quality of participation e.g. correctness, relatedness, value, is more difficult to measure. Conversation Votes [8] lets participants vote anonymously on peer contribution. As students can benefit from synchronous peer feedback [106], we briefly explore live peer-assessment through a “like” voting system.

During the “design critique” classroom sessions, giving feedback is an important learning activity. A balanced feedback session would give each group equal chances to practice this skill. By creating group mirrors to visualise these learning activities, i.e. each group’s feedback participation, this work attempts to raise awareness regarding the feedback distribution. This awareness can in turn assist in toning down over-participators and motivating under-participators, resulting in a better balance of practising feedback.
Figure 3.1: Wizard of Oz interface: The TA sets a group as presenter to initialise the visualisation. When a group starts providing feedback, the TA clicks the group’s name. When the group stops talking, the TA clicks the name again.

### 3.3 Methodology

Our evaluation study consists of two case studies performed in two Master courses where the classroom sessions are structured around “design critique”: each group gives a presentation of their project, after which the other groups provide critical feedback and ask questions for clarification. The professor and teaching assistants act as facilitators and provide feedback.

Our focus lies primarily on the usefulness and effects of the visualisations in the classroom. We therefore use a Wizard of Oz approach [62]: instead of automatically gathering the amount of feedback given by each group through microphones and audio processing, in our approach a TA uses a simple web interface to capture when each group starts and stops talking (see Figure 3.1).

The first case study, “Designs”, focuses on the design challenges for the AIV. Four designs are deployed and evaluated during an “Information Visualisation” (IV) course session. These designs visualise both quantitative and qualitative data regarding the feedback participation. The second case study “Promoting Balance” focuses on the most promising design of the first case study and explores students’ perception regarding the visualisation of participation balance. This visualisation was deployed and evaluated during the “Fundamentals of Computer-Human Interaction” (FCHI) course. Quality of feedback was recorded but not visualised during the second case study. Feedback activities were logged during both case studies and were further analysed to get insights into the effects of the AIV on the feedback balance in the classroom.

The visualisations are presented on a large display that is positioned in front of the classroom, next to the students who are presenting their work and receiving feedback (see Figure 3.2). The web interface was developed in HTML,
Figure 3.2: Students presenting their work. On the right, a large display provides live information on feedback balance.

<table>
<thead>
<tr>
<th>The InfoVisioneers</th>
<th>Like feedback</th>
</tr>
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<tbody>
<tr>
<td>LVM</td>
<td>Like feedback</td>
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<td>Inv seized</td>
<td>Like feedback</td>
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<tr>
<td>Data Chartist</td>
<td>Like feedback</td>
</tr>
<tr>
<td>Prof/TA</td>
<td>Like feedback</td>
</tr>
</tbody>
</table>

Figure 3.3: Screen-shot of a web interface that enables a student to rate a group anonymously. A “like” can be sent during and after the feedback was given.

CSS and JavaScript. The visualisations are developed using Processing.js. A Node.js server using Socket.IO\(^1\) provides real-time communication between all applications. All events are furthermore stored in MongoDB for posteriori analysis.

### 3.4 Case Study 1: Designs

#### 3.4.1 Requirements and Design Choices

Our goal is to find out if we can use AIVs to i) create a more balanced discussion by raising awareness about the balance of quantity and quality of the feedback, and ii) that are perceived useful and are accepted by students for further use in the classroom.

\(^1\)http://socket.io
A class discussion was held during an IV course session to introduce the concept of visualising feedback participation through AIVs and to gather preliminary feedback. During the first case study, we wished to briefly explore adding a qualitative aspect to the visualisation. We proposed a rating system with which students could rate peer feedback. Students responded that they prefer a positive rating system, as they did not feel comfortable with giving and receiving negative peer ratings. This led us to implement a “like” system. Each student can access a web interface (see Figure 3.3) with which the student can send a “like” to any other group as an appreciation of their questions or comments.

To arrive at a successful design, we follow Pousman & Stasko’s taxonomy [111] of four design dimensions for ambient information systems: information capacity (IC), notification level (NL), representational fidelity (RF), and aesthetic emphasis (AE). IC indicates the number of different information sources that a system can represent. NL is the degree to which the system interrupts the user. RF is the abstraction of the data, with fidelity ranging from symbolic (low) to indexical (high, e.g. a map). AE deals with the importance of aesthetics put into the system, i.e. whether being visually pleasing is a primary objective.

The information we thus wish to portray is limited to two attributes per participating group: the quantity (duration) and quality of feedback (“likes”) given after a single presentation. These attributes will show the current balance status of the group discussion, not its evolution through time. This keeps IC requirements low. Our case study needs to visualise the feedback of five groups during the length of one presentation. However, the designs discussed can easily be extended to facilitate more groups and longer sessions.

Students should be made aware of the (im)balance of feedback quantity and quality, so that they can adjust their behaviour. To adhere to the ambient nature of the visualisation, NL must remain low, so that the focus remains on the students who are presenting their work or the other students providing feedback. Information updates must thus be subtle, but apparent enough to support awareness of the balance situation.

Regarding RF, we explore different abstractions to portray the data. We hypothesise that it is not important to show exact numbers of the balance to communicate the situation regarding feedback balance in the classroom.

Our visualisations will be most effective when students accept their presence in the classroom. AE is therefore important as it can influence the attitude towards the AIV [144].
3.4.2 Proposed Designs

Based on the discussions with the students, two attributes must be visualised: likes and participation. Adhering to the dimensions proposed by Pousman & Stasko [111], we designed four dashboards that were deployed in the classroom for evaluation purposes in a realistic setting. Version A provides a direct visualisation of the data through bar charts (RF focus on quantity). Version B presents a playful approach of version A (AE focus). Version C adds group interaction to the visualisation (higher IC focus). Version D abstracts the quantitative participation information into a balance representation (RF focus on balance).

**Version A – Bars**

A straightforward way of presenting the distribution of feedback is through a histogram (see Figure 3.4.A). The quantity of feedback that a group provides is represented by the length of a bar in the top part of the visualisation. When a group gives feedback, its “feedback bar” grows. Similarly, when a group receives a “like” for its feedback from another group, its “like” bar grows by one segment in the bottom part of the visualisation. As mentioned above, exact numbers are not important but the representation of balance, under- and over-participation is. Here, a balanced discussion with regards to both quality and quantity is indicated by bars of roughly equal length.

**Version B - Trees**

Like A and inspired by Nakahara et al. [98], each “feedback” bar is replaced by a tree representing the group, creating a more “playful” visualisation (see Figure 3.4.B) where each tree grows as the corresponding group provides more feedback. Apples are added to a tree for every “like” the corresponding group receives. Similar height of trees and equal distribution of apples now indicate balance.

**Version C - Node-Link Graph**

Every group is represented by a large dot (see Figure 3.5.C). The presenting group is indicated by the pink dot. (Note that this is the only visualisation where the presenter is also visualised). The presenter dot is static, as this group does not receive “likes” and does not give feedback. All other groups are visualised by green dots. A green dot grows as the group receives more “likes”.
Figure 3.4: A. Using length to visualise quantity of feedback given and number of “likes” received. Top bars represent feedback; bottom bars represent “likes”. B. Trees as a substitute for bars. Apples represent the number of “likes” a group has received.
Figure 3.5: C. Every circle represents a group. The pink circle is the group presenting; the green circles are the groups giving feedback. The amount of feedback a group gives is visualised by the thickness of the line between the group and the presenters. The size of the circle indicates the number of likes received. D. Each group is indicated by a circle. The large white circle represents the average amount of feedback across the groups. Groups must try to stay on the outer rim to keep balance within the classroom discussion. Green orbiting dots are the “likes” received by the group.

The width of the line between the presenter and a group represents the quantity of feedback. As the group provides feedback, the line is animated by growing in width (visualising length of total feedback) and fades in and out (the group is actively talking). Equal line widths (quantity) and dot sizes (quality) between all green dots indicate a balanced discussion.

**Version D – Average**

The audience groups giving feedback are represented by pink dots (see Figure 3.5.D). Each dot is positioned on a large white circle that defines the average amount of feedback given across all groups. At the start of a session, contribution is 0 across all groups, thus all groups rest on the circle (average = 0).

Changes in group feedback balance affect the group dots, while the average circle remains static. When a group gives feedback, all dots are moved according to their distance from the average: the dot for the active group moves to the centre of the circle and inactive groups are pushed outwards. “Likes” are indicated by smaller, green dots that orbit around the pink dot representing the group whose feedback is being liked. Balance is achieved when all groups are located close to the circle, with an equal distribution of orbiting “like” dots.
3.4.3 Evaluation

Experiment Setup

We evaluated our visualisation design choices (focused on NL, AE, RF. IC is limited to two parameters) [111] on perceived awareness of and its usefulness for creating balance of feedback.

During a “design critique” session of the IV course at KU Leuven, twelve students (four groups of three students, age 21-23, all male) each present the results of their work progress. All groups in the audience, including the teacher and TA “group” provide feedback and questions. Students access the feedback web interface (see Figure 3) to send “likes” to peer groups. For our evaluation, one teacher assistant used the simple tracking interface (see Figure 1) to log the start and end times of the feedback. The display, a 60-inch TV positioned next to the presenting students, displayed a single design per presentation.

After every feedback session, the students were asked to fill in a questionnaire (C1Q1) with four questions (Q1.1-Q1.4) that used a 5-Likert scale questions (never, rarely, sometimes, often, always - strongly disagree, disagree, neither agree or disagree, agree, strongly agree) and an open question (Q1.5) regarding likes and dislikes about the visualisations.

- Q1.1. How often did you look at the visualisation?
- Q1.2. Was the visualisation distracting?
- Q1.3. The visualisation gave me a good indication of the quality of each group’s feedback/questions.
- Q1.4. The visualisation gave me a good indication whether the distribution of feedback among groups was well balanced.
- Q1.5. What did you like/dislike about the visualisation?

After the design critique studio session, students filled in another questionnaire (C1Q2). They were asked to order the four visualisations: by clarity for visualising balance of quantity (through length of time giving feedback), clarity for visualising balance of quality (through number of likes each group received), aesthetic preference, distraction level and general preference.

To validate the use of AIVs for the purpose of better balance and to get a better understanding of students’ attitude towards the public sharing of this information, five more 5-Likert scale questions (strongly disagree, disagree, neither agree or disagree, agree, strongly agree) were asked.
TOWARDS BALANCED DISCUSSIONS IN THE CLASSROOM USING AMBIENT INFORMATION VISUALISATIONS

Were you uncomfortable to see your group’s feedback information shared?

Would you want such visualisation present in other discussion settings?

Would you prefer this information to be shared personally, instead of on a more public display?

Do you think this personal approach will be as effective as a public visualisation?

Do you think such visualisations helps a discussion setting?

Figure 3.6: Results of the questionnaire (N=12) regarding all visualisations, at the end of the studio session (C1Q2)

- Q2.1. Were you uncomfortable to see your group’s feedback information shared?

- Q2.2. Would you want such visualisation to be present in other discussion settings? (e.g. other classes?)

- Q2.3. Would you prefer this information to be shared personally, instead of on a more public display? (e.g. through notifications, personal device etc.)

- Q2.4. Do you think this personal approach will be as effective as a public visualisation?

- Q2.5. Do you think such visualisations helps a discussion setting?

A confirmative answer on question C1Q2.1, i.e. the student was uncomfortable with the visualisation, was followed by requesting the student to rank the visualisations by level of discomfort.

The next section will present the general student perception regarding our AIVs in the classroom. Then we will go into more detail on the per-visualisation evaluation results.

General Perception of the AIV

The consensus was that the AIV has a perceived impact on participation during feedback (see Figure 3.6, C1Q2.5). Investigating individual questionnaire results, over-participating groups perceived it as a motivational tool, while under-participating groups experienced it (more negatively) as pressure. Three
Figure 3.7: Results to the per-visualisation questionnaires (N=12). All designs score well regarding clarity. B and C are most looked at and considered most distracting (C1Q1)

out of twelve students, all from groups with lower participation, experienced the visualisations as uncomfortable.

The public nature of the visualisations on an AIV was well received (see Figure 6, C1Q2.3-4-5): seven students would not prefer a more personalised approach, such as visualisations on personal devices or personal notifications. Nine students did not think such a personal approach would be as efficient. Nine students were convinced the visualisations are very effective for discussion sessions. Five students would want to see such visualisations used in other discussion settings.

**Visualisation-Specific Results**

Based on the resulting student order of the visualisations (see Table 3.1) and the C1Q1 questionnaire results (see Figure 3.7), this section discusses three design dimensions NL, RF and AE [111]. We elaborate further on the results in section 3.7.

**Notification Level:** A low NL is necessary to avoid distracting students too much from the actual “design critique” process. Distraction rated high for visualisation B and C. Students mentioned that visualisation C’s indication
Table 3.1: Students’ ordering of the visualisation (1 to 4) by: clarity quantity balance, clarity of quality balance, aesthetic preference, level of distraction, how uncomfortable they felt and general preference.

<table>
<thead>
<tr>
<th></th>
<th>Balance</th>
<th>Likes</th>
<th>Aesthetics</th>
<th>Distracts</th>
<th>Uncomfortable</th>
<th>Prefers</th>
</tr>
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<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>B</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>4</td>
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<td>C</td>
<td>4</td>
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<td>D</td>
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<td>3</td>
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</tbody>
</table>

of an active group (by fading in and out their feedback line, see Version C - Node-Link Graph) called too much for attention. Visualisations D and A were perceived as less distracting. While visualisation D also uses animation, its subtler nature (slow movement of dots, slow orbiting “likes”) seemed less obtrusive in calling for attention. Students reported to look at each visualisation, with a frequency lower for D and A.

Representational Fidelity: All visualisations scored well regarding clarity of balance and clarity of quality. Students rated visualisations A and B highest for clarity. C rated lowest: students found deducing balance by comparing dot size and line width difficult. Over-participators (identified through the logged feedback activity data and matched to their questionnaire results) perceived receiving “likes” as motivational. One student mentioned: “It made me want to continue giving feedback for more likes”. While visualisation D rated lower than A and B for clarity of quality, students experienced the orbiting “likes” as rewarding and fun; visualisation A was experienced as “boring”.

RF design choices can impact the way the data is perceived. Three out of twelve students experienced the visualisations as uncomfortable. D was experienced as most uncomfortable, while A as least. Visualisation D’s ideal situation (i.e. balance) is not what students seem to aim for. More contribution by a group moves their dot inwards, while pushing other groups outwards. The under-participators’ distance from the average circle is quickly experienced as insurmountable. The “playful” nature of B was described as “less threatening” by less participating groups, and “fun” and “rewarding” by active groups.

Aesthetic Emphasis: Emphasis on AE can make the visualisation more enjoyable and help improve acceptance of the visualisation. Visualisations C and D rated highest for aesthetic preference. Preference for further use of such visualisations (e.g. in other discussion settings) went to versions A and D.
CASE STUDY 1: DESIGNS

Discussion

Visualising quality and quantity of participation in a “design critique” session to pursue balance among all participating groups is promising, but challenging. Students perceive the visualisations as useful for discussions and they can promote activity in the classroom, but do not necessarily push towards a balanced distribution of feedback. Currently the designs are experienced as rewarding for over-participation and visually “punishing” for under-participation: for instance, versions A, B and C are experienced as “bigger is better”. Size and length are good indicators for quantity, but quantity is not the main message the visualisations should pass. Visualisation D does not use size as a quantity indicator, but suffers from a similar problem: students perceive a dot position within the circle (above average) as better, while a location outside the circle is experienced negatively as distance grows between under- and over-participators. This gap may seem insurmountable as time goes on, resulting in students giving up on trying to catch up.

Visualisation D was most preferred but was experienced as most uncomfortable by under-participators. This is not necessarily a bad thing. The challenge will be to transform this perception so that i) under-participators experience it as motivation instead of pressure, and ii) over-participators understand they should leave room for others to contribute.

In the current experiment, we visualise inter-group activity. Intra-group, i.e. per-student activity can be visualised in a similar manner, opening more possibilities for learning settings. Future work will explore the design changes required to accommodate larger numbers of individual subjects. The visual nature of both version C and D can for instance be used in a multi-focused visualisation: inside the dot representing a group, the visualisation can be repeated with information on the individual group members. This could provide interesting insights in both intra- and inter-group activity simultaneously.

We presented four AIVs designs to display the balance of feedback in a “design critique” session with a classroom of students. These designs have the potential to impact feedback distribution in the classroom, but are not yet experienced positively by under-participating students. Our next case study will explore how we can tackle this perception, and look more into detail on how an AIV can affect the participation in classroom discussions.
3.5 Case Study 2: Promoting Balance

3.5.1 Design Improvements

In our second case study, we attempt to improve the visualisation to help tone down over-participation and motivate under-participators. We start from design D: During the first case study, design D was preferred by students, was not considered very distracting but was experienced most uncomfortable by under-participators. To improve D so that i) under-participators experience it as motivation instead of pressure, and ii) over-participators understand they should leave room for others to contribute, we give “balance” a broader meaning: DiMicco & Bender [44] define an under- and over-participation static limit around the average (e.g. 25% of participation for four participants). Similarly, we define a “balanced” area by adding an upper and lower limit. However, in our case, the upper and lower limits alter depending on the current, live average of the feedback in the classroom:

$$l_t = p \times \frac{\sum_{i=1}^{N} (f_{it})}{N}$$ (3.1)

where $l$ is the (upper/lower) limit at a specific time $t$, $N$ is the number of groups and $f_{it}$ is the total amount of feedback given by group $i$ at a specific $t$. $p$ is a percentage which defines how far the bounds may deviate from the live average. The bounds will thus change over time, allowing more leeway for groups as time goes by (e.g. being one minute under an average of five minutes of total feedback is a greater imbalance than being one minute under an average of 20 minutes).

Figure 3.8 shows the updated version of D where a zone is created in which “balance” is achieved, i.e. the static middle (green) circle depicts the average of feedback, while the inner and outer (orange) circles show the upper- and lower-bounds.

3.5.2 Evaluation

Experiment Setup

Nineteen students (2F, age 21-23, no overlap with the first case study) participated in the evaluation during a four-hour long FCHI course at KU Leuven. Six groups (five groups of three, one group of four students) each gave a
15-minute presentation on the intermediate results of their project work. After each presentation, fifteen minutes were reserved for all groups in the audience to provide feedback and ask questions. During this case study, the teacher assistant only tracked student feedback, meaning the AIV did not visualise information regarding the teacher. Instead of students rating peers through “likes”, the teacher rated and logged the quality of the feedback given. This data was kept hidden from the students during the experiment. For a better aesthetic integration with the environment [111], the large screen was replaced by a projected version on the wall next to the presenting students.

First, all students were asked to fill in a questionnaire (C2Q1) regarding their view on the importance of peer feedback. Six 7-scale Likert questions were asked (1-strongly disagree, disagree, somewhat disagree, neither agree nor disagree, somewhat agree, agree, 7-strongly agree):
C2Q1.1. It is important to give feedback.

C2Q1.2. Feedback of the professor is more important than peer feedback.

C2Q1.3. It is important that our group gives the most feedback.

C2Q1.4. I do not care that we give few feedback.

C2Q1.5. It is important that all groups give equal feedback.

C2Q1.6. I am well aware of the distribution of feedback across groups.

Another two 5-scale Likert questions were asked (1-never, rarely, occasionally, a moderate amount, 5-a great deal):

C2Q2.1. How often do I give feedback?

C2Q2.2. How often should our group give feedback?

At the beginning of the sessions, students were made aware that there should be a balanced distribution of feedback among groups. During the first three presentations, no visualisation was shown. During the three last presentations, the improved visualisation D was projected on a wall next to the presenting students. The upper- and lower-bounds that define a “balanced” session were set at 20% distance from average [44] set the range to 50% of the static average). This means that after a total of one minute of feedback is reached, groups would be expected to be within twelve seconds of the total average. At an average of ten minutes of feedback, groups can deviate as far as two minutes.

After the first three presentations without visualisation and the next three presentations supported by the visualisation, students had to answer two questions regarding their awareness of the amount of feedback given during these three presentations (C2Q2). At the end of the sessions, students filled in a final questionnaire with six 7-scale Likert questions (1-strongly disagree, 7-strongly agree) and one 5-scale Likert question (1-never, 5-a great deal) regarding their perception of the AIV (C2Q3):

C2Q3.1. The visualisation was distracting

C2Q3.2. The visualisation helped me realise how much our group participated

C2Q3.3. The visualisation is useful to create feedback balance
Figure 3.9: Questionnaire asked at the start of the classroom session (N=19) (C2Q1)

- C2Q3.4. The visualisation played an important role to create feedback balance
- C2Q3.5. The visualisation was motivating
- C2Q3.6. The visualisation was demotivating
- C2Q3.7. How often did I look at the visualisation?

Results

Based on the questionnaire C2Q1 (see Figure 3.9), students remain neutral to whether they know how balanced the feedback is, but do have a small preference towards seeing balance. The professor’s feedback is considered more important, but they still consider giving feedback an important activity, even though most students admit they do not give a lot of feedback. The amount of feedback their group gives should not be a lot, and they are indifferent towards low participation on their behalf.

Questionnaire C2Q3 (see Figure 3.10) shows that students did find that the AIV helps them with awareness regarding their own contributions. Comparing their participation assumptions (C2Q2) with the logged data, two groups
Figure 3.10: Post classroom session questionnaire (N=19) (C2Q3)

overestimated their efforts in the sessions without the AIV. The two under-participating groups estimated their efforts correctly. For the sessions where the AIV was present, two groups overestimated and four estimated correctly.

Students mostly disagreed that the AIV is useful for balance, and were neutral towards its importance for maintaining balance. They found the AIV a little distracting. It did help somewhat with motivation and was not considered demotivating.

The ratings for feedback contribution registered by the teacher showed that quality remained equally good for all feedback sessions. Students still made meaningful contributions and asked interesting questions with the presence of the AIV.

Discussion

AIVs can assist students in remaining aware of their contributions during a “design critique” session. Students do not specifically consider balance overly important, but understand the importance of giving peer feedback. The students claim to be aware of their low feedback contribution, but are indifferent to this.
Therefore, the perceived motivational aspect of the dashboard can be of benefit to affect participation in the classroom. Section 3.6 will elaborate on this effect.

The updated D design was not considered demotivating. Broadening the range of what is considered “balance” lowered the visual distance an under-participator has from the average, which could lower the feeling of not being able to “catch up”. It also requires more over/under-participating before a group leaves the “balanced” zone. Students did still report that the visualisation had a more positive connotation with over-participation. This might be related to the labels used in the design (+limit, -limit, see Figure 8). Removing the positive and negative symbols from the upper- and lower bounds could resolve this issue, but makes it less obvious whether a group is under- or over-participating (e.g. “did I give too much or too little feedback”).

As only duration of feedback is taken into consideration, it could be expected that students will attempt to game the system. However, the ratings of feedback contributions captured by the teachers showed that the presence of the AIV did not have a negative effect on the quality of feedback contribution. As well thought-out questions and feedback would take longer to explain, the quantity visualised for such a contribution could be an indication of its quality. As the feedback occurs in a public setting, the barrier to gaming the system is higher: teachers and students might easily see through these attempts and intervene.

### 3.6 Effect on Feedback Balance

During both case studies, all activity was logged in a MongoDB database for further analysis. This section investigates the feedback participation distribution observed during the two case studies.

Figure 3.11 gives an overview of the feedback participation with and without the AIV in both the IV course session (first case study) and the FCHI course session (second case study). During the first case study, when students were not specifically asked to keep the feedback balanced, a session with the AIV caused all groups to participate. During the session without the visualisation, the under-participating group did not participate at all.

During the second case study, where students were specifically asked to participate in a balanced way, all groups participated, with or without the AIV. When comparing the balance of the IV session (see Figure 3.11) with the balance of the FCHI session (see Figure 3.12), the distribution of feedback is more balanced: deviation from the average in the IV course goes up to 60% without the AIV and goes above 30% with. Groups of the FCHI course
Figure 3.11: Distribution of participation among groups in IV. Each bar per session represents a student group. Left: four feedback sessions without (w/o) the AIV. Right: four feedback sessions with (w) AIV.

Figure 3.12: Distribution of participation among groups in FCHI. Each bar per session represents a student group. Left: three feedback sessions without (w/o) AIV. Right: three feedback sessions with (w) AIV.
Figure 3.13: Convergence towards feedback balance without the AIV (top) and with the visualisation (bottom) during the two most active feedback sessions of FCHI.

remained mostly within the range of 10%, with active groups reaching just above 20%. Groups who reported they found balance important, remain closer to the average than those who did not.

Comparing the two presentations with the highest numbers of feedback contributions (i.e. the number of times a group gives feedback or asks a
questions), there is a difference in how fast the classroom merges towards balance. In the FCHI session without the AIV (see Figure 3.13 top, 30 contributions) three groups remain very active while two groups (red and green) only “catch up” towards the end. In the active FCHI feedback session (see Figure 3.13 bottom, 40 contributions) with the AIV, all groups contribute quite early in the session, creating a balance much quicker.

There is an indication that the AIV could initiate quicker interaction from under-participants. The visual feedback seems to influence their choice-of-acting faster. The visualisation can help realise that waiting longer to give feedback makes “catching up” harder.

3.7 General Discussion

Our case studies have shown that it is possible to impact balanced participation in “design critique” sessions using an AIV of feedback participation. This section breaks down our findings per research question.

3.7.1 What are the design challenges for AIVs to promote balanced group participation in classrooms, and how can they be met? (RQ3)

Visualise balance in an abstract and neutral way: Abstracting learning analytics data to the essential message one wishes to pass helps motivate students [122]. From our designs, we learnt that focusing on a visualisation that represents balance as an abstracted quantity created better results. By creating a broader representation of what is considered balance, the perception of motivation was improved. By visually lowering the gap between under- and over-participation, and thus creating a less accurate representation of the real data, under-participants are less demotivated. It is also important to create a neutral visualisation: removing negative connotation with under-participation and positive connotation with over-participation can help tone down over-participants and have less demotivating effect on under-participants, resulting in a better user acceptance.

Add the qualitative dimension to the visualisation: Quality through the use of “likes” was perceived as motivational. Small amounts of feedback of great quality will most likely be more meaningful than lots of low quality contributions (e.g. not receiving “likes”). Therefore, merging the quantitative and qualitative parameters so that one impacts the other (e.g. average equals a calculation of
both parameters) must be further explored. Future work should also take into account that not only the AIV, but also the interaction with peer feedback (e.g. “liking” contributions), can impact participation in feedback sessions. Adding teacher’s real-time feedback rating to the visualisation is another interesting path to explore.

**Create a realistic picture of the classroom situation:** When limiting the visualisation to the duration of feedback in the FCHI course, no negative impact on feedback quality was observed. However, some students did report a fear of a detrimental effect on quality of feedback as quantity can easily be gamed. While social control could counter this, capturing more types of learner tracers can create a better picture of the students’ contributions in the classroom, such as eye gaze [113]. With this extra information, it still is important and challenging to keep IC and NL low.

### 3.7.2 Are visualisations on AIVs effective means for creating balanced group participation in classroom settings? (RQ4)

**AIVs raise awareness of the invisible:** The case studies have shown that it is possible to motivate under-participators and make clear to over-participators to leave room for others to participate. Such peer awareness is not straightforward, as one of the over-participating groups confirmed: “We realise now that we give (too) much feedback, and will now also listen more to others”. While AIVs can help raise awareness of peer activities [43], classroom layout plays an important role on the type of devices that are suited. In our case, students face the direction of the presenter. Students in the back might have a harder time to get the attention of the presenter. This problem could be eliminated by e.g. using a U-shaped table configuration in the classroom, however, this is not always feasible. The AIV can help “front-row” students become aware of the under-participation of students around them (which is harder to notice without turning around).

**Ambient feedback information can activate students:** There are indications that, in active feedback sessions, convergence to balance is achieved quicker with the presence of the visualisation. While a better balance is achieved by merely asking students to participate more, the presence of the visualisation resulted in all groups participating quicker. The visualisation can thus have a positive effect on more active contribution, keeping students on their toes through the entire session. The presence of AIVs and its effect on “competition” is not new: Shelf [43] similarly caused students to be more competitive.
work should attempt to leverage this effect to activate and motivate students which could result in more endurance during classroom sessions.

**AIV as support for teacher/presenter:** Tracking and visualising student activities can help teachers with classroom orchestration [85]. Having a better overview of the balance situation, can help with the choice of which groups should be allowed to provide feedback next. This can help the presenter give equal chances to everyone in the audience, but also help teachers to manually intervene and “nudge” under-participators to join in the discussion. It can be argued that, with a moderator, there is only need for personal (teacher/presenter) dashboards. However, as Klerkx et al. [76] frame it: *If learners are always told what to do next, then how can we expect them to possess the typical 21st century skills of collaboration, communication, critical thinking and creativity?*

### 3.8 Conclusion

A balanced participation between learners is important for achieving intended learning outcomes. This chapter explored the use of AIVs to improve the balance between groups during “design critique” studio sessions. Four visualisation designs were deployed and evaluated in a course on Information Visualisation. This helped explore the design challenges to create balanced group participation in classrooms (RQ3). While low distraction and good aesthetics are required to create an AIV suitable for the classroom, the way in which “balance” is visualised plays an important role in helping under-participators provide more feedback, and over-participators tone down their contributions. Creating a broader interval in which “balance” is defined, can positively impact motivation. Visually “punishing” over-participation similar to under-participation helps groups become aware of and reflect on their over-participation.

The resulting visualisation was deployed and evaluated in the course Fundamentals of Computer-Human Interaction (FCHI) to see whether AIVs are an effective means for creating balanced group participation (RQ4). The visualisation does help students with awareness of their participation. As students report preference towards a balanced situation, the visualisation can assist them to reach this goal. The AIV did not impact quality of feedback contributions. During active feedback sessions, the AIV helped the groups converge quicker to a balanced situation.

As such, the contribution of the chapter is two-fold: i) it presents necessary design choices for AIVs that promote feedback balance in classrooms, motivating under-participators while limiting over-participation, and ii) it shows the effects on student perception and feedback participation through the actual deployment
of such visualisations in “real classroom sessions”. Future deployments in diverse
group settings will help further investigate the impact of balance AIVs. We
therefore invite researchers and practitioners to deploy these visualisations\(^2\) in
other settings and share their findings.

\(^2\)https://github.com/svencharleer/larae.talktalk
Chapter 4

Learning analytics dashboards to support adviser-student dialogue

4.1 Introduction

Arnold & Pistilli [3] indicate that “the first year of college is arguably the most critical with regard to the retention of students into subsequent years of study”. Student retention is one of the key areas of focus of learning analytics research [3], commonly defined as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” [54]. Objectives are manifold, and include personalising learning content to increase effectiveness and efficiency of learning, increasing awareness, reflection, and motivation of students, predicting and identifying “at-risk” students in terms of drop out, and supporting interventions by instructors or study advisers [148].

In this chapter, we present a learning analytics dashboard that was designed, developed, and evaluated in collaboration with study advisers (SA). The dashboard focuses on a particular situation, which is typical for first-year students: the support of reflection on academic grades, and planning after students received these grades at the end of an examination period. The overall objective is to facilitate communication between SAs and students by visualising grade data that is commonly available in any institution. We support student
advice through reconsidering how such data is typically used during student advising sessions. So far little work has been accomplished to support SAs with data-driven insights into study success as the focus is commonly on the use of learning analytics dashboards for students or for instructors [126], for instance to intervene or to adapt learning material. Some dashboards enable study advisers to monitor student engagement and provide support to at-risk students [74], but to the best of our knowledge no studies have reported the requirements and needs of SAs and their utility and usability for SAs.

This chapter reports on the results of a design study: we analysed the workings of a comprehensive SA-student session and identified potential improvements where learning analytics data could support such sessions. We designed a visualisation to support these improvements, and evaluated the use of this visualisation to support advisers. We started with a user (experience) and task analysis proposed by Sedlmair et al. [128] to understand the users, what aspects they value most in their current experience, which information they need, and what wishes and needs they have. Our focus in this first step is on getting to know the end user and analysing what currently works well, and what does not work well. We adopted a comprehensive series of qualitative and mix-method information gathering techniques including observations and interviews. We interviewed domain experts to understand how they work and what their needs are. To obtain a deeper understanding beyond mere individuals’ personal opinions [97], we explored the domain problem further through an ethnographic study and brainstorm sessions.

This study focuses on supporting the advice sessions of the first year of the Bachelor of Engineering Science and the Bachelor of Engineering Science: Architecture at KU Leuven, Belgium. After completing secondary school, every student can enrol in a program of the Faculty of Engineering Science. As a result, most programs have a relatively high number of students entering that are not necessarily optimally qualified for the program, resulting in an overall drop-out rate of around 40% [77]. In this setting, SAs are key-actors in advising students from the start of their program on their academic performance and the impact on their future study pathway. We focus on the following research questions:

<table>
<thead>
<tr>
<th>RQ5</th>
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<tr>
<td>What are the design challenges for creating a LD to support study advice sessions, and how can they be met?</td>
</tr>
</tbody>
</table>
RQ6

How does such a LD contribute to the role of the adviser, student, and dialogue?

This chapter reports on the iterative design process and evaluations of a dashboard that supports the interaction between study adviser and student. The contribution of this chapter is threefold:

1. Firstly, we present a dashboard that addresses the needs of study advisers. The process of reaching the final design is presented as well as evaluation results that assess the usability and utility of this dashboard for study advisers.

2. Secondly, we analyse the SA-student sessions supported with the dashboard. We assess the levels of insights that were obtained, the impact on the workload of study advisers and the impact on other design goals that we identified.

3. Finally, we present lessons learnt from this design study and guidelines for the development of learning analytics dashboards for study advisers.

### 4.2 Related Work

The effect of student counselling is a well-studied subject in social and behavioural sciences [130]. In recent years, automatic data analysis to support student counselling has gained increased interest [140]. Several research communities have been studying the potential of analysing vast amounts of data that universities are collecting, including communities working on educational recommender systems [48], educational data mining [103], learning analytics [134], and academic analytics [18].

Several systematic reviews have been conducted that identify the main trends and gaps of these research efforts. We reviewed research on educational recommender systems: outcomes of our analysis [48] indicate that most recommender systems focus on fine-grained content suggestions or sequences of learning materials that are relevant for the student. A subset of these recommender systems suggests relevant courses to students, and may be useful in student counselling scenarios that try to find relevant courses for a student. Research in the learning analytics, academic analytics, and educational data mining communities has developed and evaluated algorithms for the prediction
of student performance, drop-out, and retention [103]. Some examples of the use of educational data mining for student advising are mentioned by Ranjan & Malik [115]. The authors list among others the identification of the best program based on prediction of how students will perform in the selected courses as a target objective.

Visualisation techniques are commonly leveraged in learning analytics research to put this information in the hands of human experts to support decision making. The objective is to inform and to empower instructors and learners of issues that are identified by data analysis techniques and to leverage human judgement [134]. Visualisation plays an important role to empower these users with actionable knowledge about the learning process: the overall objective is to present relevant data about study performance to support decision making for different end-users (study advisers, instructors, students, administrators, etc.). Whereas this combination of visualisation and data analysis techniques has been researched extensively under the umbrella of “learning analytics dashboards”, results of our analysis indicate that most of these dashboards are used to facilitate blended learning, face to face learning or group work [147]. Little work has been done so far to use these dashboards to support the live interaction between SA and student: some dashboards enable advisers to monitor student engagement and provide support to at risk students [74], but a “one-size-fits-all” approach is often applied that is not adjustable to the requirements of different universities, faculties, and departments [140].

The goal of this design study is to create a dashboard that supports and enables discussion between SA and student, and empowers both parties to use data as evidence to support their claims [46]. We first elaborate on the context through a need analysis with the SAs, which resulted in our different design goals. We then detail the design process to achieve these design goals and preliminary feedback of the SAs. We report on our evaluation results regarding the deployment of the dashboard and discuss our findings.

4.3 Context

The SAs involved in the current study are part of the educational support staff of KU Leuven. They are responsible for both the study advice and content-related support for first-year students in a particular program. SAs are experts in both the content of the first-year courses, the current organisation of the program, and the regulation, both program-specific as university-wide. SAs are typically part of the program advisory committees, often advise the program directors,
Figure 4.1: Study progress file. From left to right: course identifier, course name, credits, final grade, period in which grade was achieved and are responsible for handling and approving the individual study program of first-year students.

Based on interviews with the SAs, we managed to get insights on the workings, needs and requirements during the advising sessions. These sessions are private conversations between a SA, and a student (occasionally with parents) taking place in an office environment. These students typically do not have a flawless study career: they have trouble studying, would benefit from a personalised program plan, did not achieve enough credits through the year, or simply wish to re-orientate towards a new program. Students voluntarily sign up for advising sessions. Students who achieved a low study efficiency (measured as the percentage of credits successfully obtained) are invited. To gather requirements and needs of SAs, we observed five sessions with one SA and organised a brainstorm session around the functional requirements with five SAs and the head of the Tutorial Services of Engineering Science.

SAs can obtain information on the student and his/her academic performance through multiple systems: The “study progress file” (see Figure 4.1) provides an overview of the classes the student has signed up for, the obtained grades, the number of credits of each class, and the best grade of each class for the different examination periods. The Bachelor Feedback pages provide elaborate textual and graphical information on the impact of current results on future study success: using historical data of first-year students of the year 2009-2010 and 2010-2011, flow diagrams categorise students based on the number of failed (0-7/20) and tolerable (8-9/20) courses. New students can pass up to twelve credits of tolerable courses, provided they already earned a total of 50% of their credits\(^1\). Based on these data, the expected amount of time to finish a program in a general flow chart. Grades of extra tests are only available through Excel files provided by instructors. Combining and interpreting these multiple

\(^1\)https://www.kuleuven.be/english/education/student/studyprogress/tolerances
channels of information for each specific student requires effort and time, and is error-prone. In addition, data is often incomplete: grades across multiple exams of the same course are for instance often not available. SAs typically rely on experience to verbally provide information regarding course difficulty or exam success rate.

The session follows a typical plot-twist-ending storyline [100]: understand the problem of the student through questions and data (plot), find the root of the problem through the available data and dialogue (twist), and inform the student about their short- and long-term options (ending). Test and exam moments during the year form the key moments in the student’s learning path around which the story revolves.

To support these needs and requirements for improving study advising sessions, the following “Learning dashboard for Insights and Support during Study Advice” (LISSA) design goals (DG) were defined as a result of our observations and brainstorm session:

1. **Support the dialogue between SA and student** by providing an overview of study progress.
2. **Personalisation**: LISSA should facilitate a personalised experience, immediately providing the SA with data relevant to the student, such as her grades and position among peers.
3. **Trigger insights**: LISSA should provide the SA and student with a fact-based starting point for discussion, argumentation, and insights.

### 4.4 Design

During a user-centred, rapid-prototyping design approach, five SAs were involved in every step of the design through formative evaluations such as brainstorm sessions and semi-structured interviews. Two visualisation experts and the head of the Tutorial Services of Engineering Science provided feedback on every iteration. The dashboard went through six iterations: four digital mock-ups created with Sketch ² and two functional dashboards developed using D3.js ³ and Meteor ⁴. Figure 4.2 shows the final functional prototype of LISSA.

²https://www.sketchapp.com/
³https://d3js.org/
⁴https://www.meteor.com/
Figure 4.2: Final June prototype. From left to right: positioning test results for July and September (ijkingstoets) (A), mid-term tests (tussentijdse toetsen), January and June exams. Above each period: histograms of peer performance for that period and an indicator of the student’s position in relation to grades of peers in the different test periods (B). Each course result (C) is accompanied with a histogram of peer performance for that specific course. The total percentage of credits achieved in January and June is visualised in (D). Failed courses can be planned for re-sits (E, F). Length of bachelor in years is predicted through historical data (G).

4.4.1 Year Overview

To support the focus on key moments during advising sessions, LISSA provides an overview of every key moment in chronological order up until the period in which the advising sessions are held: the grades of the positioning test, mid-term tests, January exams, and June exams (see Figure 4.2.A). A general trend of performance is visualised at the top: the student path consists of histograms showing the position of the student among their peers per key moment (see Figure 4.2.B).

Every course is represented by its name and grade (out of 20). A green, orange, and red colour coding represents successful exams, tolerable grades (students can request to pass a limited number of 8-9/20 grades) and failed courses. The course is accompanied by a histogram visualising the performance of peers and the position of the student among them (black highlight, see Figure 4.2.C). The
LEARNING ANALYTICS DASHBOARDS TO SUPPORT ADVISER-STUDENT DIALOGUE

Figure 4.3: Final September prototype. Planning is replaced with overview of re-sits results (3e examenperiod) and remaining failed courses (onsuccesvolle examens) overall study success (CSE) is displayed for official exam periods January and June (see Figure 4.2.D).

For advising sessions in September, this overview is extended with the results of re-sits (see Figure 4.3).

4.4.2 Planning

For June sessions, it is important to plan the re-sits during September. Too few exams result in a credit threshold issue, while too many will most likely result in failure. The check-boxes next to the failed exams re-sit planning (see Figure 4.2.E) let adviser and student select several courses. The re-sit exam success rate graph uses historical data to provide insights into the number of students succeeding the selected number of exams in the past. In Figure 4.2.F, the success rate is 54% for three re-sits, compared to only 6% if the student decides to take all six re-sits. To avoid fitting errors, only the number of selected exams is taken into account. The number of credits achieved is important as a minimum must be achieved to ensure continuation of the Bachelor program,
as restrictions apply. The selected courses are however used to visualise the expected cumulative credits the student could achieve when he passes all selected exams.

4.4.3 Prediction

The stacked prediction bar (see Figure 4.2.G) provides historical data of students with a similar profile (based on the number of exam passed or failed) to the student: it shows the distribution of the duration of the bachelor program (three-four-five years or drop-out/“NIET”) with similar September re-sits. In this particular example, 54% of students with similar results as the student in Figure 4.2 completed their bachelor program in three years, 20% completed the program in four years, 7% in five years and 17% of students with a similar profile never completed their bachelor. This information is similar to the flow diagrams SAs have access to.

4.4.4 Data Sources

To visualise the key moments, data regarding student grades is required. This includes all first-year students of the current year to populate the courses and course histograms, the student path, and course histograms. All grades regarding the January, June and September periods are available in the KU Leuven data warehouse. Positioning tests and mid-term exams are collected through Excel files from the teachers. This resulted in a total of 7028 grades of 434 Engineering Science students and 1159 grades of 76 Engineering Science: Architecture students.

The stacked prediction bar is based on the first-year student grades of academic year 2009-2010 and 2010-2011. This provides the data needed to predict the three, four, five, or more years length of a Bachelor degree. Historical data of 466 students for Engineering Science and 145 students for Engineer Science: Architecture were added to the database.

We created a data process pipeline (see Figure 4.4) using Python scripts to convert the different files and formats into a simple representation that is imported into a MongoDB. This MongoDB serves as the back-end database for our Meteor.js dashboard application.
4.5 Preliminary Feedback

Three presentations were held to gather preliminary feedback, with the SAs of Engineering Science (n=5) and Engineering Science: Architecture (n=1), Science (eight programs) (n=7), and Engineering Technology (two programs) (n=4). During these presentations, LISSA was explained and feedback was asked regarding the perceived usefulness for the SA and the student, and issues that might arise. The feedback in general was positive and resulted in the planning of LISSA deployments in all other aforementioned programs. This section elaborates the potential impact on argumentation, workload, and issues regarding transparency and validity.

4.5.1 Data-supported Evidence

Everyone agreed that LISSA would help support and add weight to their argumentation. SAs indicated that “with the facts visualised it is easier to convince the student” and that “certain myths exist with students, like how some people manage to successfully complete seven exams during re-sits”. These myths make it hard to convince students without the support of data, while the re-sit exam success rate graph can help change students’ mind about the number of re-sits to take. SAs agreed students should not access LISSA without a SA’s guidance. However, LISSA should remain secondary to the experience and expertise of the SA: students with over-confidence or fear of failure might have difficulty understanding the context and nuance an SA could provide.
4.5.2 Workload

Having all data available at once was considered a huge advantage by all SAs. This would eliminate manual preparation on paper as multiple sources must be combined. The visual overview would help focus on the problems at hand and help position students among peers, compared to the ad-hoc approach currently used.

4.5.3 Data Transparency

Course histograms received mixed feedback. The visualisation provides information regarding exam difficulty, which was previously not easily available to the SA. These histograms could help the SA position students and motivate them, e.g. a bad grade can be positively interpreted when most peers have lower grades. But some SAs see potential issues: too much insight into course difficulty might bias students into avoiding certain courses, or even demotivate them. Moreover, the histograms are considered to be “sensitive” information, e.g. students can use the histograms to protest against the difficulty of the course (“the course is just too hard, only few students passed”) or an observed difference with respect to previous years (“last year, the exam was a lot easier”). On the other hand, some SAs considered this “open approach” of providing this elaborate data on each course more honest.

4.5.4 Validity of Data

SAs expressed concerns regarding the correctness of the exam failure prediction. SAs suggested not to base this prediction on the number of exams selected (see Figure 4.2.F), but on the specific exams selected. This way course difficulty is considered. However, as mentioned in Section 4.4, too detailed profile matching would result in over-fitting of the data and create unreliable results.

4.6 Evaluation Study

The dashboard was deployed during the advising sessions after the June exams of the first-year Bachelor in Engineering Science, and the September exams of both the first-year Bachelor in Engineer Science and Engineering Science: Architecture at the KU Leuven. SAs used the dashboard for first-year students with a full-time program, as the current LISSA prototype is built with these
students into mind. This resulted in 97 LISSA-supported sessions. Each session lasted between 15-30 minutes. Figure 4.5 shows the typical setup during an advising session: LISSA is displayed on a monitor visible to both the student and SA. Table 4.1 gives an overview of all participants and the evaluations they participated in: the period in which the sessions were held, the age and gender of the SA, their advising experience and program. Forty-four sessions with LISSA were held in June, 53 in September. All 15 observed sessions were held in September. Four SAs were interviewed afterwards.

Out of these 97 sessions, 15 sessions were observed. As it was not allowed to record the conversations, timed notes\(^5\) were taken during all sessions regarding the actions of the SA and student.

Every student participant anonymously completed a seven-question questionnaire (see Figure 4.6) regarding their experience and perception of LISSA during the session.

\(^5\)https://atom.io/packages/time-notes
Table 4.1: Overview of Engineering Science (ES) and Engineering Science: Architecture (ES:A) advisers who participated in the deployment and evaluation of LISSA.

<table>
<thead>
<tr>
<th>Period</th>
<th>Age/Gender</th>
<th>Experience</th>
<th>Program</th>
<th># with LISSA</th>
<th># Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>37/F</td>
<td>6 years</td>
<td>ES</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>June</td>
<td>34/F</td>
<td>6 years</td>
<td>ES</td>
<td>44</td>
<td>0</td>
</tr>
<tr>
<td>Sept.</td>
<td>26/M</td>
<td>sporadically</td>
<td>ES</td>
<td>53</td>
<td>11</td>
</tr>
<tr>
<td>Sept.</td>
<td>24/M</td>
<td>none</td>
<td>ES</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Sept.</td>
<td>47/F</td>
<td>13 years</td>
<td>ES:A</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

4.6.1 Supporting a personal dialogue (DG1)

Through semi-structured interviews with the SA, we learnt about the effects of LISSA on the support of dialogue during an advising session. Through observation, we also kept track of the dialogue instigated by the dashboard. During the 15 observed sessions, LISSA was the catalyst for 43% of the time on average.

While further investigation is necessary, we also observed that the way it drives the conversation depends on the experience of the SA. Experienced SAs, including the SA with supportive experience, used LISSA as backup, glancing, and interacting with it when needing specific information. The SA with no experience used it as a guide through the entire conversation, for both himself and the student.

Motivation

SAs reported LISSA helped motivate students: “I can actually show a change in progression”. Showing students their positive trend across the year (e.g. fewer failed exams towards the end of the year) impacted motivation and reassured them that their (change in) study methods worked: “It’s a visual confirmation of their efforts”. But it also helped with pushing students to pursue another career or spread their program across more years: “It clearly shows when students made no progression at all”.

Fact-based Evidence

LISSA moves advising sessions’ content from personal opinions and tacit experience towards a discussion based around factual evidence. As indicated
by an SA, “certain myths regarding exam feasibility live among the students”. To break through these myths, visualising the percentage of students that have succeeded a specific number of exams provided SAs with success rate facts and support students with the decision they wish to make: “When I show them the number of students that succeed seven or eight exams, they are surprised, but now they believe me. Before, I used my gut feeling, now I feel more certain of what I say as well”. The student questionnaires revealed that students agreed that LISSA is helpful for exam planning (see Figure 4.6).

**Narrative Thread**

LISSA also helped focus more on the conversation at hand: “It’s like a main thread guiding the conversation”, “I can talk about what to do with the results, instead of each time looking for the data, and puzzling it together” and “It saves me a lot of preparation time”. The course colour encoding provides an immediate overview of the student’s situation: “I can load up the student, make some quick conclusions based on the colours and start the conversation quicker”. The presence of LISSA provides a point of focus during the conversation, which can put the student more at ease: “Students don’t know where to look during the conversation, and avoid eye contact. The dashboard provides them a point of focus”.

### 4.6.2 Personalisation (DG2)

The key moments and student path help students understand the effect of their behaviour (“I have changed my study method in June and now see it paid off”). Peer data can provide further context. It helps position the student among peers across the student path and per course through course histograms. As SAs indicated “the course histograms show the difficulty of a course as facts”. Students often perceive their failures incorrectly: “The meaning of a 10/20 can differ. A 10/20 is a good score for Calculus, you are among the best of your class.”

Through the re-sit exam success rate graph, SAs can help students plan their workload based on their potential success rate. The stacked prediction bar facilitates even longer term planning. In these cases, SA nuance plays an important role: “Some students might be overconfident, thinking they will be the exception that belongs to the 5% who do succeed with their profile”.

To understand the student’s perception, we set up an anonymous questionnaire for students to complete after participating in a LISSA-supported session.
Figure 4.6: Overview of the results of questions regarding student perception of LISSA (top: June, bottom: September. 1 = strongly disagree, 5 = strongly agree). On the box plot the dark line indicates the median, “+” the mean, and dots the outliers.

Figure 4.6 shows the results of 44 completed questionnaires during the advising sessions in June and the 53 completed questionnaires during the advising sessions in September. The results were positive: students considered the dashboard an added value which provided insights into their situation. They were confident the data was correct, that it added value to the conversation and helped their planning. From both the questionnaires and student/parent reactions during the advising sessions, we have learnt that there is an interest for such dashboard for personal use without SAs.

4.6.3 Insights (DG3)

LISSA triggers statements and questions, by either the SA or student (or parent). These can in turn result in further argumentation, reasoning, or confirmation. The level of interpretation defines the level of insights: it can be stated that a
Figure 4.7: Levels of insight. L1: simple statements/questions triggered by LISSA. L2: the SA’s interpretation of the data. L3: LISSA triggers discussions that lead to further insights.

course is hard, explaining the bad grade. Or a student can provide a background story providing deeper insight into a larger problem.

From semi-structured interviews, we learnt that SAs focus on getting insights into the problems of the students to help them. This includes understanding their current situation (e.g. personal/family issues, fear of failure), find changes in behaviour (e.g. study methods), understand their capacities, help plan their future (either within the program, or finding a suitable new program). This section reports on the observation made regarding insights during 15 advising sessions.

We use the three levels of insight defined by Claes & Vande Moere [32]: factual insights (L1), interpretative insights (L2) relying on knowledge and experiences, and reflective insights (L3) based on subjective, emotional and personal connotations (see Figure 1.2).

**L1: Factual**

LISSA provides factual data such as the list of grades per *key moment* and predictions regarding exam success and bachelor duration. These data can be used to support statements and start conversation regarding a specific issue: “You did not succeed a single exam in September” (*key moments*), “94% of students with a similar profile did not achieve a Bachelor in the past.” (*stacked prediction bar*). Course colour coding attracted attention to specific grades or lack thereof: “What happened to Calculus”, “How did you experience that exam”, “This was a bad grade.”, “You didn’t participate in the second positioning test.”

**L2: Interpretative**

Factual observations can lead to questions for further insights, or can be interpreted: “You took eight exams and passed almost all of them. You
can handle quite some workload.” A bad grade can be nuanced through the peer information provided by the course histograms: “Almost everyone failed Mechanics”. While this is factual data regarding peer performance, it is sometimes interpreted as the difficulty of a course. SAs interpret mediocre grades as warnings: “These 10/20 scores could have been 9/20, it might be better to spread the courses across four years”. These warnings can be signs of workload problems, which the SA can help with through change of course planning.

Combing different key moments, the difference in colour coding between them, and interpreting the student path” can result in motivational insights: “I see I have improved over the semesters.” (student) or “I see a huge improvement the second semester. What happened?”

The stacked prediction bar facilitates future planning (“It is more realistic to plan for a four-year Bachelor according to the dashboard”) but can benefit from further interpretation. The bar can indicate that 64% of similar students failed
the bachelor. However, the final key moment overview of courses could provide the SA with further insights regarding “what-if” situations: “If just one of these 9 out of 20 grades was a failed grade, your profile would instead match a prediction where 94% of students failed their bachelor.”

L3: Reflective

When the SA lacks the information to interpret the results, a question regarding the observation of e.g. a bad grade triggers the student into further reflection: “I didn’t prepare well”, “I made some dumb mistakes during the exam”, “I found the course very difficult”, “I was behind on the course material”. This helped the SA understand whether there was a problem regarding workload, procrastination, or (lack of) study methods.

Noticing progression across key moments through a change of colour (red to green courses), or the student path (an upwards line, see Figure 4.3) helped pinpoint the cause: “I went from studying at home to studying at the library”, “I worked harder in June”, helping students realise their change in methods could be helping their progression.

Figure 4.8 shows the distribution and number of insights for each observed session. A total number of 59 factual (fx), 42 interpretative (ix) and 56 reflective (rx) insights were recorded. Nearly half of these insights occurred during the sessions with the SA with no experience (k=inexperienced SA, last 4 rows): 24 factual, 20 interpretative and 23 reflective insights were observed over just four sessions. With the experienced SA (j1-j11), the same number of insights was recorded, but they were recorded over a larger set of sessions. During these sessions, we noticed LISSA may be particularly helpful for inexperienced SAs. It can be observed that both interpretative and reflective insights were recorded in every session, going beyond observation of mere facts.

Figure 4.9 provides an example of how a factual observation results in a reflection. However, in Figure 8 we notice a pattern that appears more often: a factual observation with a reflection as result is usually triggered by a remark of the SA and a reasoning by the student. Interpretations are often the result of a factual observation, but without the SA verbally mentioning this fact (and thus it is not observed).
4.7 Discussion and Lessons Learnt

4.7.1 The role of the Learning Analytics data

LA dashboards are often developed for specific institutions with certain data requirements. The Learning Analytics data necessary to deploy LISSA is very basic: grades of students across key moments and data regarding student success (derived from historical grade data). This data is usually available in most higher education institutions, but limited to staff. Yet, we have shown that this data placed in a student advising context, can help support students, provide insights into their progress and help plan their future.

LISSA is based on factual data. Exam success rate and bachelor duration show what has happened historically as facts and provide no calculated estimations. SAs know to interpret this data differently than e.g. course histograms which show data regarding the specific student. This reliable way of visualizing the data provides reassurance among both SAs and students about the advice they are giving and receiving.

Data regarding high school grades, motivation and concentration is also available at our institute. This could enrich LISSA, providing an even better advising session experience. However, some of this information is subjective. This subjectivity must be encoded in the dashboard to assure a correct interpretation. Personal background data regarding socio-economic status, parents’ education, gender, and high school achievement can provide further insights and help the SA understand the student’s situation better. However, this unalterable data does not provide the students with actionable insights. It is therefore important to investigate how to integrate this data in an ethical manner.

Figure 4.9: An example of the steps LISSA triggers from insight level 1 to 3.
4.7.2 The role of the Visualisation

LISSA is a supportive tool, a catalyst that can start and drive a conversation, provide facts to support argumentation and help gain further insights. Resulting decisions have potentially life-changing consequences and thus the design should visualise the data in an objective way. A minimal design without animations allows LISSA to remain on the background. By implementing only little interaction (choosing the number of planned exams), the focus can remain on the contextualisation. This static approach also means that no one is “in charge”, allowing for both the student and the SA to drive the conversation, and make sense of the data in a collaborative way.

4.7.3 The role of the Student Adviser

LISSA facilitates insights at multiple levels, but these insights benefit from guidance by the SA. Even though the data is objective, there is still a need for critical and reflective interpretation by domain experts (SAs). Overconfident students might interpret an overall negative result as a surmountable problem, whereas the SA could advice and plan a more achievable program, preventing the student from wasting years on incorrect choices. LISSA can portray a student in a negative way, while a discussion with the student might reveal problems that are easily resolved, e.g. a change in study method, a new program, or a change in attitude. Without the SA’s guidance, such students might choose not to continue their Bachelor program.

LISSA still leaves room for personal opinions and tacit experience, as they still play an important role during advising sessions by allowing SAs to e.g. emphasise certain results to push them on the correct path. Many external factors, such as information gathered through discussion and previous SA experiences with students, impact the decision to deviate from the factual data or interpret it differently. While LISSA would benefit from encoding these data into the visualisation, collecting, and quantifying them is no simple task.

4.7.4 The role of Narrative

By leveraging a story driven approach [12], LISSA serves as a guide through the conversation. Segel & Heer [129] define different design spaces in which the balance between an author-driven and reader-driven visualisation plays an important role. These roles are less defined with LISSA. The SA is both the reader and author [100]: she observes and interprets the data (reader) which in turn is used as conversation starter through remarks and questions (author).
The student receives this information and attempts to reflect on the statements and questions (reader). In turn the student can elaborate and explain the data further from his point of view (author). LISSA facilitates this freedom of conversation flow and authorship thanks to its supportive, passive role.

### 4.7.5 The role of Visual Encoding

Colour encoding represents the state of a course. A red course indicates the exam was failed and must be retaken. However, variations in failed grades are not represented by the colour encoding: 0/20 is coloured identical to 7/20, even though there is a big gap in performance difference.

While this facilitates at-a-glance interpretation, it lacks nuance. SAs can put this data into context, but this harsh encoding could unnecessarily demotivate the student and create a negative setting for the remainder of the advising session. Gradient colours could help integrate this nuance into the visualisation sacrificing the immediate and easy to grasp overview. However, some SAs argue that a failed grade is bad and should be visualised as such: “It’s more important to see the number of failed and succeeded exams than their exact grades”. An adaptive solution where an overall negative result becomes more nuanced through extra color variations could be considered to tackle this problem.

### 4.7.6 Transparency

During the semi-structured interviews and workshops, ethical issues arose regarding confronting the students with the data.

Some SAs did not show LISSA to students with a very high number of failed courses: “It’s not a good idea to start an already negative conversation off with such a negative visual message”. While some students might benefit from an “eye-opener”, SAs prefer to use LISSA as a motivational tool. When no positive interpretation is possible, ignoring LISSA might be the better option. The role of the SA plays yet again an important role, deciding whether LISSA is appropriate for this situation. One possible solution could be to include the option to hide parts of LISSA, revealing each section to ease the student into conversation, or to keep some information hidden in case it is irrelevant or too confronting (e.g. the student gets too emotional). The advisers at KU Leuven do not focus on retention, but instead on finding a good match for further career choices, thus negative information can still be helpful for planning a change to other programs.
An important role of LISSA is the ability to position a student among peers. In general, the use of histograms was considered very useful and positioning had positive effects such as motivating the student when a bad grade is still good among peers, or a course failure rate is very high. However, histograms caused concerns with some SAs. One SA reported: “I never compare a student with peers. Sometimes a student gave his all, and comparison will not change that”. Some SAs worried about de-motivation: a student on the low end of the histogram might see succeeding the course as an unachievable goal.

The “sensitive nature” of the data histograms is a concern as it reveals information about course difficulty variation. A course might have a high success rate one year, and a low success rate the next year. The reason behind this fluctuation might be hard to pin down (e.g. an easier exam, a different approach in teaching, different student profiles), but could result in students and parents protesting. SAs believe that this should not be an issue if LISSA is only accessible to students during the SA sessions.

There is however a demand by students to gain access to LISSA outside the SA sessions. But SAs fear that the data visualised can be greatly misinterpreted without their guidance: students with fear of failure or over-confident students might interpret the data incorrectly. Parents can play a negative role into either pushing too hard, or interpreting mediocre results as insurmountable. The lack of knowledge about higher education with parents without a degree might stop a student pursuing an achievable degree. These problems might result in wrong decisions regarding exam and study career planning. SAs do see potential in providing reduced information, but what this reduction entails must be further discussed and evaluated.

4.8 Conclusion

This chapter presented LISSA, a learning analytics dashboard that was designed, developed, and evaluated in collaboration with SAs to facilitate communication between SAs and students by visualising commonly available grade data. We presented the design process and evaluation results regarding usability, impact, and insights.

LISSA supports the current SA-student dialogue, helps SAs motivate students, and triggers conversation. Through simple grade information combined with peer positioning and historical data, it provides SAs with the tools to add depth and nuance to the session. It also provides insights at a factual, interpretative, and reflective level through the visualised data and by allowing both SA and student to take the control of the authorship.
LISSA resulted in a tool that users enjoy using, “looks great”, provides them with trustworthy data and an added value, and will continue to be part of the advising sessions. The central ICTS (Information and Communication: Technology and Systems) and data management services of KU Leuven expressed their interest in developing a dashboard, integrated with the KU Leuven data warehouse and with a focus on scalability, based on the results of this work.

Although interesting results have been obtained, there are some limitations that should be articulated. The study included 19 SAs, but was limited to five SAs actively using LISSA during sessions with students. Further investigation is required to understand the value of LISSA during advising sessions at other programs and institutions, with different student types, and different data set sizes, including data from programs with lower and higher student numbers. Long-term deployments are also needed to assess the impact on student learning. The context of our future work will be broadened through deployments across a range of degrees, such as Science and Social Science degrees, at KU Leuven and Leiden University.

While the proposed dashboard focuses on data on academic performance and progress, integration of additional information on a student’s background, learning and studying skills (e.g. measured in the LASSI test [154]), and academic engagement can provide even further insights. This data can greatly improve the SAs’ image of the student, facilitating an even more focused and informed assistance.
Chapter 5

Conclusion

In this dissertation, we have investigated LD design and deployment in blended learning, group work, and advising scenarios through an extensive iterative process in close collaboration with experts, teachers, and students. Chapter 2 investigated the design choices to help and motivate students to explore their learning process and that of peers. Chapter 3 focused on live classroom interaction and provided insights into the design and deployment of ambient LDs to support balance of activity. Chapter 4 investigated the design of LDs to support the dialogue between study adviser and student. This chapter concludes the thesis with achievements and contributions to the research field, and reflects on future research opportunities and limitations.

5.1 Summary & Contributions

LDs visualise learning activities to play a supportive role for teachers [87, 113], provide students with ways of self- and peer-monitoring [125], which in turn can promote reflection, insights, and impact behaviour [147]. But first we must understand what learner traces provide relevant information for teachers and students, how the traces should be visualised in a useful way to provide insights, and how we can promote active usage by all parties. In this work, we explored the design choices to answer these questions. We end up with guidelines that help increase exposure to LA data, raise awareness of relevant activities, and motivate students to explore their learner paths and that of peers.
5.1.1 Chapter 2: Contributions and Real-world Impact

Summarising the contributions of Chapter 2:

- Over the course of two academic years (2013-2014 and 2014-2015), a total of 60 students and 20 people with teaching responsibilities/pedagogical research experience participated in an iterative design-based research process (dashboard usage and observation, discussions, interviews, and questionnaires) resulting in five dashboards.

- This iterative process resulted in seven lessons (see Section 2.5) that can assist future dashboard design and research in blended learning environments. We learnt that abstracting LA data helps deal with the abundance of data, but important details might get lost. It is important to provide both overview and detail [132]: through augmentation of the abstracted data by e.g. quality indicators through feedback information, relevant data can be found quicker. Feedback is also relevant to help learners learn from others’ mistakes, while it makes teachers aware of colleagues’ activities. The bread crumbs generated through learning activities can help understand the path a student took, for teachers as a basis for evaluation, or for the student and peers to learn from past and present experiences. By integrating LDs into the work-flow, we can improve acceptance of the tools. And finally, collaborative LD created interesting discourse previously not observed with single user LDs.

Summarising the real-world impact of Chapter 2:

- During the weSPOT project, the inquiry-based learning dashboard LARAe has been used in schools (test beds) across Europe (Bulgaria, Slovenia, Netherlands, Austria, United Kingdom), by a total of 461 students. After the project, it is still part of the weSPOT inquiry suite, which has been used by 95 students in Graz, Austria during the year 2016-2017.

- Our guidelines have been published at the European Conference on Technology-Enhanced Learning [23], a leading conference in the domain of learning technologies (Acceptance rate: 25%).

- At the time of writing this work have been reported on in fourteen publications in which the author of this thesis participated. Seven papers elaborate on the designs, deployments, and evaluations of the five dashboards of Chapter 2 and allowed us to present and receive feedback from the Learning Analytics and Technology-Enhanced Learning community on our work [120, 27, 28, 29, 20, 123, 21]. Built on top of
this foundation, we define the lessons learnt in [23]. In [22], we design and evaluate glyphs to support our collaborative exploration through LA visualisation. We participated in Ruiz et al. [117]’s exploration of emotions in the classroom by designing and evaluating an emotion-based LD. In [89, 84], our work around collaborative LD helped define a framework for characterising the design space of interactive surfaces and natural user interfaces in LA. de Freitas et al [42] summarises the findings around gamification through LDs.

● Based on this work, we were invited to organise the Visual Learning Analytics workshop at the Learning Analytics Summer Institute 2014, Harvard, Cambridge, MA. In this workshop, we introduced good visualisation practises for LDs.

While our findings result from evaluations in blended learning environments, we believe our guidelines can be useful in a broader context. Chapter 3 and Chapter 4 built upon the lessons of Chapter 2, and more specifically expanded on the idea of collaborative LA through group work and advising sessions.

5.1.2 Chapter 3: Contributions and Real-world Impact

To improve balance in feedback between student groups in the classroom, Chapter 3 focused on live interaction between student groups during presentation sessions. To design a live LD, we took an ambient display approach and designed a visualisation accordingly.

Summarising the contributions of Chapter 3:

● Twelve students participated in the design and evaluation of the dashboard during a course of 2014-2015. Nineteen students experienced the resulting design and partook in an evaluation during a course of the academic year 2015-2016. This participatory, iterative design resulted in a dashboard that raised awareness of their level of classroom discussion participation and that of peers, and improved the time it took to activate students.

● This process resulted in the description of the design process and design of an ambient LD. We learnt that it is important to focus on visualising the essential message, in our case, balance. By creating a less precise representation, under-participants experienced the dashboard more positively, while still toning down over-participation. This could be further improved by adding qualitative components, augmenting the abstract representation by e.g. feedback indicators.
Summarising the real-world impact of Chapter 3:

- This work is published in the “Special Issue on Awareness and Reflection in Technology-Enhanced Learning” of the International Journal of Technology-Enhanced Learning (eight out of 21 submissions accepted) [25].

- The work is the basis for a new research collaboration on ambient displays and their use to facilitate balanced group work with the University of Sydney.

### 5.1.3 Chapter 4: Contributions and Real-world Impact

To support the dialogue between study advisers and students, we have designed a LD based on basic grade data available at the university. Chapter 4 describes this design and the evaluation of its role to support the on-on-one conversations during an advising session.

Summarising the contributions of Chapter 4:

- Through collaboration with two visualisation experts and 19 study advisers over the course of a year, we designed a dashboard to support the dialogue between study adviser and student.

- The process resulted in a description of the design process and six lessons learnt on which future design and research regarding supportive dashboards for student advice can further build upon. Keeping the design simple and presenting the data as-is, the LD becomes trustworthy and leaves the interpretation to the user. The visualised data is sufficient to play a supportive role, facilitating both student and adviser to become the “author” of the story, interpreting the data as the conversation goes along. We have learnt that the role of the study adviser remains important to counter misinterpretation and to keep or push the student to a certain path. Their presence is also necessary from an ethical perspective: certain information is sensitive and should be kept private; the adviser might decide not to show the dashboard when the data paints a too negative picture.

Summarising the real world-impact of Chapter 4:

- At the time of writing, LISSA has been deployed in twelve programs across the Engineering Science, Science, and Engineering Technology departments across four campuses of KU Leuven. Fifteen study advisers have used the dashboard with students during a total of 165 sessions.
Thanks to our successful evaluations and deployments, the central ICTS (Information and Communication: Technology and Systems) and data management services of KU Leuven expressed their interest in developing a dashboard, integrated with the KU Leuven data warehouse, based on the SA dashboard design.

The chapter has been accepted for publication [30] in IEEE Transactions on Learning Technologies, a top journal in the domain (IF most recent: 1.129, 5-year IF: 1.608, Acceptance rate: 11%).

5.2 Reflections & Limitations

This section reflects on the work in this thesis and discusses its limitations.

5.2.1 Context

Our work is limited to three learning environments. Our design guidelines in Chapter 2 originated from the iterative design and deployment of multiple dashboards in Blog-supported and Inquiry-based learning scenarios. Still, some guidelines proved their usefulness in the design of the other contexts in Chapter 3 and Chapter 4.

The size of the “classrooms” is limited to 20 to 40 students on average. While this results in a large amount of data (e.g. 100+ posts and 1000+ comments during one semester), it does not compare to data generated by e.g. MOOCs (e.g. 6.9 million video watching sessions [64]). We still believe many of our guidelines remain useful: in large data sets, abstraction becomes even more important as access to all individual artefacts and learner paths becomes unfeasible. Data mining techniques can help weed out irrelevant data. By combining data mining to filter relevant data with our proposed visual approaches, more insights can be gained from big LA data sets. More data means more examples of “good” learner paths resulting in “good” outcomes. Mining these paths and visualising specific subsets for the benefits of both teacher and student can improve the learning process of both [149].

The work in Chapter 4 is scalable to any higher education institution due to its use of generally available data (grades). This means that the concept, but also our own Student Adviser Dashboard prototype, can be deployed for most programs at any higher institution.
5.2.2 Student Participants

The participants of these studies were students of the Bachelor and Master in Engineering Science program at KU Leuven, Belgium. Chapter 2 and Chapter 3’s participants are 22-24 year old, with a certain maturity. One could argue that some of our approaches could affect younger students differently: older, more experienced students might be more assertive when confronted with LA data. However, from the limited data gathered from the pilots in European schools, we learnt that students, ranging from 12 to 18 year old, understood, accepted, and actively used our dashboards during Inquiry-based courses.

Engineering Science students might be more accepting of data-driven approaches. In Chapter 4 the target audience is on average 17 to 19 year old. They are in the middle or at the end of their first year in the Bachelor of Engineering Science program. These students have not yet been moulded to think like an Engineer (and with overall drop-out rate of around 40% [77], they might never be), but were very enthusiastic of this visual approach, resulting in the student union requesting a faculty-wide deployment. To understand the effect on a broader type of students, we have planned further research at both KU Leuven and Leiden University, with programs such as Archaeology and History partaking in the studies.

5.2.3 Methodology

The work has followed a design-based research approach, involving participants through the entire process. These participants are students, course instructors, study advisers, experts in the field of data visualisation, and pedagogical researchers from the weSPOT project. This interdisciplinary approach helped validate the findings of this work.

Course instructors played an important role in the early design process, e.g. in Chapter 2 badges were designed based on the course activities the instructors wished to promote, in Chapter 3 a dashboard was designed in order to meet the need of better feedback balance. We have explored multiple possibilities and collected the most important lessons in 2. While no generic “one size fits all” solution results from this approach, tailor-made dashboards that tackle specific course needs at a fine granular level have shown great potential. We therefore urge other LA researchers to further explore specific learning situations in which LA can help.

Involving students in the process also means students are aware of what is being measured. This is, however, the purpose of LA dashboards: we make
students aware of the important factors in a course, measure those, and feed this information back to them. One could argue that this knowledge of being measured is part of the change of behaviour. Still, to maintain this change, we believe a constant awareness of these data is necessary. Even if the dashboard becomes obsolete with time, and positive behaviour remains intact, the dashboard has succeeded in its goal.

5.2.4 Ethics

From Chapter 4, we have learnt that the involvement of an expert (here: study adviser) remains important in the interpretation of the data. Visualisations can be powerful in persuading a students to take specific actions. While student-facing dashboards without external input are useful (see Chapter 2), the designer has a big responsibility, as these dashboards can have life-impacting effects. Involving experts is crucial, not only to be pedagogically correct, but also ethically. While the lessons of this dissertation can help researchers and designers create better dashboards, we urge everyone to take a similar interdisciplinary, participatory approach to ensure dashboards that will be deployed at large scale have gone through extensive ethical considerations.

5.2.5 Impact

Currently, our evaluations focus on perception, of both the observer during tests and the teachers and students. While we cannot conclude these LDs have any educational impact, we have helped strengthen the foundation on which LD design can further build. Introducing LDs without proof of impact into educational systems is difficult. But delivering proof requires long term exposure to and usage of the LDs. To partially solve this catch-22, we provide proof at small scale, showing specific impacts on user workflow, awareness, and acceptance. The resulting guidelines help lay the groundwork.

5.2.6 Capturing & Scalability

In Chapter 2 we relied on the work of Santos et al. [119], which provided us the traces of the Blended Learning environments, both social media activities as well as the activities in the weSPOT inquiry environment. Chapter 3 relies on manual human tracking of activities in the classroom to provide the dashboard with live data. Chapter 4’s dashboard relies on data exports from the KU Leuven data warehouse, which is imported through Python scripts from multiple spreadsheet
files with minor, but required, human intervention. This process chain must be optimised and automated if we wish to make our approach scalable for more faculties.

The focus of this thesis lies in the design of the visualisations and not the back-end that supports it, nor the capturing of the data. By focusing on the user through an iterative, participatory design, we developed prototypes that tested our concepts in realistic environments, providing proof regarding usability, usefulness and possible impact. Technologies such as Processing.js, Google App Engine, Node.js, Meteor.js, D3.js, helped us to rapidly build working prototypes.

In the case of Chapter 4’s Study Adviser Dashboard, a solid application was created that users enjoy using, provides them with trustworthy data, “looks great”, and provides an added value. This has helped us convince more users to use the dashboard during their actual work, and has paved the way for a new KU Leuven dashboard inspired by ours, integrated into the data warehouse with an eye on scalability. The strength of this work therefore lies in its lessons and ideas which commercial dashboard developers can rely on.

5.2.7 Gamification

To motivate students towards specific goals, gamification can help. Chapter 2 briefly mentions badges, which define specific course goals students should work towards, or certain warning signs students should avoid. Chapter 3 gamifies the classroom through a live visualisation which works as a catalyst that activates students. The thesis only scratches the surface, but shows that gamification in dashboards can support further reflection and exploration on the LA data. Gamification can help structure the abstracted layer, as an anchor point towards more details.

5.3 Outlook & Final Reflections

In this thesis, we have explored different designs and settings for learning analytics dashboards. This resulted in a list of design choices, or lessons learnt, that can help increase the acceptance of the dashboards by students and teachers, raise awareness of important activities, and motivate students to dig deeper into the path that defines their learning activities. We have shown the potential of collaboration around LA through two case studies: live dashboards to orchestrate feedback activities in the classroom, and support of the dialogue during advising sessions with students. This research is a starting point to pave
part of the way for further investigation on how these dashboards can impact students, teachers, and study advisers in the long run to improve the learning process, results, and shorten the study career. We have only touched the surface of this topic, but hope to have inspired LA and LD research to explore further settings that can benefit from our setup and initial results.

This thesis did not focus on capturing new learner tracers: dashboards were built upon the data available (except for Chapter 3). However, more data will result in more design challenges and opportunities. As sensors improve and are becoming cheaper, biometric data (e.g. brainwave activity [4], stress levels [150]) and environmental factors (e.g. room temperature, noise [38]) will provide a more detailed and realistic picture of the learning setting. An interesting further line of research would be to extend our designs to enable insight based on such new data sources.

We are also proud that our work has advanced beyond “the lab” and user evaluations, and has been deployed and used in schools across Europe. LARAn has been used during pilots in Bulgaria, Slovenia, Netherlands, Austria, and United Kingdom, by a total of 461 students, with more deployments planned. LISSA has been used in 165 sessions across 14 programs to assist advisers and students in gaining insight into their progress and planning, resulting in interest by the IT services of KU Leuven to take up the dashboard. We hope our results and designs inspire future development of many other dashboards.

The findings in this work should not be limited to the field of Learning Analytics alone. The design guidelines of Chapter 2 can be applied to any scenario where awareness and reflection regarding large sets of data is important. We believe the general field of Quantified Self could benefit from our results, as well as competitive sports and eSports\(^1\), raising awareness of team and opponent activities through dashboards to help players gain better insight into the game. Chapter 4 focuses on advising sessions for students, but any experience where experts need to pass information to laymen, and support them in understanding and finding new insights, can build upon our findings. Ethical implications and life affecting results through misinterpretation go beyond education: medical advice is for instance better not left to interpretation [41, 53], while assumptions about employee data can result in incorrect resignations or promotions. We therefore hope to see other fields explore the visualisation of sensitive data for dialogue support through dashboards, and hope to be part of expanding it towards other fields ourselves.

\(^1\)https://en.wikipedia.org/wiki/ESports
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List of Publications

This chapter lists all publications by the main author of this thesis (at the time of publication of the thesis).

Articles in internationally reviewed academic journals


Article in academic book, internationally recognised scientific publisher


International Conference Papers


