The Learning Tracker

A Learner Dashboard that Encourages Self-regulation in MOOC Learners

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Challenge the future

The Learning Tracker

A Learner Dashboard that Encourages Self-Regulation in MOOC Learners

by

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The best teachers are those who show you where to look, but don’t tell you what to see.
Alexandra K. Trenfor

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Abstract

Massive Open Online Courses (MOOCs) have the potential to make quality education affordable and available to the masses and reduce the gap between the most privileged and the most disadvantaged learners worldwide. However, this potential is overshadowed by low completion rates, often below 15%. Due to the high level of autonomy that is required when learning with a MOOC, literature identifies limited self-regulated learning skills as one of the causes that lead to early dropouts in MOOCs. Moreover, existing tools designed to aid learners in the online learning environment fail to provide the support needed for the development of such skills.

The aim of the present work is to bridge this gap by investigating how self-regulated learning skills can be enhanced by encouraging metacognition and reflection in MOOC learners by means of social comparison. To this end, following an iterative process, we have developed the `Learning Tracker`, an interactive widget which allows learners to visualise their learning behaviour and compare it to that of previous graduates of the same MOOC. Each iteration was extensively evaluated in live TU Delft MOOCs running on the edX platform while engaging over 20.000 MOOC learners over the whole duration of each MOOC.

Our results show that learners that have access to the `Learning Tracker` are more likely to graduate the MOOC. Moreover, we have observed that the widget has a positive impact on learners' engagement and reduces procrastination. However, we have little evidence that learners improved their self-regulated learning skills by the end of the MOOCs. Based on our results, we argue that the mere fact of receiving feedback on a limited number of learning habits could trigger self-reflection in learners and lead to improved learner performance.

This work underlines the powerful effect feedback and self-reflection on one's behaviour has on learning performance. We recommend that future research should investigate learners' feedback literacy and devise effective ways of presenting learners with personalised feedback based on their goals, learning skill level and cultural background.

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Chapter 1

Introduction

Massive Open Online Courses (MOOCs) have sparked the interest of higher education institutions, as well as that of the industry and the media which called 2012 the "year of the MOOCs" [126]. Labelled *the future of education* [15], MOOCs are online courses that can be attended by a large number of learners as they are readily available to anyone with Internet access. The high interest in MOOCs and their recent exponential growth is fuelled by many claims that MOOCs will spark a revolution in education by solving many educational problems [18]. Using technology to provide affordable learning opportunities to large number of learners, MOOCs are expected to reduce the educational gap between the most privileged and the most disadvantaged learners [77, 64, 165]. At the same time, MOOCs are seen as the "silver bullet" for solving the attainment challenges in US higher education [136]. These high expectations together with the low barrier for registration are reflected in the massive MOOC enrolment figures. By 2015, over 35 million learners worldwide registered for at least one MOOC [2, 120]. Currently, more than 500 universities and institutions are offering over 4,200 MOOCs and these numbers are expected to rise even more [2].

Despite this broad reach, one of the main challenges MOOCs face is the massive dropout rates with a steep participation drop starting in the first week [166]. Several studies report completion rates[1] below 15% [73], often as low as 7% [129]. Clow [38] explained the very steep decrease of engagement over the duration of any MOOC by comparing it to the marketing purchasing model and called it the *funnel of participation*. Since there are no knowledge requirements for entrance, except some considerations on what prior knowledge is recommended, the bar for enrolling in a MOOC is very low, resulting in massive enrolments. After the initial registration, only a few of the students engage in any activity in the course and even less produce meaningful progress. Finally, only a small fraction of those that showed activity finish the course.

Several works investigated reasons that drive learners to disengage and eventually dropout of MOOCs. On the one hand, numerous lines of research investigated this issue from the learners' perspective by collecting and analysing opinions from MOOC learners. The most frequent reasons for dropout reported by learners include: lack of time or poor time management [69, 84, 119, 77, 12], lack of real intention to complete the course [92, 160, 108], low motivation in the absence of university grades or credit [93, 133], level of difficulty of the course and lack of support from course staff [123, 133], and low self-efficacy [65].

On the other hand, a few researchers rely on learning sciences to define characteristics that make students "good learners" and keep them engaged and active. Thus, they recognize low learning skills and poor study habits as a cause behind the high dropout rates in MOOCs [144, 10, 65]. Additionally, engagement in a MOOC is influenced by prior experience in learning with a MOOC and the learner's motivation [111]. Interviews with learners do not reveal these issues because it is even more difficult for learners without such skills to consciously assess how efficient their learning is.

In order to be able to recognize the effectiveness of their learning skills, learners need to possess a certain level of metacognitive awareness [85]. Metacognition is defined as "the knowledge about and regulation of one's cognitive activities" [56]. Moreover, in order to improve their learning skills and reach their goals, learners need to be able to control, manage and plan their learning actions [171]. This ability is known as self-regulated learning (SRL) [170]. The novelty of the MOOC

[1] *Completion rate* is defined as the percentage of learners that earned a certificate of completion or obtained a passing grade.

environment poses further challenges for novice learners. Learning with a MOOC demands high levels of autonomy [123] in terms of keeping their motivation high, defining learning paths, and engaging with the other MOOC participants [166]. In the classroom, students do not need to bother with managing their learning because teachers monitor their learning, set deadlines and offer incentives that foster good study habits [93]. Thus, the emphasis on self-guided learning promoted by MOOCs makes them ill-suited for learners who are less efficient at defining a learning path by themselves [109, 105]. It has been empirically shown that learners with higher education degrees have higher chances of completion because they are more skilled in regulating their learning behaviour making it easier for these learners to take advantage of the online instruction provided in MOOCs [63]. Gutiérrez-Rojas et al. [64] argue that this discrepancy between the levels of learning skills deepens the educational gap between those more and less educated, diminishing the potential of MOOCs.

Threfore, several researchers recommend that MOOC platforms should provide tools helping learners to optimize their learning and develop metacognitive skills indispensable for self-regulating learning processes [84, 119]. Thus, MOOC developers should focus on creating tools that better support learners to learn, rather than be only repositories of knowledge. However, existing MOOC platforms are not designed to support learners in developing their learning skills. As Rai et al. [133] emphasized, "modern innovative education tools help students to understand what to learn, but fail to produce enough interest on how to learn, and also fail to produce critical thinking among students."

Through the work presented in this thesis, we aim to bridge this existing gap by relying on previous research in the fields of educational sciences, learning analytics and learner dashboards.

Firstly, based on Zimmerman's studies related to self-regulated learning [169], we propose that one way to develop critical thinking and self-regulation skills in MOOC learners and thus, improving their chances of success, is to encourage learners to *reflect* on their learning behaviour and study habits.

Secondly, existing MOOC platform incorporate learner tracking functionality resulting in large amounts of data that describes learners' online actions. As envisioned by Papanikolaou [124], we harness the potential of this vast amount of learner data in order to detect and describe cognitive activities and to cultivate metacognitive skills such as reflection, planning and self-monitoring.

Thirdly, learner dashboards have been devised as effective tools to visualize data about learner activities to support awareness, reflection, sense-making and behaviour change in online or blended learning environments[2] [158]. Although literature presents numerous examples of learner dashboards, we identified several shortcomings. The first thing we noticed is that most of the existing learning analytics dashboards are intended for teachers and less are aimed to support learners. Moreover, very few learner dashboards which target learners encourage and support the development of SRL skills. Another major drawback is that very few dashboards were prototyped for MOOC environments [141]. Finally, most of the current learner dashboard solutions have not been evaluated on a large scale, but rather focused on small groups of learners on a short period of time.

The purpose of this work is to investigate how self-regulating skills can be enhanced by encouraging metacognition and reflection in MOOC learners by means of social comparison. To this end, we developed the `Learning Tracker`, an interactive widget that could be integrated in a learner dashboard aimed at learners. The `Learning Tracker` allows MOOC learners to compare their learning behaviour to that of previous graduates of the same MOOC, which we named *successful* learners. In order to develop our widget, we first considered existing learner dashboard implementations and designed an initial prototype. Following a design-based research methodology, we deployed the prototype in a real-world MOOC offered by TU Delft on the edX[3] platform. Based on the data analysis performed on the log traces of learners who were exposed to the `Learning Tracker`, we refined our design and performed another evaluation on two other live TU Delft MOOCs.

Our work is guided by the following research questions:

RQ1: Are learners more likely to complete the course when they can compare their behaviour to that of previous graduates?

[2] Blended learning is a formal education program that combines traditional classroom methods and independent study (i.e. learners have control over time, place and path) via digital and online media.

[3] https://www.edx.org/

RQ2: To what extent is learners' behaviour affected by comparing themselves to previously successful learners?

1. Do learners become more engaged with the MOOC when they can compare their behaviour to that of successful learners?
2. Do learners show improvement of their time-management skills when they compare their behaviour to that of successful learners?
3. Do learners change their behaviour so it becomes similar to that of successful learners when they can compare themselves to it?

With our work, we bring several contributions to the fields of learning analytics and MOOCs. Preliminary results of the evaluation of the `Learning Tracker` were already presented in a demonstration paper [47] at the Learning Analytics for Learners Workshop[4] at Learning Analytics and Knowledge 2016 in April 2016. We summarize our contributions as follows.

Firstly, we introduce an interactive widget that visualises learners' behaviour with the purpose of developing learners' self-regulated learning skills by means of reflection. Secondly, we have deployed and evaluated the widget in several real-world MOOCs across the whole duration of the MOOCs reaching more than 20.000 learners. Longitudinal studies of such magnitude are rarely encountered in literature. Thirdly, the results showed the effectiveness of our design across all evaluated MOOCs, as learners that are exposed to the `Learning Tracker` are more likely to complete the course due to changes in their behaviour. Finally, based on our findings, we argue that the mere fact of being exposed to feedback on learning behaviour might lead to changes in a learner's overall behaviour and not only in the areas they received feedback on.

[4]http://css-kmi.tugraz.at/mkrwww/leas-box/lakws16/home.html

Chapter 2

Background

The present work builds on research in: (i) feedback and reflection as ways of increasing learners' self-regulated learning skills; (ii) learning analytics and open learner models as ways of processing and modelling data describing learners' behaviour; and (iii) learner dashboards as means of visualising learner behaviour in a human understandable form.

The following sections discuss each of the aforementioned topics illustrating current status of the field and the work done in MOOCs so far. We close the chapter by outlining existing shortcomings of learner dashboards that we aim to mitigate in the present thesis work.

2.1 Massive Open Online Courses

Massive Open Online Courses (MOOCs) are part of "a continuous trend of innovation, experimentation and use of technology to provide learning opportunities for large numbers of learners" [148]. MOOCs are technology enhanced learning environments initially designed for the lifelong learning market [136]. More recently, MOOC are developed with the clear purpose of improving the learning experience and providing more affordable learning opportunities for learners in any geographical location [57].

A MOOC is an online course which can be attended by a large number of participants, hence the term *massive*. MOOCs have a fixed duration and follow a certain pedagogy. The course is *open*, meaning that there are no admission requirements and learners can access the course content and submit assessments without paying fees. As they are *online*, people can access them on the Internet. This enables learners who do not have access to traditional higher education to take advantage of other learning opportunities.

Literature acknowledges two main types of MOOCs: cMOOCs and xMOOCs, each with their own technological and pedagogical characteristics [148, 49, 10]. The first MOOCs appeared as an alternative to the traditional learning pedagogy of universities in 2008 when Stephen Downes and George Siemens designed their first open online course "CCK08 Connectivism and Connective Knowledge". Their purpose was to better understand how online learning worked [146]. This type of MOOC follows a 'bottom-up' approach based on the connectivist theory proposed by Siemens where learners are in control of curating the content [149]. Learning is seen as the process of generating networks between learners and using them for creating and sharing knowledge [49]. These MOOC were named cMOOCs as a reference to their *connectivist* component.

On the other hand, xMOOCs emerged in 2011 with the purpose of making courses from respected institutions available to the masses. The courses were online, free and with no barriers to entry [18]. The x in xMOOC comes from the term *extension* which was used by MIT and Harvard University in order to label the online version of their courses [20]. Thus, xMOOCs follow a more traditional 'top-down' approach in which the instructors define clear learning objectives, structure the curriculum and establish the assessments [49]. While they offer discussion forums that support collaboration and knowledge sharing, xMOOCs emphasize individual learning rather than learning from peers [43] and encourage the learners to passively receive input from experts [71].

The present research is conducted solely on xMOOCs. As TU Delft is a research partner of the edX platform, we had access to learner data extracted from the log traces of the learners enrolled in the MOOCs offered by TU Delft. All courses offered by TU Delft are xMOOCs. Further on, we will refer to xMOOCs as MOOCs.

2.1.1 Structure of xMOOCs

The xMOOC formalism is prominent in many of the MOOCs offered by top universities on platforms like edX, Coursera, FutureLearn and Udacity. Although many of the courses provided by universities on MOOC platforms are taught in the respective campuses as well [93], there are several important benefits MOOCs have over traditional learning environments. Firstly, unlike classroom lectures, knowledge delivery and practice are intertwined. In such a MOOC, short lecture videos are complemented by quiz sessions in which learners can immediately apply and test the knowledge they gained. Additionally, learners can interact in discussion pages, browse reading material, or complete peer review assignments. According to Agarwal, this approach enables active learning [3]. Active learning has been shown to lead to higher learning gains in MOOC learners [91]. Secondly, there is instant feedback and automatic grading for the assignments and answers submitted by the learners. Instant feedback on the correctness of quiz answers has been shown to be highly correlated to achievement and making progress [34]. Thirdly, learners can skip or revisit material, pause, rewind, speed up/down the videos. This puts them in charge of their learning paths and encourages a self-paced and flexible style of learning. In turn, this freedom requires the learners to drive the learning process more independently compared to the classroom environment [123].

As the present work is based on MOOCs offered by TU Delft on the edX platform, the current paragraph describes the structure of MOOCs as available on edX. As shown in Figure 2.1, each course is structured into a series of *modules* (usually up to 16 modules) which are listed vertically on the left side of the course pages. In general, modules are released on a weekly basis, but learners have the possibility to navigate freely within the already published material. Each module is divided into several sections called *learning sequences*. Each learning sequence contains either a lecture or a graded assessment. *Lectures* consist of instructional videos, reading materials or practice quiz problems. A *graded assessment* is either a weekly problem set, a peer-review assignment, or a mid-term or final exam.

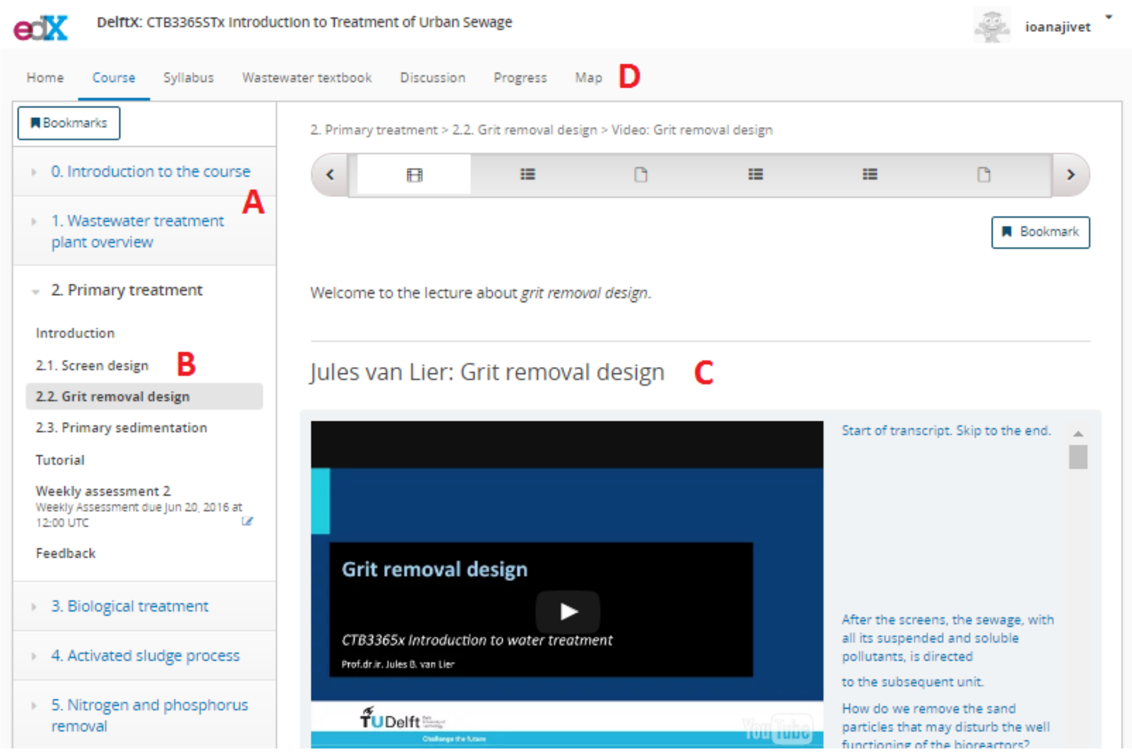

Figure 2.1: The content of a MOOC on the edX platform is structured into a series of modules (A), where each module contains several sections (B). Each section is called a *learning sequence* and contains either video lectures, reading materials and/or assessment problems (C). Additional sections are available for the learners through a top-level menu (D).

For each course, apart from the learning material, learners have available several sections, including a home section with course updates from the course staff, forum pages, a wiki page with additional reading material and a *progress page*. The progress page, further described in Section 2.6, offers a simple learner dashboard on which the learners can visualise their current course progress in terms of attempted quiz questions and the total assessment score. By developing the `Learning Tracker`, we aim to complement the information displayed on the progress page to better support learners throughout their learning experience in TU Delft edX MOOCs.

2.2 Self-regulated learning

The following section introduces self-regulated learning (SRL) as a critical skill in the online learning environment. We further present previous work that aimed to encourage self-regulation in MOOC learners. We conclude the section by discussing feedback as means of triggering self-reflection and supporting SRL.

Self-regulated learning can be understood as the ability to control, manage and plan learning activities and behavioral processes that support learners in reaching their goals [85]. When applied in a wide sense, SRL means that students can choose what, when and where to learn. In a narrow sense, SRL assumes that when students are given a learning task, they self-manage the learning processes involved in doing the task [31]. Apart from the regulation of one's own learning activities, self-regulated learning also involves cognitive, motivational and emotional aspects [16, 17, 170].

Zimmerman [169] suggested a social cognitive model of self-regulated learning according to which self-regulation is achieved in cycles consisting of *forethought*, *performance* and *self-reflection* as illustrated in Figure 2.2.

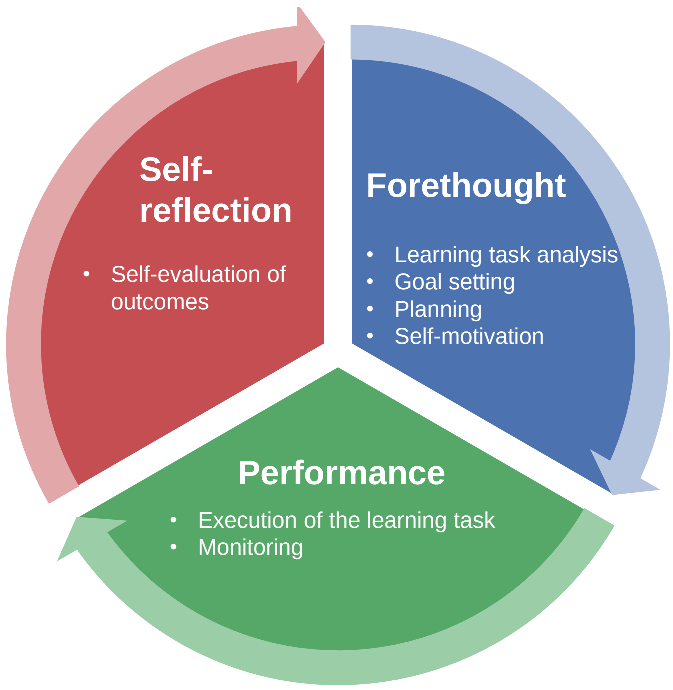

Figure 2.2: Zimmerman's [169] social cognitive model of self-regulated learning and the learning activities associated with each phase of the cycle.

Time management, self-teaching methods, and metacognitive evaluation of one's own understanding are listed as self-regulation skills [170]. According to Paris and Byrnes [127], self-regulatory skills include setting realistic goals, approaching tasks with confidence and positive expectations and overcoming obstacles with persistence and inventive problem solving. Butler et al. [30] showed that these skills recursively influence learning outcomes, motivation and further self-regulation.

Thus, in order to support learners' self-regulation in online learning environments, designers and developers need to provide tools that scaffold the development of a range of self-regulation skills, including realistic goal setting and planning, problem solving, self-teaching methods, time management and self-monitoring.

2.2.1 SRL in online learning

SRL strategies have been studied for decades in traditional classroom settings showing that students with higher levels of SRL tend to have better academic achievements [6] although the learning process is mainly facilitated by the teachers. However, with the rise of online learning environments whose major features are flexibility, openness and the absence of deep interaction between learners and instructors, the ability to self-regulate is becoming more important [132, 161].

Previous research shows that SRL strategies can positively impact student achievement in the online learning environment. Strategies of time management, metacognition, and effort regulation have been correlated with higher academic outcomes [23] and course completion [132]. Several researchers argue that technology enhanced learning environments, particularly online courses, need to support and guide learners to strengthen their regulatory skills in order to help them persist in the course [10, 153, 84]. However, current MOOC platforms offer their students no guidance concerning this matter and a lot of learners struggle to attain the level of self-discipline needed to become the managers of their own learning [119].

Although low learning skills are currently listed as one of the reasons behind the high dropout rates [65], we argue that the need to develop SRL skills in the online environment could be seen as an opportunity to improve the overall quality of learning and to empower learners to seek lifelong learning. As Zimmerman et al. [172] note, few teachers effectively prepare students to learn on their own. However, this shortcoming can be mitigated through an online learning environment that scaffolds the development of SRL skills.

2.2.2 Encouraging SRL in MOOCs

Research on MOOCs suggests that time management, planning, and self-monitoring skills are required to complete the course [85, 64], but most MOOCs are not designed in ways that encourage self-regulated learning [105]. Thus, many learners that are lacking self-regulatory skills find themselves struggling to complete the course [87].

Several solutions have been proposed so far, but none proved to have any effect on learners' self-regulation or performance. Kizilcec [85] showed that just prompting MOOC learners with ways to engage in self-regulated learning does not improve their course persistence or achievement. The same conclusion was drawn by Davis et al. [48] after empirically investigating in the MOOC setting two types of instructional interventions found to be effective in traditional educational environments (study planning and retrieval practice).

Gutiérrez-Rojas et al. [64] present the design of a tool that scaffolds self-learning in MOOCs and advises MOOC participants on how to successfully complete the course. The application provides personalized planning, tips and hints for time management, study habits and team work. The application is to use crowdsourcing to gather the data needed to provide customized support for different student profiles. However, the design remains at a conceptual level as the tool has not been implemented or evaluated with real MOOCs.

Nawrot and Doucet [119] discuss time management support on MOOC platforms in relation to Zimmerman's SRL cycle [169] presented in the beginning of this section. They claim that MOOC platforms should support learners in identifying tasks, allocating time and scheduling activities throughout the *forethought* phase. The *performance* phase can be supported by sending reminders and providing progress visualisation tools. The same visualisation tools are also used to encourage evaluation by triggering *self-reflection*. To implement these features, the platforms should leverage the behavioural dataset generated by the MOOC community that are already available to provide personalised support to the learners. However, the effectiveness of their solutions has not been tested empirically.

2.2.3 Metacognition and feedback as support for SRL

All the solutions presented in the previous subsection offer learners advice and guidance on how to improve their learning and develop their self-regulation skills, but fail to make learners aware of their skill level. As Kizilcec [84] suggests, learners are able to notice the lack of self-regulatory skills or evaluate their skill level only when they possess a certain level of metacognitive awareness. Metacognition is defined as cognition about cognition: thoughts about thoughts, knowledge about knowledge or reflections about actions [125]. According to Pintrich [130], metacognitive aware learners possess knowledge about (i) general strategies for learning and thinking, (ii) cognitive tasks, as well as when and why to use different strategies, and (iii) the self in relation to cognitive and emotional components of performance. Moreover, effective self-regulation relies on accurate self-assessment of "what is known or not known" [140].

Pintrich [130] suggests that the most effective way of increasing awareness of metacognitive knowledge in a classroom is by exposing and discussing suck knowledge whenever it becomes visible through learners' actions. Thus, as learners hear and see how their classmates approach a task, they can compare their own strategies and make judgements on their utility and effectiveness.

However, in a MOOC environment, learners are geographically dispersed and their contact is limited to discussion forums and extremely rarely through face-to-face meetings [24]. Moreover, due to the massive amount of learners that engage with the course, it is extremely difficult for course staff to facilitate discussions which expose metacognitive knowledge. In order to overcome these challenges, we propose feedback as means to support SRL by increasing learners' metacognitive awareness in a MOOC environment.

Feedback is a central component for self-regulated learning [30]. Feedback is "an information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding" [67]. Well-designed feedback has been shown to have a positive impact on learning, supporting learners through the learning process [66, 145]. Thus, feedback is a powerful tool that can enhance performance and achievement by closing the gap between the learner's current understanding and the desired goal.

Hattie and Timperly [67] review the evidence related to the impact of feedback on learning and achievement and proposed four levels of feedback, from specific to generic: (i) *feedback on task execution* targets how well tasks are performed; (ii) *feedback on learning strategies* focuses on processed needed to perform tasks; (iii) *feedback on self-regulation* evaluates self-monitoring and regulation of action; (iv) *feedback on the self* concerns personal evaluations and learner's affect. In an ideal learning environment, learners seek and receive all four types of feedback. However, the most effective forms of feedback are feedback on learning strategies and feedback on self-regulation [67].

A study of the design of 76 randomly selected MOOCs concluded that although organisation and presentation of the course material was of high quality, very few designs supported feedback towards the learners [103]. Moreover, the most common means of providing feedback to the learners in MOOCs is automatic quiz grading which exemplifies feedback on task execution. The two most effective types of feedback (on learning strategies and on self-regulation) are rarely considered by MOOC developers. According to Kluger and DeNisi [89], feedback that involves self-regulation is effective to the degree to which it enhances self-efficacy and leads students to invest more effort or commitment to the task. Thus, two possible evaluation criteria for the effectiveness of the `Learning Tracker` on self-regulation are the amount of effort that learners invest in the MOOCs and their engagement with the MOOC.

Self-regulated learning skills (e.g. goal setting, time management, self-monitoring and self-evalution) have been shown to enhance learning and increase learners' performance. In our work, we aim to support learners to develop their self-regulated learning skills by encouraging them to reflect on their behaviour. We trigger reflection by providing learners with feedback on their learning strategies and their self-regulation.

2.3 Social learning and social comparison

In order to offer learners a solid anchor for reflection, we rely on the effects of social learning and social comparison. Learning with others is an essential means for supporting deeper learning [19]. Social learning requires individuals to share their ideas, learn through teaching and communicate with others who may have different perspectives or greater expertise [88]. Educational science theories also highlight the social nature of learning, where learning also occurs by simply observing skilled practitioners [9].

In MOOCs, social learning occurs mostly in forums, as they are the primary opportunity where learners can interact with each other. Brinton et al. [22] classified forum threads in three groups: (i) small-talk, (ii) course logistics and (iii) course-specific questions. The final category contains threads related to the course material or ideas and concepts related to the topics covered by the course. However, topics that address study habits are missing. We speculate that one possible reason for the absence of threads that cover this topic is the lack of self-awareness of learners.

Some authors suggest that reflecting on one's learning process requires high levels of self-awareness which are not common [84] and even if learners reflect on their learning behaviour, it is difficult for them to evaluate it.

Festinger [54] theorizes that in the absence of objective means of comparison, people evaluate their abilities by comparison to others. In a learning environment, empirical studies with different types of social visualisations that rely on social comparison have shown that comparing oneself to one's peers or the entire class could increase a student's motivation to learn and improve their participation in educational activities [96]. In the context of online learning, Papanikolaou [124] observed that comparing one's behaviour to a "desired" one plays a critical role in how learners reflect on their success or failure. In case of success, the comparison helps learners recognize the learning strategies they adopted and helps them to optimise their strategies. On the other hand, in case of failure, the desired state motivates learners to re-evaluate and change their strategies. In light of this finding, Papanikolaou suggests that it might be useful for learners to compare their state with an "ideal" model in order to identify differences in their learning process. This model can be proposed by the instructor or it can be based on the behaviour of individual peers or the whole group [124].
In the design of the `Learning Tracker`, we leverage the effects of social comparison on learners' performance, motivation and engagement. On the widget, learners can visualise their behaviour compared to that of successful learners, offering them an "ideal" model against which they can evaluate the effectiveness of their study habits.

2.4 Learning Analytics

Learning analytics (LA) has been defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [151]. LA emerged from the need to harness the value of the increasingly large datasets describing interaction data, personal data and academic information generated by the widespread of leaning management systems [52].

Ruiperez et al. [135] identified two main approaches for using learning analytics techniques to make decisions related to learning processes. On one hand, LA is used to provide learners and teachers with visual information that they can interpret and use as a support for making informed decisions. On the other hand, LA is used to feed data to recommenders and adaptive systems that run automatically and do not require student or teacher interventions. However, Siemens argues that the purpose of LA is to inform and empower learners in order to better leverage human judgement [150]. Baker also observed a shift from using data mining to support automated intervention to using it to support reporting [7].

LA was used to investigate the impact of learning design on student behaviour, satisfaction and performance, allowing teachers and instructors to identify trends in learning and teaching from rich data sources [134]. A successful example of using LA is Course Signals [4], a student success system available on Purdue's LMS through which faculty can provide meaningful feedback to student based on data collected by instructional tools. The systems determines in real time which students might be at risk, indicated by their performance, effort within a course, prior academic history and demographics. Based on this information, instructors then schedule interventions. The positive effects of Course Signals were visible in the increase in satisfactory grades in individual courses and the overall retention rate of the university.

One of the few systems that uses Learning Analytics in the context of MOOCs is LASyM [154]. LASyM mines data generated by MOOC learners through learning operations, analyses their behaviour from the perspective of persistence and interaction in order to identify potential dropouts. The system is aimed at MOOC providers and is a first step in implementing components that deliver early intervention strategies to reduce the high dropout rate in MOOCs.

So far, LA has been used to model learning behaviour and to identify students "at risk" [159]. In other words, learning analytics has been implemented as a warning trigger for institutions and educators, but the power of LA is in utilizing it as a driver and support tool for learner-managed systems of learning. MOOCs provide a rich context for applying LA because of the large amount of data that they generate. At the same time, MOOCs require the use of learning analytics because instructors do not have the resources and the time to analyse, interpret and feedback learners' learning processes on a large scale [135]. However, LA are most effective when they are an integrated part of a whole system of learner support, which is hard to deliver in a MOOC [38].

We address these difficult gaps by implementing the `Learning Tracker` as a learning analytics tools aimed at MOOC learners which analyses and visualises MOOC learner data. To harness the full potential of the widget, we have implemented the widget as a seamless integration for the edX platform, complementing the *Progress* page as described in Section 2.6.

2.5 Open Learner Models

Following Bull and Kay's work, the `Learning Tracker` can be considered an Open Learner Model (OLM). The current section presents the particularities of OLMs and discusses existing OLM implementations in online learning environments, focusing on MOOCs.

OLMs are defined as learner models that allow a user, usually the learner they represent, to view and inspect a model in a human understandable form [28]. Thus, an OLM presents opportunities for learner reflection, metacognition and deep learning [80, 27]. Through OLMs, learners gain greater control over their learning, as they have access to information that they can use to make decisions about their learning [76]. Additionally, they are an accessible means for learners to monitor their progress and plan their learning, starting with setting goals and defining ways to achieve them [77]. Open learner models can be seen as a specific type of learning analytics because they leverage learning analytics techniques to build learner models [75]. However, OLMs have been typically developed for learners to help them reflect on their learning, while learning analytics visualisations were mainly intended to support teachers and other stakeholder.

OLMs have been demonstrated to enhance learning by increasing the learners' awareness of their level of knowledge and the learning process in general, as well as students' engagement and motivation [113, 167]. It has also been found that not all students are good at evaluating their knowledge, but allowing the student to visualise the learner model may help their self-evaluation [112].

Bull and Kay introduced SMILI☺ [26], an OLM framework that provides a systematic way to describe and compare the many and diverse forms of OLMs. Their proposed framework addresses questions like *what* is open, *how* the data is presented and *who* controls the access to the OLM. In a follow-up paper [29], in light of the changing nature of the learner models and their role, the same authors extended the framework with two additional aspects: *what* is the purpose of the OLM and *who* are the intended users.

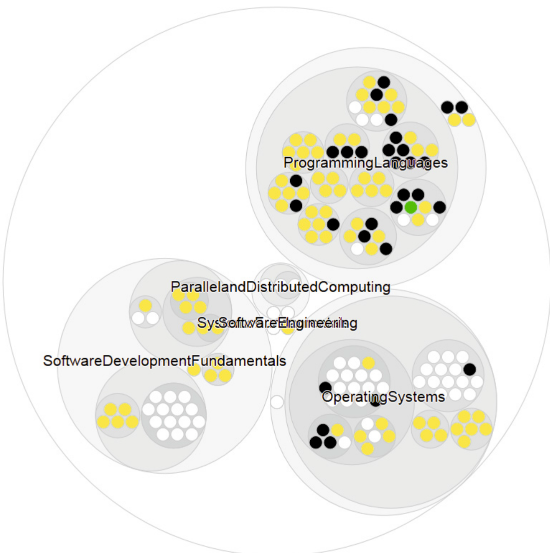

Figure 2.3: MOOClm interface illustrating a student's performance against a reference model. Black dots represent "known" items, white dots are "unknown", yellow dots are items "expected to be know, but unknown" and green dots are items that are "known, beyond the current week's material". [44].

Most of the existing OLM interfaces were designed for Intelligent Tutoring Systems [27], but recent applications that embody the ideas behind OLMs were also designed to support learners in large scale online learning [29]. One such example is found on the Khan Academy online platform[1]. Once a learner has completed a pretest for a course, they are shown an overview of their progress. The progress is visualised through a skillometer for fine-grained skills and badges for coarse grained skills [29, 44]. MOOClm [44] generates an OLM and the underlying learner model for a *C and Unix* MOOC on the Open edX platform. In order to create the OLM, the authors drew associations between several events recorded in the edX activity trace logs and the accomplishment of course learning objectives. Based on a variety of sources for defining learning objectives, a set of "reference models" against which the student can compare their own performance were created (e.g. a model covering all learning objectives covered by the MOOC or a model covering all learning objectives in the ACM CS2013 curriculum). MOOClm is presented in Figure 2.3.

2.6 Learner dashboards

Over the past decades, with the exponential growth in data volume and the applications of *big data*, dashboards have become a means of visualizing large amounts of data. Dashboards are "a visual display of the most important information needed to achieve one or more objectives that has been consolidated on a single computer screen so it can be monitor at a glance" [55].

Learning dashboards have been devised as effective tools to capture data about learner activities and visualise this data to support awareness, reflection, sense-making and behaviour change in online or blended learning environment [158]. Schwendimann et al. [141] identified a lack of an agreed and shared learning dashboard definition and proposed the following: "a single display that aggregates multiple visualisations of different indicators about learner(s), learning process(es) and/or learning context(s)".

The major goal of learning dashboards is to support improvements in student learning and performance [164]. This can be achieved by empowering teachers or learners themselves. Dashboards for *teachers and instructors* inform them of a student's learning status in real-time and support teachers in performing their roles effectively in areas including class management, learning facilitation, provision of feedbacks, and evaluation and grading [128]. Examples include Pulse [33] in a physical classrom, CourseVis [107] in a course management system or edX Insights[2] in a MOOC environment.

On the other hand, dashboards aimed at *learners* present learning patterns to students themselves, helping them improve their learning strategies and supporting student motivation. Such interfaces are considered implementations of OLM since they reveal to the learners an assessment of their skills or behaviours [25]. Due to their simplicity in displaying information through visual elements like charts, graphs and indicators, they have been considered a typical methods for increasing learner awareness, reflection and ability to self-evaluate, supporting learners to achieve their goals [131, 137]. Learner dashboards should leverage social learning in ways that allow learners to compare their progress to that of their peers or previous learners who have taken the course [152, 124].

Several studies showed that learner dashboards have a positive effect on learning [99], by stimulating behavioural, metacognitive and emotional components of SRL. On a *behavioural level*, most of the dashboards show metrics related to how time is spent in the learning environment, social interactions, effort indicators of students and learner performance on assessments. Visualising progress on learning dashboards has been proven to enhance performance and engagement, resulting in higher final grades [82]. On a *metacognitive level*, learning dashboards stimulate self-reflection in relation to how learners navigate and use the available material or how they interact with their peers [139, 60]. Kim [82] explained that learning dashboards trigger awareness and reflection in learners by "indicating discrepancies between the goals and the current states in the self-regulation process" [82]. Corrin and de Barba [46] discovered that the majority of students interpret feedback delivered through learning analytics dashboards in a way that promoted reflection on their performance and engagement. Finally, learning dashboards also affect the *emotional component* of SRL by influencing motivation [83] or reducing deactivating emotions like boredom and lack of excitement [116]. Although learning dashboards have been reported to increase motivation towards the course subject, learners that are above the class average might not experience the same because they are not challenged enough [46, 82].

[1] https://www.khanacademy.org

[2] http://edx.readthedocs.io/projects/edx-insights/en/latest/

Several scholars advocate for a shift towards learner-centred analytics where learning analytics are used as a tool for reflection and metacognition to support SRL [153, 37, 50]. However, systematic literature reviews show that the majority of existing learner dahsboards seek to enable teachers or both teachers and learners and only a few dashboards are aimed only at learners [157, 128, 141]. Recognizing this gap, we provide an overview on various existing learning dashboards, with the purpose of highlighting several dashboards aimed at learners.

2.6.1 Overview on existing learner dashboards

Early dashboards were aimed at teachers and were focused on the physical classroom. An example is Pulse [33], an interface that visualised the physical activity of the students' body like speaking, moving between seats and making gestures via a video-conferencing system. As early as 2004, with CourseVis [106, 107] the focus started to shift towards e-learning environments where personalized and adaptive learning support is more important, but more difficult to provide. CourseVis is a system that obtains tracking data from a course management system, processes the data, and generates graphical representations that can be explored and manipulated by course instructors to examine social (participation in discussion and group work), cognitive (performance and level of knowledge), and behavioural (accesses to the course, material usage and progress) aspects of distance students. Although initial evaluations with small focus groups showed promising results, the tool has not been tested empirically on a large scale.

Similar early dashboards targeted at learners in learning management systems are SAM [58], GLASS [95] and Moodog [168]. Student Activity Meter (SAM) [58] provides visual analysis of the time learners spend on learning activities and statistics of document use. The development of SAM followed a design-based research methodology, each iteration being evaluated in a different setting. However, the evaluation of SAM was focused on the usability, use and usefulness of different visualisations rather than its impact on learning achievements or learning behaviours. GLASS (Gradient's Learning Analytics System) [95] is a web-based visualisation platform that modularizes the generation of visualisations from datasets containing a large number of recorded events. The platform provides both teachers and learners with feedback on activities and performance. Zhang [168] introduced Moodog, a Moodle [3] plugin for visualizing data from activity logs by aggregating low-level activity records into key metrics that describe students' use of online course materials. It provides different perspectives to both learners and instructors. The learners have the possibility to easily compare their own progress with that of their peers. The visualisation is primitive, consisting of bars for each resource and each student. The usability of the plugin was tested on a group of 38 students.

More recent learner dashboards that aimed to trigger self-reflection by revealing learner behaviour can be exemplified by INSIRE*us* [124], StepUp! [137], LAPA [128] and Mastery Grids [62].

Papanikolaou [124] designed a tool that supports learners' reflection by visualising interaction behaviour. She proposes indicators that describe cognitive and social aspects of the interaction. The cognitive indicators reflect the quality of the learner's individual activity with course material and integrated tools, while social indicators refer to communication, collaboration and cooperation between the individuals. INSPIRE*us* was tested on a class of 50 students with the purpose of investigating how learners interpret specific visualisations on their interaction behaviour.

StepUp! is a student activity visualisation tool that uses learning analytics technology to enable self-reflection on activities and comparison with peers [137]. Learners can get information on the time they spend with different tools while working on assignments for an on-campus course. StepUp! was evaluated in several user-centred studies where small groups of learners were interviewed about its usefulness and its effects [122, 139]. Results showed that StepUp! is a useful tool that enriches student experiences by allowing them to better understand how themselves and others spend their efforts. However, users were not convinced of the added value and were not motivated to use the dashboard.

LAPA (Learning Analytics for Prediction and Action) [128] is a learning analytics dashboard for learners that shows students' online behavior patterns in a virtual learning environment of a private university. LAPA support students' time management and self-regulation by displaying meaningful metrics (total log-in time, log-in frequency and log-in regularity, and visits on the board and repository) that predict students' learning achievement. The evaluation results indicated that

[3] https://moodle.org/

this tool did not significantly impact students' learning achievement, but allowed learners to better understand their behaviour.

Finally, Mastery Grids [62] combines OLM and social comparison features to aid learners in identifying the most suitable learning path while supporting SRL and allowing learners to monitor their course progress. Mastery Grids was developed as a social progress visualisation interface on which learners can visualise their progress compared to that of the class average. Several semester-long classroom studies [62, 98] showed a positive impact on learners' engagement, efficiency, effectiveness, and motivation.

2.6.2 Learner dashboards for MOOCs

The dashboards presented above are used in traditional face-to-face teaching, course management systems, intelligent tutoring systems or blended learning settings. However, very few dashboards were prototyped for MOOC environments and most of them focus on supporting teachers [141].

Kia's work presented in [81] is an instructor analytics module for moocRP[4], an open source open learning analytics platform. This dashboard allows instructors to investigate how students' attributes such as age, gender, location, and educational background relate to their performance and achievement by offering the possibility to filter the data displayed on the dashboard.

Similarly, edX has developed edX Insights[5], a platform that makes information about student activity, background, and performance throughout the course available to course team members, as shown in figure 2.4.

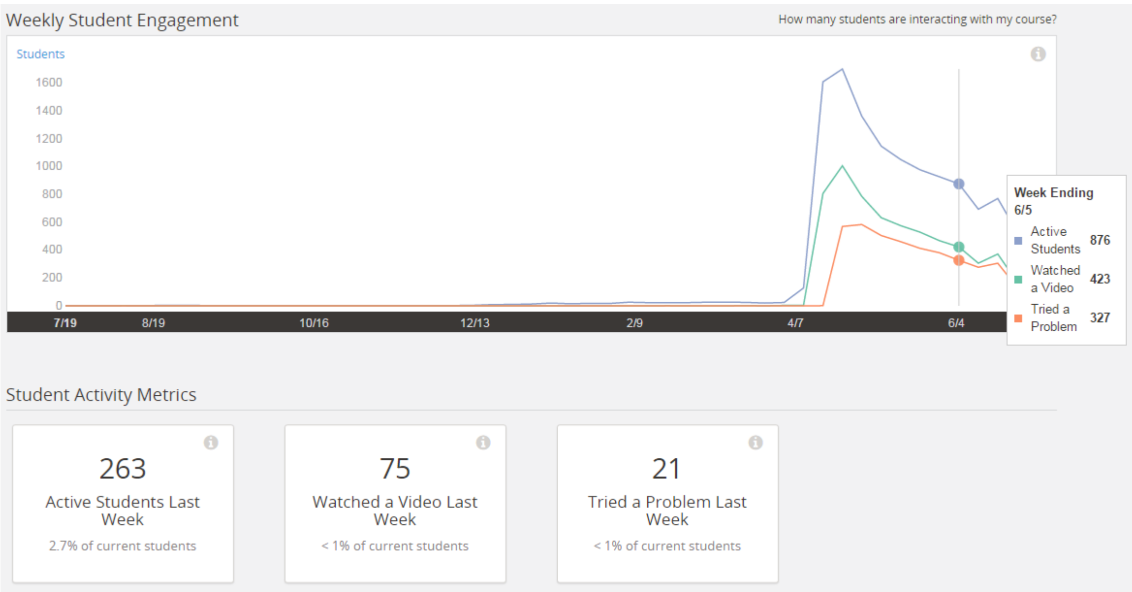

Figure 2.4: edX Insights dashboard displaying information on weekly student engagement for one DelftX MOOC deployed on the edX platform.

FutureLearn platform [6] offers a learning analytics dashboard for instructors and course designers developed by the University of Southampton [94]. The dashboard visualises student progress from two key perspectives: social interactions and performance.

Open-DLAs is a LA dashboard developed for the Open edX platform [39]. The dashboard is intended for instructors and it visualises the progress of learners' activity taking into account navigation, social interactions and interaction with educational resources. The dashboard was tested with two runs of four MOOCs created by the University Autonóma of Madrid (Spain) on the edX platform, but results of the evaluation are not available.

The collection of MOOC dashboards that seek to empower learners is even poorer. Figures 2.5 and 2.6 show the available dashboards for learners on edX and Coursera, two of the main MOOC platforms. Learners receive information on the course progress in terms of the number of weekly

[4]https://github.com/kk415kk/moocRP
[5]http://edx-insights.readthedocs.io/en/latest/index.html
[6]https://www.futurelearn.com

assessments completed and their current assessment score through simple visualisations with text and bar charts.

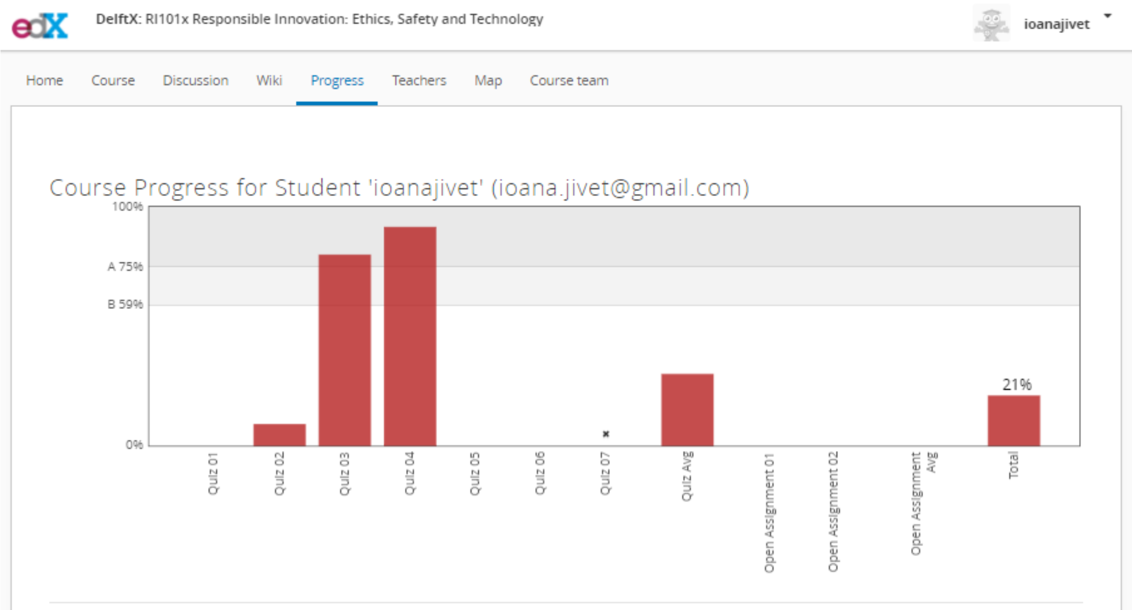

Figure 2.5: Sample edX dashboard: learners can follow their weekly and total assessment scores.

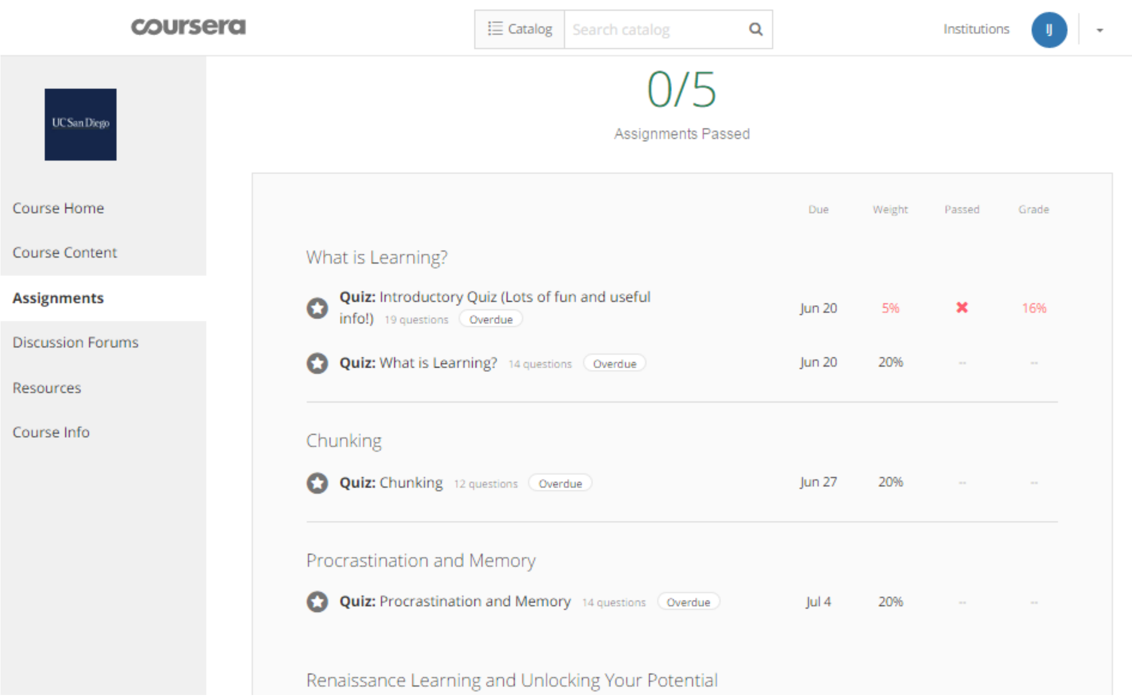

Figure 2.6: Sample Coursera dashboard: learners can follow their grades for each quiz, whether or not they passed and the total number of quizzes passed.

Other solutions proposed for MOOC platform have only been prototyped and rarely evaluated on a large scale. For example, Vovides and Inman [159] propose an analytics model that is meant to capture and also support further development of learners' reflective sense-making of ill-structured ethical problems. The proposed model is a combination of activity data describing the interaction with an online system, as well as learning artefacts that resulted from working on the online system. Testing of a prototype learner-managed dashboard that implements the proposed model on a GeorgetownX MOOC deployed on edX is ongoing. The dashboard is presented in Figure 2.7.

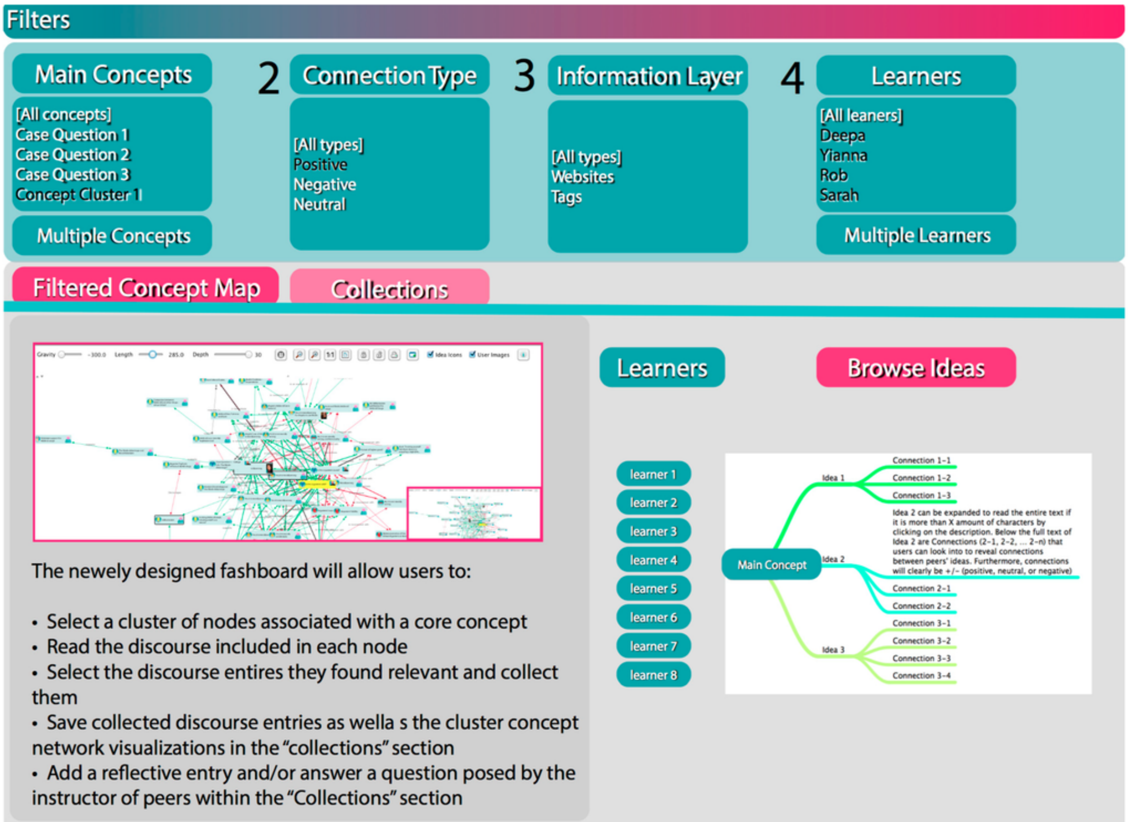

Figure 2.7: Schematic of the learner-managed dashboard that supports learners' reflective sense-making of ill-structured ethical problems [159].

2.7 Current learner dashboard shortcomings

We identified several gaps related to the design and implementation of existing learning dashboards.

Firstly, with the recent rise of MOOCs and the novelty of a new learning environment, the lack of learning dashboards on existing MOOC platforms that aid learners through the learning process is critical. This becomes obvious if we analyse the support current MOOC platforms offer to their users. Although effort has been put into analytics tools that support course staff in improving their courses (e.g. edX Insights), even the most popular platforms do not offer the same opportunities to their learners.

Secondly, current learning dashboards do not encourage learners to *learn how to learn*, but rather focus on *what to learn*. Several learning dashboards are meant as navigation support tools, showing learners what topics to cover, what sections to focus on, what areas they are weaker in. However, they do not aid learners in how to use the resources, how to optimize their learning strategies or how to create and maintain efficient and effective study habits.

Thirdly, we consider that learning analytics dashboards for MOOCs should be designed having a single group of intended end users. Since learning dashboards have different goals that are determined by who are the target users (i.e. monitoring students in the case of teacher and self-monitoring in the case of student), dashboards that are designed to serve both learners and teachers do not provide suitable support for either. For example, in the case of a MOOC with 10,000 learners, instructors might not be interested in singling out individual learners for personalized intervention, but rather identify groups or trends among the learners. At the same time, we hypothesise that self-reflection in learners cannot be fostered without personalized feedback.

Finally, most of the current learning dashboard solutions have not been evaluated on a large scale, but their evaluation focused on small groups of students. Moreover, evaluations investigated usability, highlighting potential impact on learning, but neglected to prove their effect. Most learner dashboard evaluations do not assess whether dashboards contribute to behavior change because such assessment requires longitudinal studies [157].

Considering these current limitations, we design, deploy and empirically evaluate a learning analytics widget that could be integrated in a learner dashboard on the edX platform. The widget aims to support MOOC learners in the learning process by fostering self-regulated learning through reflection on learning behaviour. The `Learning Tracker` is presented in the following chapter.

Chapter 3

The Learning Tracker

To address the current lack of learning support on MOOC platforms, we developed the `Learning Tracker`, a learning widget that could be integrated in a learner dashboard. The `Learning Tracker` aims to support MOOC learners in becoming more efficient by supporting them to develop their self-regulated learning skills. In the design of the widget, we follow Baker's alternate paradigm for online learning [7] in which we use information extracted from learning data to empower human decision making rather than feed it to intelligent learning systems. We leverage the human intelligence by encouraging learners to *reflect* on their own learning activities. Instead of suggesting learners what course of action to follow, we give learners access to easily interpretable data that allows them to reflect on their behaviour and find better learning strategies by themselves. Our approach is backed by research on self-regulated learning that demonstrates that learners who were encouraged to reflect on their learning, gained more knowledge [74]. Furthermore, the students' simple metacognitive awareness of particular aspects of their learning processes could enhance their self-control [171].

To this end, we implemented the `Learning Tracker` as an Open Learning Model that supports metacognitive processes of planning, monitoring and reflection [29]. The widget was developed through an iterative process, following the design-based research methodology [41]. Each iteration was evaluated in live MOOCs offered by TU Delft on the edX platform followed up by improvements in the design and implementation of subsequent iterations.

The `Learning Tracker` uses low-level data from trace logs and condenses it into indicators that describe several learning habits. This set of indicators aims to offer a comprehensive description of one's online learning behaviour at a certain point in time. Learners have access to the representation of their behaviour through an interactive widget. We intend for it to provide useful information in the *forethought* phase of Zimmerman's SRL cycle [170] as learners can use it to identify areas of improvement and set goals. The same information can also be used in the *self-reflection* phase as learners can evaluate their progress.

To help learners in getting a better understanding of the effectiveness of their study habits, their learning behaviour is contextualized with the model of a *successful learner*, offering an anchor point for comparison. Papanikolaou [124] showed that comparing their behaviour to a desired one motivates learners to recognise the strategies they adopt and helps them to optimise their learning in order to achieve their goal.

The current chapter describes the underlying principles that guided the design of the `Learning Tracker`, the design rationale and the challenges tackled through its development. We conclude the chapter with details related to the technical implementation of the widget.

3.1 Foundations

The design of the `Learning Tracker` is based on three assumptions that we made in the context of this thesis project:

1. We presume that effective learning behaviour can be modelled and adopted by others.
2. We define successful learners as learners that complete MOOCs.
3. We leave the decision on how to evaluate the displayed information up to the students.

Effective learning behaviour can be modelled and adopted by others As described in Section 2.3, social comparison can enhance learning. Loboda et al. [98] showed that stronger students guide weaker students by "showing" them *what* to learn and which course materials to access. Replying on learning theories that consider learning a cognitive process [61] and Bandura's theory [9] that people learn from one another through observation, imitation, and modeling, we argue that weaker students would be able to improve their learning even more if stronger students "show" them *how* to learn as well. Based on the same rationale, one of the cornerstone hypotheses of this research is that:

> *By observing and imitating the learning behaviour of stronger students, weaker students would improve their learning behaviour and thus perform better and learn more efficiently. In other words, stronger students could guide weaker students not only in terms of* what to do*, but also in terms of* how to do it*.*

Successful learners are learners that complete MOOCs Literature presents many definitions for successful students that have evolved based on the development of the field since MOOCs were first launched back in 2008. The most common way to define a successful learner is to consider learners that completed the course and earned a certificate [110, 133]. Several researchers argue that course completion and success are not synonymous [14, 97] because learners approach MOOCs with different goals and have different definitions of success [163]: either completing the course with a graded certificate, gaining knowledge in the topic, learning only one or two new skills, or just satisfying their curiosity about how MOOCs work.

Although the debate is ongoing, for the purpose of this study, we considered certificate receivers from previous runs of the course as *successful learners* for several reasons. As it is common for the same MOOC to run several times with minor adjustments to the content and structure, our definition of *successful learners* would remain relevant for the majority of ongoing MOOCs.

Firstly, obtaining a certificate can be considered a proxy for learning [114] since certificates are issued based on the final grade of the learner and final grades are meant to reflect the percentage of the course knowledge a student has.

Secondly, on the `Learning Tracker` current learners can compare their behaviour to that of successful learners. Graduates behaviour is already recorded and it can not change any more. On the other hand, if comparison was done against current peers, successful learners would be extremely hard to identify before the course has ended considering the accuracy of current completion prediction tools. Completers represent a small and unknown share of the total enrolled learners.

Thirdly, considering the last year's graduates as a reference point, the behaviour of successful learners can be modelled based on real, factual data and not on the course team's expectations of what a successful learner is.

Decision power and action lies with the learner The `Learning Tracker` widget has a passive role and it should serve as a triggering point for learners to become aware of their learning behaviour. The widget only displays information that would allow learners to self-reflect, make informed decisions and take actions concerning their learning habits. For this reason, the data displayed is not interpreted or evaluated further, there is no classification of the learner's behaviour in good or bad, no predictions on the completion status are made and no improvement actions are suggested.

3.2 Design

To develop the `Learning Tracker`, we applied an approach similar to the design-based research methodology [41] that promotes rapid prototyping and evaluation of ideas in short cycles. This method was applied for the development of similar dashboards [58, 159, 137]. We developed the `Learning Tracker` widget in two iterations over the course of six months. Each iteration was evaluated in a realistic setting as the `Learning Tracker` was deployed on live TU Delft MOOCs offered on the edX platform.

In the development of the `Learning Tracker`, two main issues were addressed: (i) identifying meaningful information to be displayed and (ii) devising a visualisation that supports reflection.

Durall and Gros [50] acknowledged these issues as the main challenges in the design of tools for reflection that make use of learning analytics.

We tackled the first challenge by defining a *learner model* that describes the learning behaviour through a set of metrics that quantify learning habits. We then used low-level activity data to create two types of learner profiles based on the model. One profile described the *successful learner* while the other one described *each learner currently enrolled* in the MOOC. We addressed the visualisation challenge by presenting the two models on a display that ensured a concise representation of the metrics and allowed easy comparison between the models. The two components – information and visualisation, are closely interlinked and interdependent as one can influence the other. For example, the chosen visualisation can limit the number of metrics that can be displayed.

We continue with sections describing how each challenge was addressed in the first iteration of the `Learning Tracker`, followed by the improvements made in the second iteration.

3.2.1 Learner information

Most of the existing learning platforms today track the learners' online activity by gathering low level learning data in the form of collections of user events stored in trace log files or databases. This enormous amount of data does not convey any meaning alone, but by processing it into higher level indicators, we can make use of it and gain insight into the learning process [118]. One of the biggest challenges which remains is to identify how the learning process and the learners' behaviour is reflected in the low-level activity.

Defining the learner model

In order to distil learning behaviour from low-level data, we modelled behaviour through a set of indicators that we quantified into *metrics*. The metrics characterize different study habits that together describe the learning behaviour of learners. Since the learners have access to the metrics through the widget, the metric selection has to be guided by the following criteria:

- *Easy to understand* – the users do not need additional explanations to understand the meaning of the metric.
- *Traceable* – the value of metric can be calculated based on low-level data (events, clickstreams etc.) obtained from the platform logs; e.g. the average times a learner logs in can be calculated because every time a users logs in on the platform, the event is recorded in the trace logs.
- *Actionable* – upon reflection, the learners can immediately change their behaviour through simple actions; e.g. if the average times a learner logs into the platform is low, they might benefit from making an effort in logging in more frequently.

We selected the metrics by firstly determining key aspects of successful learner behaviour, followed by establishing indicators that represent the expression of such behaviour. There are many reasons why learners drop-out [123], but identifying what has been shown to make learners successful offers a sound starting point in investigating metrics that would be relevant for learners and increase their success. We identified learning behaviour that makes learners successful by inspecting theories that are grounded in learning psychology literature, prior works that have investigated the factors impacting learner success in MOOCs and applying our intuition. In line with the definition for *successful learners* adopted in the beginning of this chapter, the first iteration of the `Learning Tracker` focuses on three aspects of effective learner behaviour:

- course material coverage
- level of engagement
- time management as a self-regulated learning skill

Following the criteria described above, we defined a set of metrics for each of the three aspects as shown in Table 3.1. It is noteworthy to mention that *engagement* and *time management* metrics describe behaviour, whereas *course coverage* measure learner's progress. The engagement metrics describe **how the learners interact** with the course material and with their peers, while the time management metrics focus on **how learners plan and organise** their learning time. On the other hand, course coverage metrics indicate **what course material** the learners interacted with. Although course coverage is a measure that shows learners how far along they are with regards to the progress of the course and not how they got there, we considered the cluster relevant to the purpose of the `Learning Tracker`. Papanikolaou [124] showed evidence that an indicator of learner's progress triggers learners to think about the way they use resources and their usefulness in achieving outcomes. The following paragraphs describe in detail each of the clusters and their respective selected metrics.

Table 3.1: The metrics that build the learner model used for the first iteration of the widget, their description and the unit of measurement for time metrics (h for hours, m for minutes and s for seconds).

Cluster	Metric	Description	Unit
Course coverage	number of quiz questions attempted	Number of graded quiz questions attempted	-
	number of videos watched	Number of video lectures accessed	-
Engagement	time on the platform	Amount of time spent on the course pages	s
	time watching videos	Amount of time spent watching video lectures	s
	ratio video-time/total-time	The fraction of time spent watching video lectures while on the course pages	-
Time management	timeliness of submission	The average time between the last attempt on graded quiz questions and the deadline for submission	h

Cluster 1: Course coverage Although some studies found that certificate earners skip on average 22% of the course content [63], several works show that high course material coverage is an indicator for successful completion of the course [5, 42, 138].

Considering the structure of the MOOC the `Learning Tracker` was intended for, we selected two metrics that measure course coverage: *the number of video lectures watched* and *the number of graded quiz questions attempted*. Since we did not have information on the video segments within a video which learners watched, the metric *number of video lectures watched* was operationalized through the number of video lectures accessed. Based on literature findings, both metrics are good indicators of learners' success. Athira et al. [5] suggested that the most frequent occurring behaviour of successful learners is browsing video lectures and attempting quizzes. Mukala et al. [115] discovered that successful students are more committed to watching videos than unsuccessful students. Moreover, their findings show a positive correlation between the watched status of a video and the grade obtained in quizzes related to the same video. This suggests that the more videos learners watch, the more they will learn, contributing to their success.

Another reason for reporting *the number of quiz questions attempted* is that in the MOOCs chosen for experiments, the grade obtained in weekly assessments contributes to the final grade. Since a certificate is obtained based on the final grade, the number of quiz answers submitted directly impacts the learner's certificate achievement.

Cluster 2: Engagement The metrics in this cluster were dedicated to describing how learners *engaged with the course material*, in particular how they spend their time on the platform and what resources they use. The total-time law in psychology explains that the amount of learning is a direct function of study time [45]. Conducting experiments on the Khan Academy platform, Muñoz et al. [118] confirmed that the total time spent on the platform is strongly related to the number of videos watched and the number of exercises successfully attempted. Sharma, Jermann and Dillenbourg [143] also recognized that the students who pass the course engage more with the course content than those who fail. Finally, Miyamoto [114] showed that the level of participation is a predictor of better grades and course completion. Thus, the *time spent on the course pages* can be a good parameter to measure the effort learners invest in the MOOC [158, 124].

To enrich the information conveyed by the *time spent on platform* metric, the `Learning Tracker` investigates also **how** this time is used. Similarly, StepUp! [137] and SAM [58] report to the learners how much time they send on the platform and how they distribute it on using different tools in open learning environments. However, in our design, the focus was placed on how learners use video-lectures. This was expressed by metrics that give absolute numbers e.g. *time spent watching videos*, and metrics that indicate ratios e.g. *ratio video-time/total-time*. The *ratio video-time/total-time* metric represents the fraction of time spent watching video lectures while being on the course pages.

Cluster 3: Time management The *timeliness of submission* indicator measures learner's proactivity. The metric reflects the average time between the last attempt on the graded quiz questions and the submission deadline of the assessment. The metric was included based on the premise that learners gain more knowledge and thus increase their chances of graduating if they complete the assessments without the pressure of an immediate deadline. A similar metric was used by Sharma et al. [143], revealing that successful learners were procrastinating significantly less than the others. Chen and DeBoer [34] also showed that the extent to which students start the homework before the due date is very strongly tied to their level of achievement.

Generating information sets

Based on the learner model described above, we generated two information sets: (i) one instance for the *average graduate* and (ii) one instance for each *learner currently enrolled* in the MOOC.

The information set describing the behaviour of the *average graduate* was generated once (off-line) using the log traces of the previous edition of the course. The information set consists of series of weekly snapshots of the *average graduate*'s behaviour. Each snapshot is constructed of the metric values and characterizes the learning habits of the *average graduate* for that respective week. We synthesized the learner profiles computed for each graduate into a single profile that describes the *average graduate*. On the other hand, in order to obtain the information sets for learners currently enrolled in the course, we used log traces generated in the current edition of the MOOC. We generated one profile for each learner. Similar to the profile of the *average graduate*, the current learner profile was composed of a collection of snapshots. As the course progressed, the profile was updated by adding another snapshot every week. Each weekly snapshot describes the activity of the learner (or the average graduate) from the beginning of the course up to the beginning of the respective week.

For both profiles, we were constrained to compute the behaviour snapshots on a weekly basis due to edX data availability. EdX makes research data (i.e. trace logs and database snapshots) available for download for its partners only once a week.

A. Metric calculation The low-level user activity data used as input data for the `Learning Tracker` was extracted from edX log traces. The log traces provide comment logs, quiz results, step activity, enrolment activity, and peer-review activity. Additionally, they contain metadata such as timestamps for each event, and anonymised author identifiers [1]. The log traces are processed via Python scripts, extracting data that describes high-level traces. The high-level traces contained information about each session logged by the learners, the videos watched, the quizzes submitted and the visits to the forum pages. The high-level trace log data used by the `Learning Tracker` was modelled following the MOOCdb data model[1] and is illustrated in Figure 3.1.

The calculation of most of the used metrics is based directly on counting or averaging values from the tables presented in Figure 3.1. For example, *time on the platform* is calculated by summing the field *duration* from the *sessions* table for every session logged by a learner and *number of videos accessed* is operationalized as the number of entries in the *observations* table that contain distinct video identifiers. However, the metric *timeliness of submission* should be highlighted as its calculation required additional data processing.

The *timeliness of weekly assessment submissions* is determined based on the submission time of answers to graded quiz questions belonging to a weekly assessment that contributes to the final grade. The metric is calculated by averaging the time between the moment a user submitted an answer to a graded quiz questions and the deadline of the weekly assessment the quiz question belongs to. The lower the value of the metric, the closer to the deadline the submission was done. If the quiz answer is submitted after the deadline, it is considered overdue and it is not included in the calculation of the average.

B. Average graduate synthesis Last year's graduates were considered learners that obtained a passing grade at the end of the MOOC. After calculating the six metric values in each week for each graduate, the data was aggregated into a single value per metric for each week. The *average* across all these learners for each indicator was considered as an adequate means of aggregating the data as it is an indicative of the tendency of the whole group. The successful learners did not exhibit a uniform behaviour and each indicator was covering a long range of values. To avoid

[1] http://moocdb.csail.mit.edu/

outliers altering the resulting mean, for each metric the values that fall in the bottom 5% and the top 5% of the data range were omitted.

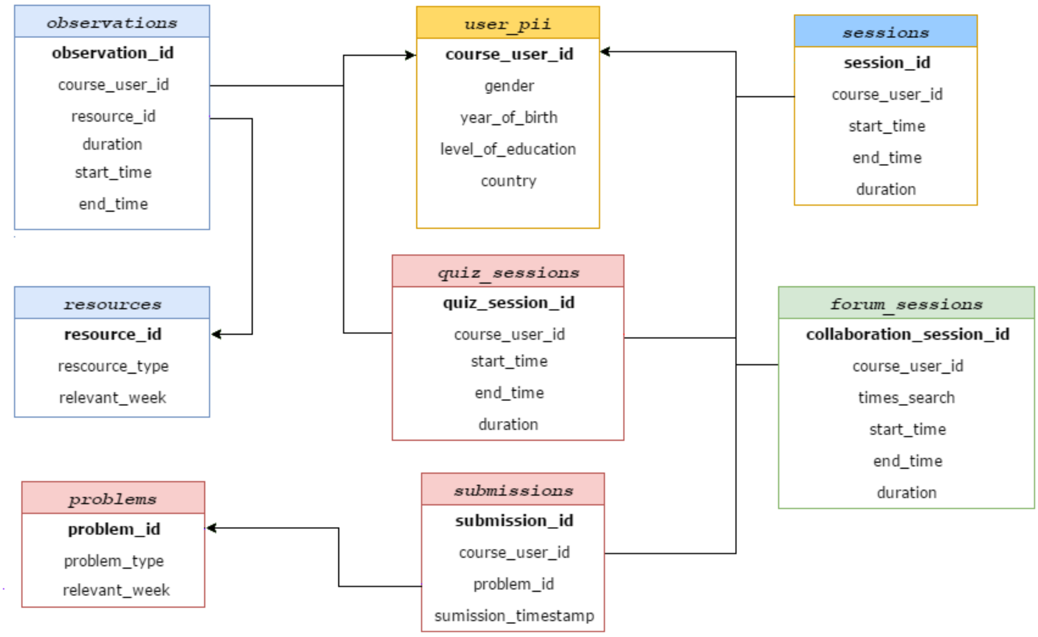

Figure 3.1: The structure of the data files used as input for the metric calculation and the relationships between the fields of each file

3.2.2 Visualisation

Humans can process large amount of data if presented in a meaningful way. Transforming this data into knowledge is a cognitive process that can be greatly influenced by the way in which data is presented. Therefore, visual representations of data are critical to sense-making. The following lines describe the visualisation design rationale behind the `Learning Tracker`.

Chart type After considering several visualisation options (including bar charts, gauges and calendar charts like in [137, 128]), we decided that the most suitable solution is a spider chart as visualised in Figure 3.2. A spider chart allows the display of multivariate data in the form of a two-dimensional chart of three or more quantitative variables represented on radial axes starting from the same point. The advantages of spider charts over the other options are:

- concise visualization of numerous indicators in a small space
- overall evaluation of one's performance and consistency across all metrics
- simple representation of metrics - data is shown as single points along radial straight lines
- information sets are illustrated as data series
- easily comparable medium - information sets are represented as differently coloured areas that can be stacked

Displayed information We designed the visualisation in a way that conveys only the essential information and it does not clutter the display. The information displayed on the widget has only two dimensions: (i) the information set that characterizes a category of learners and (ii) the metrics that describes a specific aspect of the learning behaviour. The widget has been stripped of any needless textual information. The only textual elements are the name of the behaviour metrics displayed and the legend containing the name of the two information sets. The main element that conveys information is graphical: the area determined by connecting the data points of each metric for one information set.

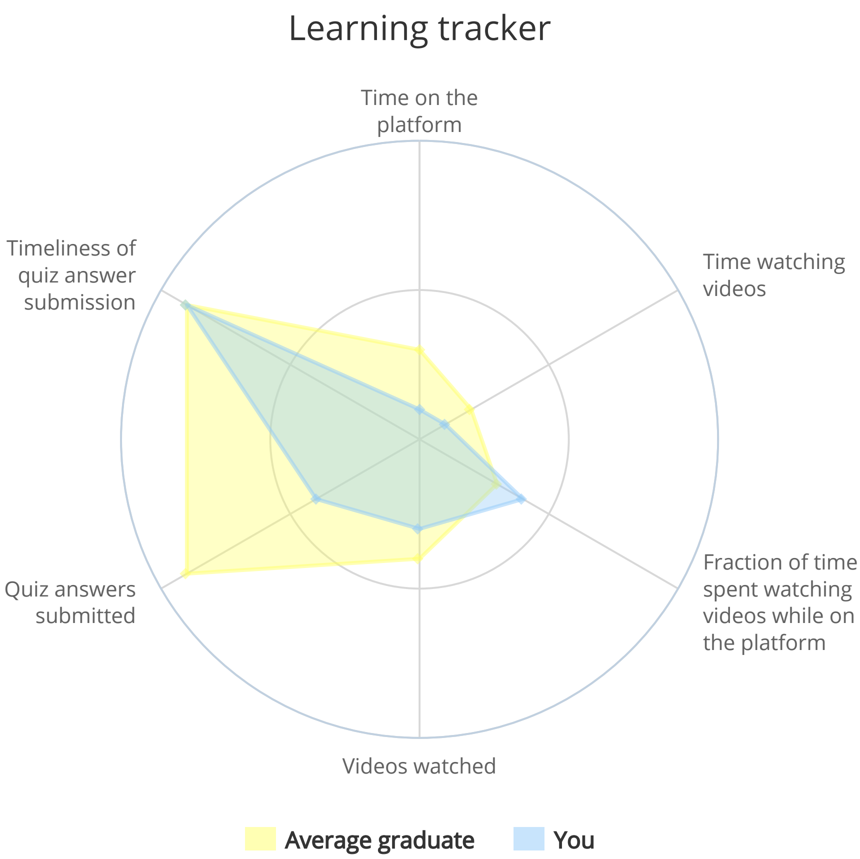

Figure 3.2: The `Learning Tracker` visual design. The spider chart provides a concise visualization of several metrics in a small space and it offers a simple overall evaluation of one's performance and consistency across all metrics.

a. Information sets On the `Learning Tracker`, the learners can view two information sets describing learning behaviour: (i) their own learning behaviour up until the beginning of the current week and (ii) the behaviour of last year's graduates up until the beginning of the current week. Figure 3.3 shows two snapshots of the *average graduate*'s behaviour of how the learning habits evolve from the beginning of a course until close to the end.

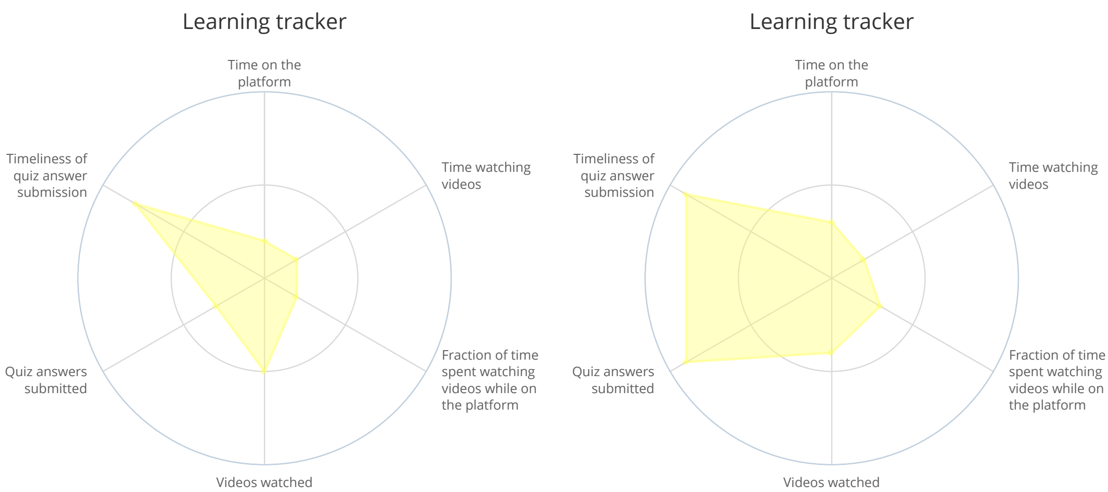

Figure 3.3: The evolution of the *average graduate* learning behaviour in a test MOOC from week 2 (left) until the end of the course - week 10 (right).

b. Metrics Each information set is described by metrics. To narrow the learner's attention on specific learning habits, the number of metrics displayed on the widget is limited to six. To allow for a consistent representation in the same graph, the data points have been scaled in a range from 0 to 10, where, in general, 0 indicates no activity. An exception is the metric *timeliness of quiz submission* for which the 0 value indicates that the learners submit the assignments within one hour before the recommended deadline or past this deadline. Also, a value of 0 for the metric *average time between sessions* indicates that the learner register maximum one session on the platform and thus the metric can not be computed. 10 corresponds to the maximum value for the respective metric among the last year's graduates except the bottom 5% and the top 5% of the data range to avoid outliers. Thus the value of the outer ring increases each week, and the zero point remains constant. The values for both previous and current edition were scaled against the same maximum value to keep the same scale. Since the value in the current edition could exceed the maximum value set by the previous edition, any metric value exceeding this maximum was scaled to 10.

Colour Each one of the two information sets is assigned a colour. The colour coding for each set helps learners to visually correlate and compare their learning behaviour to the one of last year's graduates over its diverse aspects. In order to minimize any feelings of external judgement or assessment from the visualizations, the colours used in the design are kept neutral (blue and yellow). There are no red "danger zones" as red is implicitly associated with failure and danger and lowers motivation in an achievement context [51]. On the other hand, there are also no green "safety zones" on the chart with the purpose of increasing awareness and encouraging growth via visualized feedback.

3.2.3 Evaluation

The initial `Learning Tracker` prototype was evaluated in a between-group study using a TU Delft MOOC offered on the edX platform between January 12 and March 29, 2016. The experimental setup and the detailed analysis of the findings are presented in detail in Chapter 4 and 5, respectively. A brief analysis performed two weeks before the experiment ended revealed that the graduation percentage was higher among learners that had access to the widget and already completed the course. Additionally, we identified that the widget had a significant effect on the metrics *number of grade quiz questions attempted* and the *timeliness of quiz answer submissions.*

3.2.4 Second iteration of the `Learning Tracker`

Based on the results of the first iteration, we made improvements to the widget both in the data processing and in the visualisation, preparing the widget for a second set of experiments. The second iteration of the widget was deployed on two other TU Delft MOOCs offered as well on edX in the period April-June 2016. The following section describes the main adjustments to the widget, while a summary of all the changes can be found at the end of the section.

A. Changes related to the information displayed

In the second iteration, we made three changes related to the information displayed on the widget and its implementation: (i) we changed the metrics that were displayed to the learners to better support self-regulation skills, (ii) we added an additional information set that describes the behaviour of the *average graduate* at the end of the current week, and (iii) we added a tracking feature in order to monitor learners' interaction with the widget. Each adjustment is described in detail in the following paragraphs.

1. Displaying different configurations of metrics

One of the major adjustments to the `Learning Tracker` in the second iteration was the replacement of four of the metrics displayed on the widget as described in Section 3.2.1. To ensure the metrics are relevant and they convey meaningful information, the metrics that showed to have an impact on the learners were kept in the subsequent two studies to verify the results obtained. These two metrics are *the number of quiz answers submitted* and *the timeliness of quiz answer submissions.* The other four metrics were mainly replaced with metrics that better emphasize the time-management aspect imposed by self-regulated learning as described in Section 2.2. Table 3.2 gives an overview on the metrics used in the two designs of the widget. We further describe the additions to each of the metric clusters.

Table 3.2: Overview on the metrics used in this research, their description and the unit of measurement for time metrics (h for hours, m for minutes and s for seconds).

Cluster	Metric	Description	Unit
Course coverage	number of quiz answers submitted	Number of graded quiz questions attempted	-
Engagement	time-on-task	The fraction of time performing learning activities while on the course pages	-
	number of forum sessions	Number of times the learner visits the forum pages of the course	-
Time management	sessions/week	The average number of times the learner logs into the course pages	-
	average length of a session	The average length of a visit on the course pages	m
	average time between sessions	The average time between two consecutive visits on the course pages	h
	timeliness of submission	The average time between the last attempt on graded quiz questions and the deadline for submission	h

Cluster 1: Course coverage As the metric *number of video lectures watched* did not show to have any effect on learners' behaviour in the evaluation of the first iteration, we removed it from the following iteration. Apart from *number of quiz questions attempted*, no other metrics were added to this cluster, as the feedback reported by the second iteration was focused on engagement and self-regulated learning skills.

Cluster 2: Engagement In literature, engagement is described by two dimensions: engagement with course material through individual activities and interaction with the community of other learners [68]. High engagement on both aspects is an indicator that a learner is actively participating in a course.

To describe *engagement with course material* we added the metric *time-on-task*. The metric is a generalization of *ratio video/total time* and represents the proportion of time that learners spend on learning activities. In addition to watching video lectures, we extended the range of learning activities to visiting forum pages and visiting weekly assessment pages, similar to [114]. However, it should be mentioned that value of 100% for the *time-on-task* metric is not ideal as reflection time is a vital aspect of online learning [71]. Thus, learners need to offer themselves enough time to process the new information while on the course pages and the learning tracker shows which ratio successful students in the past have exhibited.

In this iteration, we also investigated the *engagement with course community.* Literature shows that learners can improve their learning by connecting with their network or community. Haug et al. [68] claim that social connectivity can influence involvement and learning in Open Courses. In a MOOC environment, the feature most relied on to encourage connection and knowledge sharing between learners are the discussion forums, although they are notoriously underused [101].

The correlation between activity on the forum and final grades or course retention has been heavily investigated. Numerous studies found that certificate earners used the forum at a much higher rate and forum participation could be used as a predictor for completion [40, 21, 36, 138, 72]. However, Kizilcec et al. [88] found evidence that suggests that there is no causality link that points from forum participation to persistence. Instead, both learners' forum activity and persistence in the course are influenced by a third variable, such as motivation for enrolment or time constraints.

We report learners' engagement with the course community by adding the metric *number of forum sessions.* This metric accounts for any activity in the forum, including just reading posts written by other learners, posting questions, or replying to threads.

Cluster 3: Time management Although the amount of time spent on studying is important, the way the study time is used also impacts the learning. The *spacing effect* is a phenomenon well known in psychology where long-term retention is improved if the same material is shown in distributed presentations adding up to a given amount of time rather than in massed presentations of same total length [32].

Miyamoto [114] demonstrated the validity of the *spacing effect* in MOOCs by investigating the relationship between how students allocate their time in MOOCs and how they perform. His results showed that students who distribute their time into a larger number of sessions had higher levels of certification than students who spent similar to total time on-site divided into fewer sessions. Thus, the author argued that student learning can be improved by encouraging learners to divide their total study time in multiple sessions.

At the same time, the distribution of sessions over the duration of the course has also been shown to impact the learning outcome. Muñoz et al. [118] tracked the time distribution of use of the platform by measuring the learner's constancy - checking whether the learner was studying in a constant way during several days or was studying strongly only for a few days. Their results also indicate that students might learn better for the long term if they do it in a constant way.

To encourage learners to distribute their study sessions and to regularly dedicate time to studying, the `Learning Tracker` widget displays *average sessions per week*, *average length of a session* and *average time between consecutive sessions*. In a similar work, apart from the total log-in time, Park et al. [128] also used the log-in frequency and the log-in regularity. However, the effectiveness of the metrics on learner behaviour was not investigated.

Metric calculation As the calculation of two newly added metrics is not trivial, we describe them in the following paragraphs.

Average time between sessions This metric is defined as the average time between two consecutive sessions logged in the trace files. However, to account for short breaks during one learning session (e.g. when a learner logs several sessions 5 minutes apart) that lower the value of the indicator, all consecutive sessions with less than 1 hour in between are considered belonging to the same session. The effective value of the metric is calculated by averaging the time between two consecutive blocks of sessions. In case the learner has only one logged session, the metric is not calculated and is represented on the widget as 0.

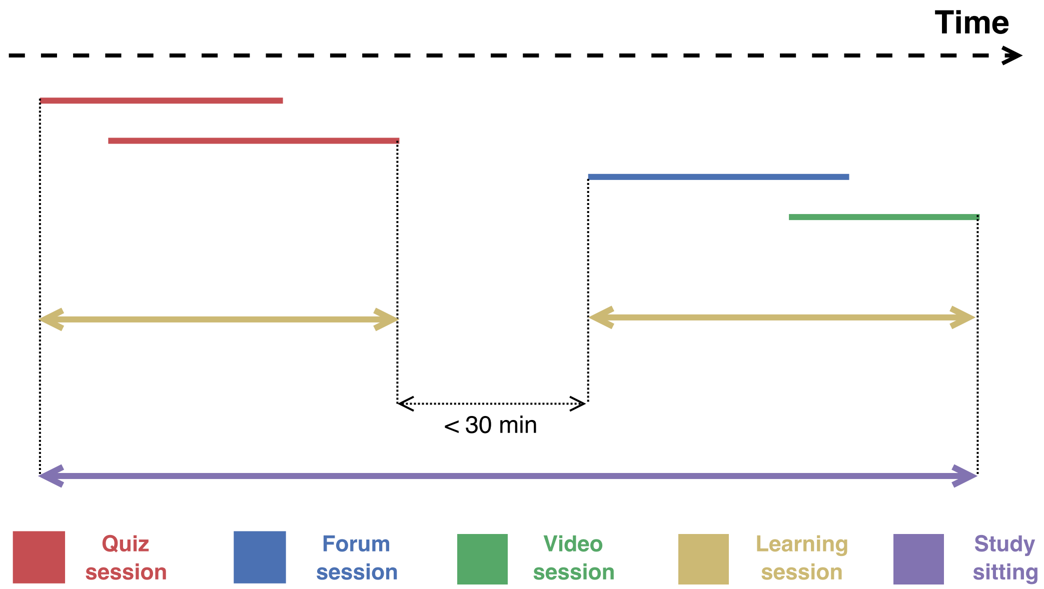

Figure 3.4: The construction of a study sitting. Overlapping learning activities (possibly as a result of several browser tabs open simultaneously or errors in the logging) are merged into learning sessions (orange). They include quiz sessions, forum sessions and video watching sessions. Learning sessions are counted as time-on-task. A study sitting is then constructed by consecutive learning sessions with an inactive time of maximum 30 minutes in between.

Time-on-task Several inconsistencies in the edX trace logs hindered the calculation of the *time-on-task* indicator. For example, the logs contained overlapping *quiz session* or *forum sessions* timestamps that did not overlap with any logged *session* timestamps. This meant that this quiz or forum time was not accounted as time spent on the course page. Possible reasons for these inconsistencies are errors in the tracing code or having course pages simultaneously open in several browser tabs.

As a solution, we defined and constructed *study sittings* as a sequence of learning activities with less than 30 minutes of inactivity in between. Learning activities were considered to be (i) a video watching session, (ii) a quiz session and (iii) a forum session. A similar approach was used in [114], where a session was defined as a collection of click events separated by 30 minutes of inactivity. Figure 3.4 illustrates the way a study sitting is constructed.

2. Adding another information set

We extended the information sets available on the widget with *the behaviour of last year's graduates at the end of the current week*. By providing access to the graduates' data at two points in time (i.e. end of last week and end of the current week), the role of the widget is two-fold. Firstly, it encourages *reflection* on one's study habits by comparing their progress with the one of graduates at the certain point in time. Secondly, it also offers support in *planning* current week's study by allowing learners to peek into the future and see how the average graduate's status looked like at the end of the respective week in the previous edition of the course. To visually suggest the contrasting purpose between the two, the information set describing the behaviour of graduates up to the end of the week is graphically represented as a line and not as an area as illustrated in Figure 3.6 on the right.

3. Tracking interaction with the widget

The pilot study was based on the assumption that learners in the test group check the widget regularly. However, having access to the `Learning Tracker` does not imply that in reality learners use the widget. The reasons for this might be as diverse as not reading the introduction page of the module, and thus not knowing about the widget's existence, or lacking a genuine interest in such a tool.

To make the studies independent of this assumption and their results more reliable, we integrated functionality that tracks the interaction with the `Learning Tracker`. To keep the amount of data collected reasonable and limited to essentials, only two types of events were tracked:

- *loading the widget* - a measure for how many times a user is viewing the widget
- *showing or hiding an information set* - a measure for how much the user is interacting with the widget and in what ways

However, this data is not shown to the learner, but used in our results analysis.

B. Changes related to the visualisation

Figure 3.5 illustrates the different designs used in the pilot and main studies. The two main adjustments made to the visualisation refer to (i) the addition of interactive elements and (ii) the randomization of the order in which metrics are displayed on the widget.

1. Adding interactive elements

We enhanced the widget with interactive elements as shown in Figure 3.6. Firstly, by hovering over any data point, a **tool-tip** is displayed with the actual values of the indicator for all the active information sets: *learner, graduates last week* or *graduates this week*. This additional information would allow the learners to assess how much effort they still have to put in to reach the average graduate's threshold. Secondly, to keep the graph light and simple for comparison, learners can choose which information set to show or hide on the chart by clicking on the set's name in the legend. By default, the status of successful students at the end of the current week is hidden so reflection is the first cognitive process that is triggered. Learners have to actively choose to display the information set describing the average graduate for the end of the current week.

These additions extend the way the learner can interact with the widget, but they do not allow the learner to alter the underlying model or make corrections to the information displayed. A study conducted by Bull [25] showed that learners prefer to use *inspectable learner models* - where the user has no control over the model data), rather than *editable* - where the learner has complete control over the model, or *negotiated* - where there is joint control.

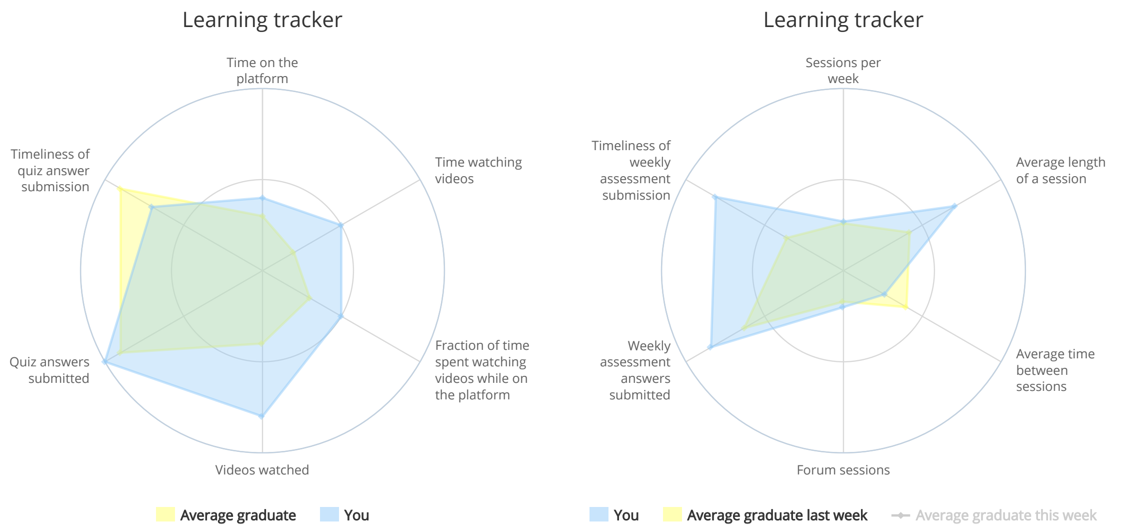

Figure 3.5: Widget design in the pilot study (left) and the main studies (right). The main differences visible in this figure are the change in metrics and the additional information set (average graduate this week).

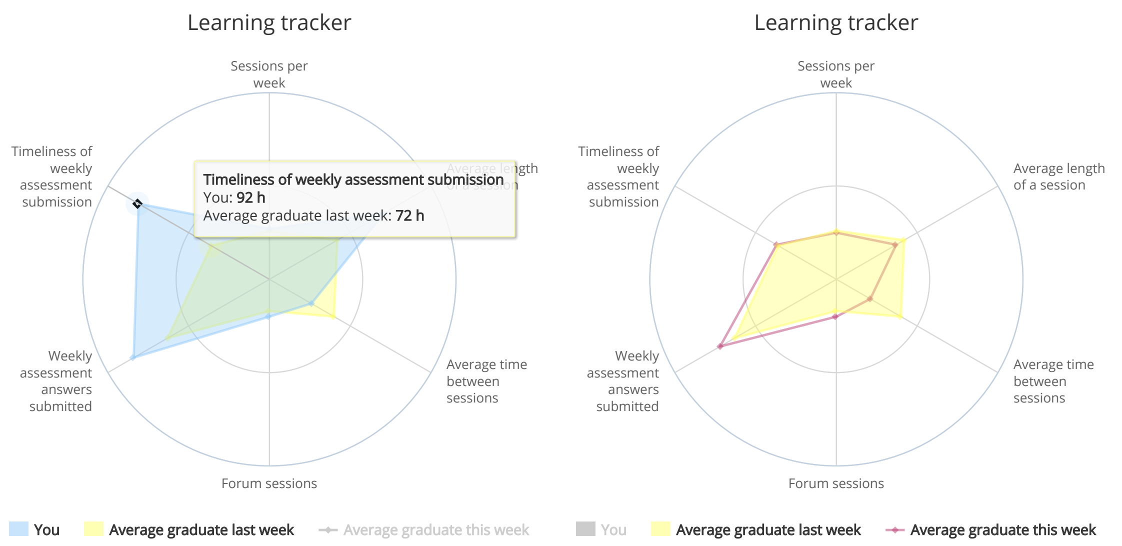

Figure 3.6: Interactive elements of the widget: an activated tool-tip with additional information for data points (left) and an instance of the widget with the information set *You* hidden and the two information sets describing the *Average graduate* shown (right).

2. Variable metric order on the widget

A well known phenomena in psychology named the *primacy effect* occurs when people are forming a summary impression of a single entity at first sight. The effect speculates that the earliest information seen or received has a larger impact on the global impression than later information does [102]. The primacy effect is also debated in search engine development where Keane et al. [79] demonstrated that people do manifest some bias, favouring items at the top of search results lists.

Through its circular design, the `Learning Tracker` avoids the trap of ordered lists that might direct the attention of the reader to its first entries. However, one might argue that the metric displayed at the top of the widget can generate a primacy effect and bias the learner's opinion towards the information displayed on the widget. To tackle this issue, we presented three versions of the widget that had a different metric displayed at the top as shown in Figure 3.7. Each version of the widget was rotated counter-clockwise with respectively 0, 2 and 4 positions. In this manner, each of the metrics *sessions per week*, *average time between session* and *weekly assessment answers submitted* were at the top of the widget.

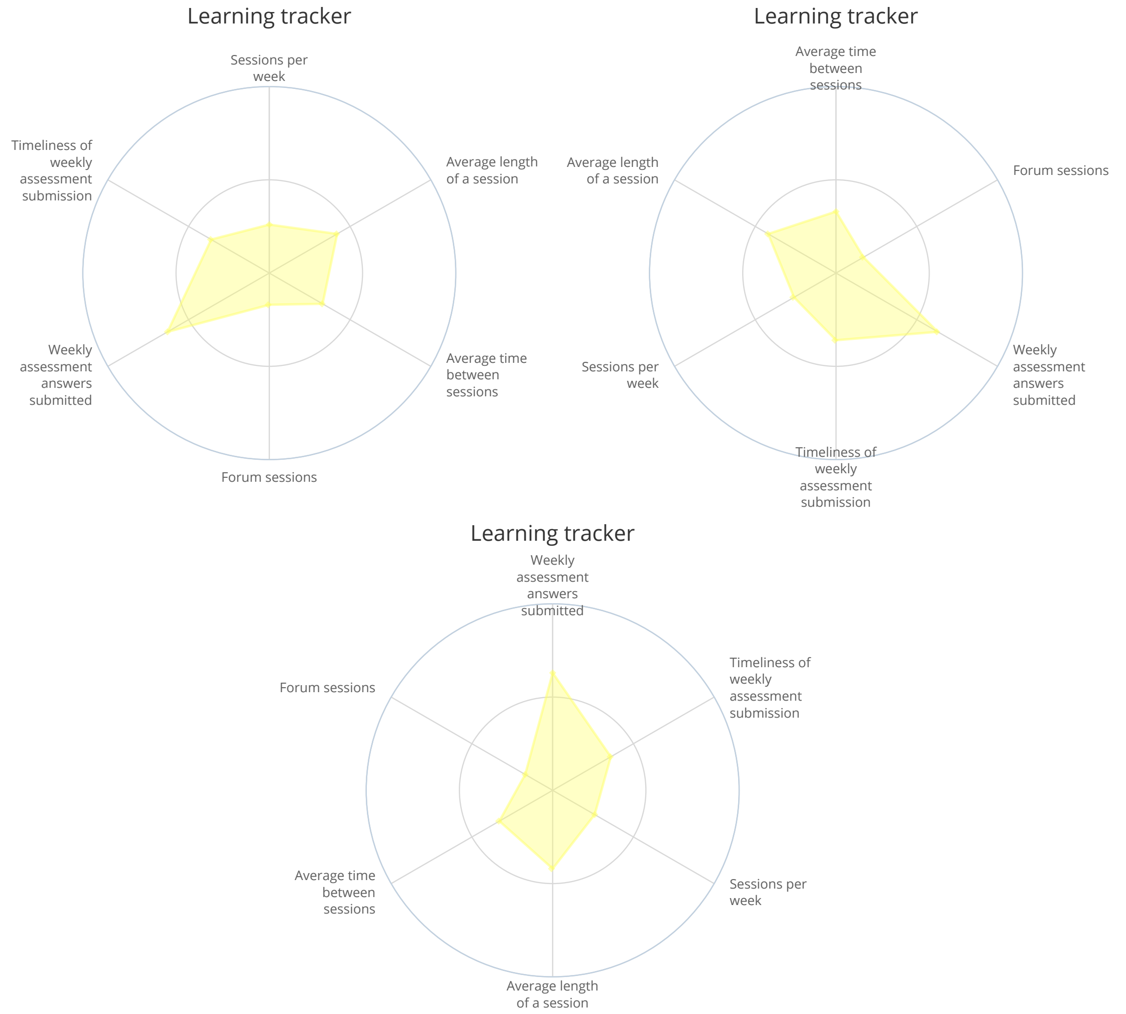

Figure 3.7: The three versions of the `Learning Tracker` illustrating the variable metric order on the display. The spiderchart is rotated counter-clockwise 0, 2 and 4 positions. Every version presents a different metric at the top.

Below we summarize the improvements made to the first iteration of the `Learning Tracker`. The points marked with (I) cover changes in the information displayed on the widget or in the way metrics are calculated, while the differences marked with (V) refer to adjustments in the visual display.

- (I) different metrics are displayed on the widget
- (I) an additional information set describing the average learner at the end of the current week is available
- (V) interactive elements are added: tooltips over data points showing metric values and possibility of showing or hiding information sets
- (V) the order in which metrics are displayed on the spiderchart varies
- (V) the interaction with the widget is tracked

3.3 Technical implementation

The implementation of the widget covered two main aspects: the visualisation and the information to be displayed. As the `Learning Tracker` was developed for the edX platform, several design and implementation decisions were influenced by the technical possibilities offered by edX. The implementation of the `Learning Tracker` followed three steps:

1. creating the graphic display
2. processing the raw data into learner profiles to be displayed on the widget
3. populating the widget with the information contained by the learner profiles

In its essence, the `Learning Tracker` is a JavaScript script that draws a chart with two or three information sets. The series describing the behaviour of successful learners stay the same for all learners, while the metric values describing learner's behaviour are personalised. All the generation steps listed above were coded into a software tool using the Java programming language. As input, the system uses the CSV (Comma Separated Values) files that contain the pre-processed data from learner trace logs. Through a sequence of modules, the tool calculates the metric values and scales them in preparation for display on the widget. As output, the tool writes one script containing personalized information for each learner.

Graphic display The visualisation was generated using Highcharts[2], an external charting library. Highcharts is written in pure JavaScript, relying only on native browser technologies which allows for an easy integration of the `Learning Tracker` on any website. The installation of the dashboard is reduced to adding a JavaScript script into the web page. The features that were reasons for choosing Highcharts are:

- supports a wide range of chart types
- highly flexible design, as every element of the chart is configurable
- offers a simple configuration syntax for charts through a JavaScript object
- allows hooks for programming against the chart via numerous events
- supports external data loading
- does not require client side plugins and is highly compatible with mobile and desktop browsers

By using Highcharts, the configuration of the graphic display is done in a JavaScript script by setting appropriate options for a JavaScript object that instantiates a chart. The configurable elements of the chart range from the type of chart and its aesthetics to setting up interactive elements like tooltips and data loading animations.

Data processing In the data processing step, the learner profiles are generated by calculating the metric values from low-level activity data. The computation followed the metric definitions described in Section 3.2.1.

Figure 3.8 illustrates the `Learning Tracker` data processing module along with the input and output files. As mentioned in 3.2.1, there are two types of learner profiles to be computed i.e. the average graduate and the current learners, that follow different computation paths. The input data is received Comma Separated Values (CSV) files with the structure pictured in Figure 3.1.

The *average graduate* profile is calculated once, before the `Learning Tracker` is deployed in any MOOC. The *current learner* profiles are computed and updated on a weekly basis. The output files contain the scaled and non-scaled metric values, for all the enrolled learners in the MOOC based on the most recent trace log data.

[2]http://www.highcharts.com/

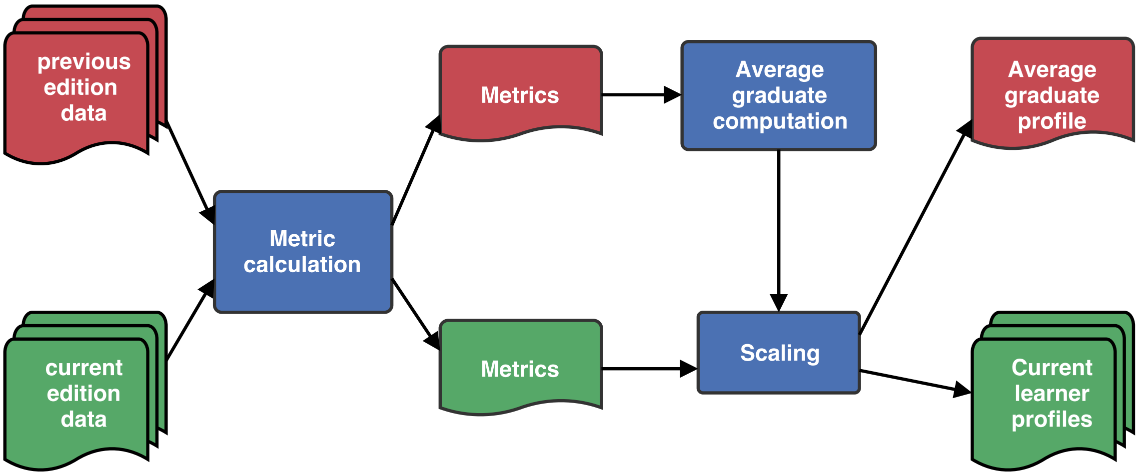

Figure 3.8: The data processing module as part of the `Learning Tracker` generation tool. The *blue* blocks represent data processing module. The *red* path illustrates the generation process for the average graduate profile. The *green* path follows the generation process for current learner profiles. As output, there is one profile for the average graduate and one profile for each currently enrolled learner. The average graduate profile is generate once, before the course starts. The profiles of current learners are generated on a weekly basis once the learner data is updated.

Script generation In the final step, the `Learning Tracker` generation tool writes the JS script containing the personalized learning profile for each currently enrolled learner. The widget is populated with data by setting the *series* field of the Highcharts chart object with metric values for each of the three information sets. This module uses as input the files generated in the *data processing* module.

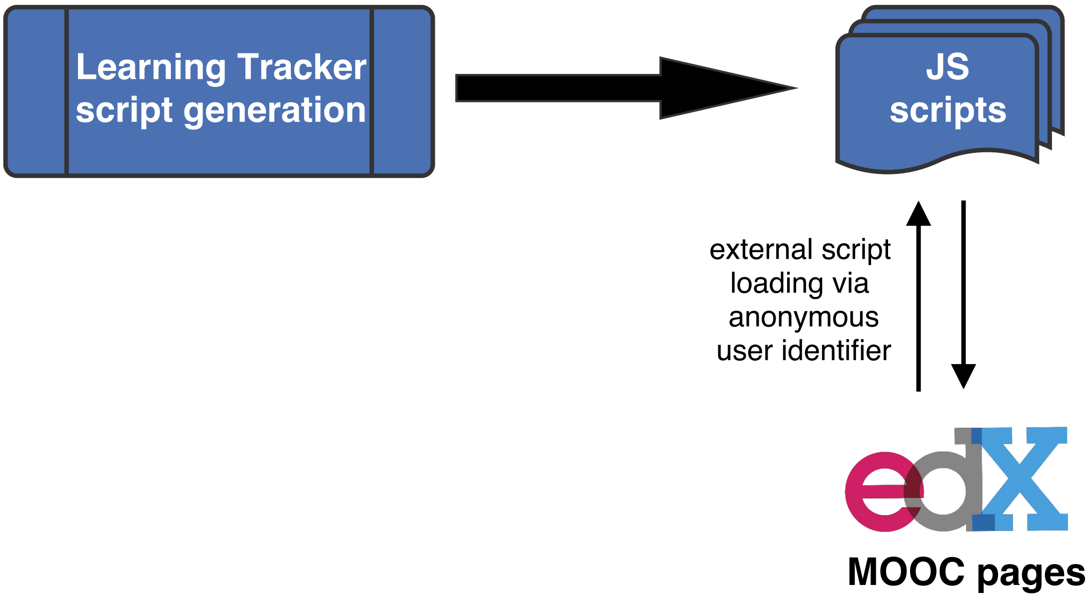

Figure 3.9: Overview on the technical elements of integrating the `Learning Tracker` on the edX platform. Once generated, the widget scripts are uploaded on the edX FTP server. From there, they are loaded as external scripts on the edX course pages via the anonymous edX user identifier.

Integration with edX The `Learning Tracker` was integrated with the MOOC pages on the edX platform through a JavaScript snippet that was individually added on the introductory sub-module page of every learning module. The snippet covered the following functionality:

- loading the `Learning Tracker` dependencies: two Highcharts scripts available online

- loading the `Learning Tracker` script
- loading the widget interaction tracking code
- inserting into the page an HTML `div` element that contained the widget and the explanatory text

The widget is a JavaScript script and thus it can easily be integrated with edX. For each learner, the `Learning Tracker` code is stored into a JavaScript file named after the learner's edX anonymous user identifier. The JS scripts containing the personalized widget code for each learner were generated at the beginning of the week once the edX trace log data became available. Once uploaded on the edX FTP server, the scripts were loaded in the MOOC pages as external scripts.

An up-to-date version of the `Learning Tracker` code is available on GitHub in the following repository: `https://github.com/ioanajivet/LearningTracker`.

The present chapter described the development of the `Learning Tracker`. Following an iterative approach, we designed and implemented an initial version of the widget and deployed it in a real-world MOOC offered by TU Delft on the edX platform. Based on the results of a preliminary analysis, we made adjustments to the type of information displayed on the widget and to the visualisation and deployed a second iteration of the `Learning Tracker` in two other TU Delft MOOCs. The experimental setup along with the results of our extensive analysis are presented in the following chapters.

Chapter 4

Research design

We designed the `Learning Tracker` as a feedback tool that offers learners the possibility to reflect on their learning behaviour compared to that of previously successful learners. To evaluate how helpful the `Learning Tracker` is in aiding learners to become more effective, every iteration of the widget was evaluated in live TU Delft MOOCs running their second edition on the edX platform.

The studies were conducted on three real-world MOOCs across the entire duration of each course, engaging over 20.000 learners. We highlight this aspect as one of the main contributions of this work. Longitudinal studies of such magnitude across several MOOCs are rare in research. This approach allowed us to evaluate several aspects of the `Learning Tracker` and monitor learners' behaviour over extended periods of time.

Our investigation was guided by two main research questions with several subpoints:

RQ1: Are learners more likely to complete the course when they can compare their behaviour to that of previous graduates?

RQ2: To what extent is learners' behaviour affected by comparing themselves to previously successful learners?

1. Do learners become more engaged with the MOOC when they can compare their behaviour to that of successful learners?
2. Do learners show improvement of their time-management skills when they compare their behaviour to that of successful learners?
3. Do learners change their behaviour so it becomes similar to that of successful learners when they can compare themselves to it?

The following chapter presents the three MOOCs used for evaluating the `Learning Tracker` and the adopted experimental setup.

4.1 MOOCs used for the live experiments

The first iteration of the `Learning Tracker` was tested on `WaterX` during January-March 2016, while the second iteration was deployed on `SewageX` and `InnovationX`. The current section provides details on the enrolment and completion statistics, the structure of the MOOCs and their participants.

`WaterX` - *CTB3365DWx Introduction to Drinking Water Treatment*[1], is the first MOOC of the *Water Management* XSeries Program, a group of three edX courses offered by TU Delft that aim to provide learners with a rich understanding in the field of safe water supply and hygienic water treatment. This MOOC aims to teach the role of conventional technologies for drinking water treatment and is based on a third year BSc course of the study Civil Engineering of TU Delft. The estimated effort a learner has to invest for course completion is 6 - 8 hours/week.

`SewageX` - *CTB3365STx Introduction to Treatment of Urban Sewage*[2] is the second MOOC in

[1]https://courses.edx.org/courses/course-v1:DelftX+CTB3365DWx+1T2016/info
[2]https://courses.edx.org/courses/course-v1:DelftX+CTB3365STx+1T2016/info

the *Water Management* XSeries offered by TU Delft in the field of Civil Engineering and its academic goal is to teach learners about urban water services, focusing on basic sewage treatment technologies. The weekly effort recommended by the course team is also 6 - 8 hours.

`InnovationX` - *RI101x Responsible Innovation: Ethics, Safety and technology*[3], independent from the previous two, is offered by the Faculty of Technology, Policy and Management at TU Delft and aims to provide learners with an in-depth knowledge of what responsible innovation entails. By presenting relevant case studies, the course team seeks to impart a judgement that considers moral values as requirements for design of new technology.

Table 4.1 provides an overview of three MOOCs and their enrolment data in both editions used in the study. The table provides information on both editions of the course as data from both runs was used to generate information for the `Learning Tracker`. The first edition was used to generate the model of the successful learner, while learners from the second edition were presented with the `Learning Tracker`. Specific differences between the current and previous edition of each MOOC are discussed in the Section 4.1.2, along with the adjustments made for the `Learning Tracker` widget deployed in each MOOC.

Table 4.1: Overview of the three TU Delft MOOCs in which the widget was tested. The percentage of learners that graduated (i.e. obtained a final grade above a certain threshold set by the course team) is calculated based on the total number of learners enrolled at the beginning of the course.

	`WaterX`		`SewageX`		`InnovationX`	
	2014	2016	2015	2016	2014	2016
Start date	Oct 28, 2014	Jan 12, 2016	Jan 27, 2015	Apr 12, 2016	Nov 25, 2014	Apr 11, 2016
End date	Jan 13, 2015	Mar 29, 2016	Apr 7, 2015	Jun 20, 2016	Feb 13, 2015	June 14, 2016
Length	10 weeks	11 weeks	10 weeks	10 weeks	11 weeks	9 weeks
Enrollement	10 695	10 943	8 935	8 014	8 850	2 274
Graduates	281 (2.63%)	348 (3.18%)	469 (5.25%)	302 (3.76%)	383 (4.32%)	101 (4.44%)

4.1.1 Course material

Learning material All three MOOCs followed a similar structure, a structure particular to xMOOCs as described in Section 2.1. The learning material was divided into modules that consisted of several sub-modules with learning sequences. Each interactive learning sequence included short video lectures of 3 to 15 minutes, readings in the form of handouts based on the course textbook, non-graded practice knowledge quizzes to deepen the knowledge and graded weekly quizzes that counted towards the final grade (as presented in table 4.3). The quiz questions were multiple-choice or required numeric answers. Answer-check mechanisms were also provided so that learners could receive immediate feedback on their performance. Learners had up to 3 attempts available for some of the quiz questions. Table 4.2 summarizes the learning material available for each MOOC in terms of video-lectures, practice quiz questions and graded quiz questions.

Table 4.2: The learning material available for each MOOC in terms of video-lectures, practice quiz questions and graded quiz questions.

	`WaterX`	`SewageX`	`InnovationX`
Video lectures	58	81	53
Practice quiz questions	63	261	0
Graded quiz questions	25	35	76

In contrast to the other two MOOCs used in this study, `InnovationX` did not provide learners with practice quiz questions in each sub-module but rather provided more reading material and encouraged learners to engage in forum discussions. However, this particular setup does not affect the implementation of the `Learning Tracker` as we calculate the metrics based on the graded quiz questions.

[3] https://courses.edx.org/courses/course-v1:DelftX+RI101x+1T2016/info

Content release schedule The three MOOCs used different schedules for publishing content to their learners. The learning material of `WaterX` and `SewageX` was divided into five and six modules respectively, each module being release in one education week. After the education weeks, learners had four and three weeks, respectively, to finalize the graded assessments. Figure 4.1 (top and middle) sketches the timeline of the two courses, marking content release weeks and assignment deadlines.

`InnovationX` followed a different content release schedule. The seven modules were structured in three blocks and the learning material was published on three release dates, one for each block as shown in Figure 4.1 (bottom).

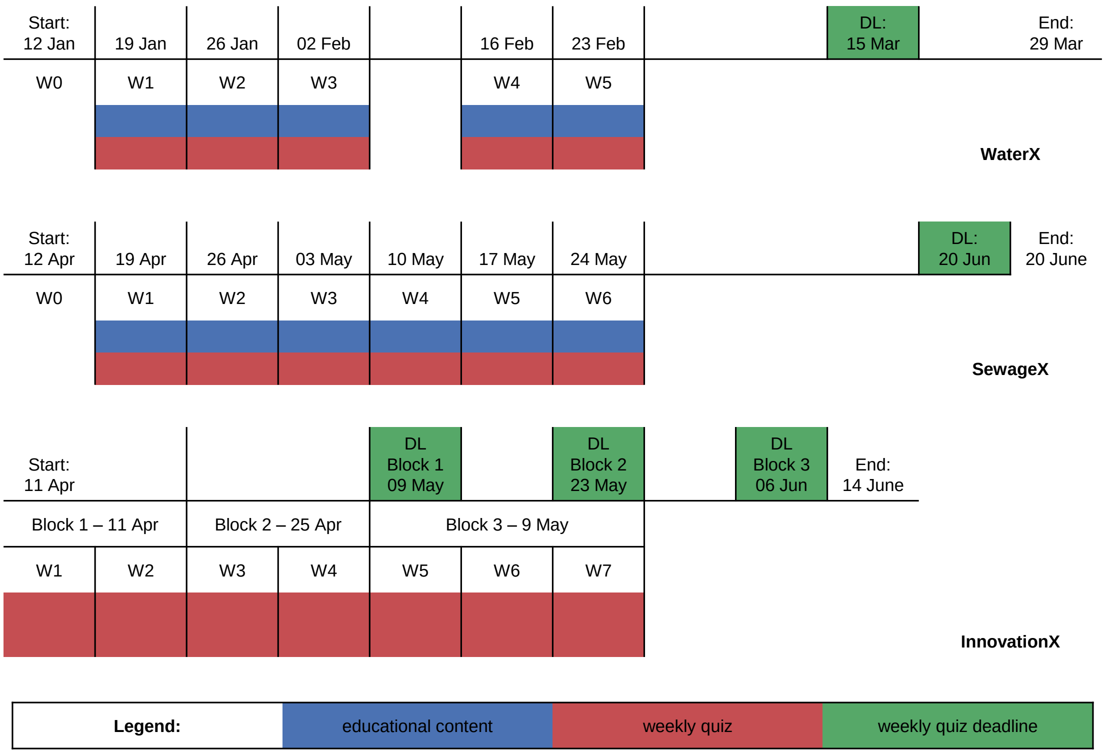

Figure 4.1: The structure and release schedules for the three MOOC, marking the content publishing dates and weekly assessment quiz deadlines.

Grading In order to graduate the MOOC and receive a completion certificate, learners had to score at least 60% on the final grade in all three courses, although the grading schemes differed. The grading scheme consisted of peer reviewed assignments and weekly assessments which included graded quizzes. The grading scheme for each course is summarized in Table 4.3.

Table 4.3: The weight of the weekly assessments and the peer reviewed assessments that contributed to the final grade. In contrast to the other two courses, `SewageX` did not request any additional assignments other than the weekly assessments.

	`WaterX`	`SewageX`	`InnovationX`
Weekly assessments	75%	100%	70%
Peer review assignments	25%	-	30%

The deadlines to submit the weekly assessments also varied depending on the course. For both `WaterX` and `SewageX`, there was one deadline for all the weekly assessments set in the last week of the course, while for `InnovationX` the deadlines for each weekly quiz were set four weeks after the publishing date of the content block they belonged to.

4.1.2 Course specific widget adjustments

Considering the differences between the three MOOCs with respect to the learning material, the content release schedules and the grading schemes, the `Learning Tracker` deployed in each experiment was adjusted to the particularities of each MOOC. A major difference between the `Learning Tracker` versions offered in the three MOOCs described above is the configuration of metrics displayed on the widget. The pilot study deployed on `WaterX` focused more on *course coverage* and *engagement* metrics, while the main experiments run on `SewageX` and `InnovationX` put an emphasis on *SRL time management* metrics. Table 4.4 presents an overview on the metrics available for learners in each of the studied MOOCs. The metrics are described in detail in Sections 3.2.1 and 3.2.4.

Table 4.4: The six metrics tested with the `Learning Tracker` in each of the three studies.

Cluster	Metric	`WaterX`	`SewageX`	`InnovationX`
Course coverage	number of quiz answers submitted	x	x	x
	number of videos watched	x		
Engagement	time on the platform	x		
	time spent watching videos	x		
	ratio video/total time	x		
	time-on-task			x
	number of forum sessions		x	
SRL time management	sessions/week		x	x
	average length of a session		x	x
	average time between sessions		x	x
	timeliness of submission	x	x	x

From year to year, it is usual that the course staff updates the course material or makes changes to its structure or grading scheme. These changes can affect the behaviour of the learners in ways that make comparison with last year's graduates obsolete. To prevent such consequences, several specific adjustments were made to the three versions of the widget, as listed below.

`WaterX` The grading scheme of the course changed as this year's edition did not include a final exam, making the submission of the weekly assessments more important. Additionally, in the previous edition the weekly assessments were due two weeks after they were released while in the current edition, there was a common deadline for all the assessments towards the end of the course. In these conditions, the metric *timeliness of weekly assessment submission* highlights the self-regulatory behaviour even more as students are required to pace their study and avoid bulk-learning close to the final deadline. To reveal this behaviour, this metric was calculated considering the deadline of each weekly assessment to be two weeks after its release.

`SewageX` The same issue appeared in the second course, as the deadline for weekly assessments was set on the last day of the course. In this case, the metric *timeliness of assessment submission* followed the same solution as for the `WaterX` study. The weekly assessment submission deadline was considered to be two weeks after the quiz was published to the learners.

`InnovationX` The third study had to account for even bigger changes between the two editions of the MOOC. In the previous edition, the course content was structured into four parts and the content release scheme followed four release dates. For the second edition, the course staff restructured the course content by merging the last two parts. This meant that the material for the last educational week was made available two weeks sooner to the learners. This change can potentially influence the metrics *weekly assessment answers submitted* and *timeliness of weekly assessment submission* to have higher values for this year's learners.

Additionally, the length of the course in 2016 was 9 weeks compared to 11 weeks in 2014. The two extra weeks were covering the winter holiday break and they did not include any new content or deadlines. To account for this, in the calculation of last year's graduate metrics, any event occurring in weeks 4 and 5 was incorporated in the calculation of the metrics of week 6, resulting in only one value for each metric.

A unique element of `InnovationX` that we leveraged in the calculation of the metric *timeliness of weekly assessment submission* was the concept of a *recommended deadline*. Since the course content was released in blocks and the learning material was available in bulk, the course staff proposed learning paths and encouraged learners to regulate their learning by recommending deadlines. As presented in Figure 4.2, the recommended deadlines for the weekly assessments suggest that learners should complete one module each week. To measure the learners' self-regulation abilities, the metric *timelines of weekly assessment submission* considered as a deadline the *recommended deadline* and not the *actual deadline*.

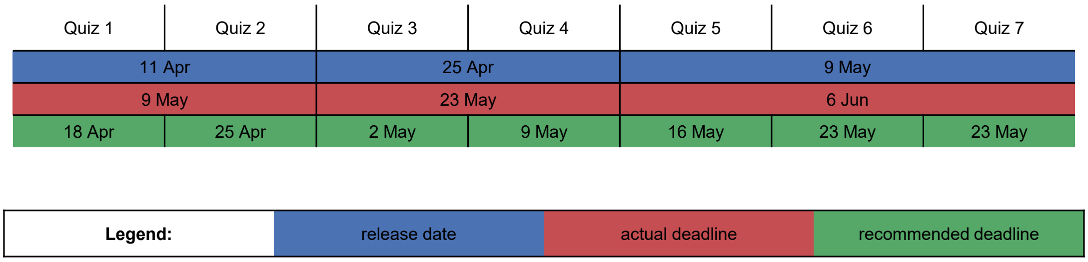

Figure 4.2: The grading scheme for `InnovationX`, highlighting the content release dates, recommended deadlines and actual deadlines for each weekly assessment quiz.

The metric *time-on-task* was evaluated only in the study covering `InnovationX`. As explained in Section 3.2.1, to overcome the inconsistencies in the edX log traces data, instead of using the data describing *sessions* provided by edX, we calculated *study sittings* based on the learning activities performed by learners. For consistency, all other relevant metrics i.e. *sessions per week, average length of a session* and *average time between sessions*, used in the third study were calculated based on the *study sitting* concept.

A final difference between the two experiments run on `SewageX` and `InnovationX` to evaluate the second iteration of the widget is the authenticity of the data displayed on the widget for the information sets describing the *average graduate*. The information for the `SewageX` widget was calculated based on the values of last edition's graduates. On the other hand, the *average graduate* values for the `Learning Tracker` deployed in `InnovationX` were not accurate and they do not express the behaviour of the average graduate in the `InnovationX` MOOC, but the behaviour of graduates in `SewageX`. However, in both setups, the metric values of the current learners were accurately calculated.

This setup was not initially intended, but an error in the script generation code was discovered only in week 6 of the course. A comparison between the two average graduate profiles revealed that they are similar for the five metrics which were tested in both MOOCs. However, the values for the sixth metric differed because the widget displayed *number of forum contributions* in `SewageX` and *time-on-task* for `InnovationX`. As a solution, three scenarios were considered:

1. *updating all the previously published widgets with the accurate data for the sixth metric* In this situation, all the data up to week 6 should have been discarded. Considering that the number of active learners decreases exponentially as the MOOC moves forward, the amount of data obtained in this scenario would be very limited.

2. *generating the* `Learning Tracker` *from week 6 onward using the accurate data for the sixth metric* Previously recorded data would not be valid in this case either. Moreover, confusion might arise among the learners in the test group because the data displayed on the widget would change from one week to the other. The learners do have access to next week's data for the information sets describing the behaviour of average graduates by activating the information set *average graduate this week*.

3. *continue generating the* `Learning Tracker` *for the remaining weeks with the erroneous data for the sixth metric* In this situation, all data recorded during the run of the MOOC would be consistent and can be used for evaluating the widget, as the information sets learners see did not change. However, the data analysis needs to take into account the fact that the values of the *time-on-task* metric for the average graduate are not authentic.

After analysing the three possible scenarios, we decided to continue generating the `Learning Tracker` with, in this case, irrelevant data for the metric *time-on-task* for *average graduate* information set in `InnovationX`. This decision was based on the assumption that providing the behaviour of *previously successful learners* as an anchor point for comparison could trigger a beneficial reflection process - no matter if the data displayed is random or accurate.

4.2 Experimental setup

In order to answer the research questions outlined in the previous section, each iteration of the `Learning Tracker` was tested on a different MOOC on the edX platform. In each study, we adopted the between-group testing method (or A/B testing or Randomized Controlled Trial) which requires dividing the test population in subgroups that are exposed to different conditions. Thus, we distributed the MOOC learners into a *test group* that had access to the widget, and a *control group* that was not shown the widget. The learners were randomly assigned to one of the two groups based on the parity of their edX user identifier. The assignment of learners to each group remained stable throughout the course. The sizes of the two groups were comparable for each course as reported in table 4.5.

Table 4.5: The number of enrolled learners for each MOOC and their division in test and control groups.

	`WaterX`	`SewageX`	`InnovationX`
Test group	5,460	4,038	1,184
Control group	5,483	4,099	1,168
Total enrolled	10,943	8,137	2,352

We chose to apply this method as it allows us to monitor the use of the `Learning Tracker` in a realistic setting and to assess its impact by comparing the behaviour of the test group with that of the control group. The control group provided a baseline against which any change in the behaviour of the test group could be observed. Additionally, since the method requires a live experiment, the behaviour of the two groups can be evaluated based on the log traces generated over the duration of the experiment. Thus, we can assess the impact of the `Learning Tracker`in terms of learner performance by relying on recorded data and not on subjective evaluations on usefulness and usability provided by learners as seen in [107, 59]. The between-group experimental design is largely used in psychological, economic, and sociological experiments, but has recently been applied in the learning analytics community for evaluating several interventions [116, 82, 85, 128].

At the start of every course week, together with the release of a new learning module, an updated version of the `Learning Tracker` widget was made available to the learners in the test group. The information shown on the widget was cumulative and the metrics were calculated aggregating the data of all the weeks up to that point in the course. The widget was placed in the introduction sub-module of every new learning module and learners could navigate back to previously released modules to track their progress over the weeks. Alongside the data visualisations shown in Figure 4.3, a short explanatory text was also provided. To keep the widget free of personalized interpretations of the displayed information, the explanatory text contained an example of a possible interpretation of a metric:

> *If you see that the yellow "Average graduate last week" value for the "Average time between sessions" (calculated by averaging the time between two consecutive visits of the course material) is considerably higher than your blue value for that metric, then you might benefit from making an extra effort to return to the platform more often.*

Additionally, to emphasize the reflective purpose of the `Learning Tracker` the following statement was also included in the explanatory text:

> *These graphs are not meant to be judgements or assessments of your learning in any way; rather, they are a source of feedback for you, the learner, to make you more aware of your study habits and, hopefully, help you change them for the better!*

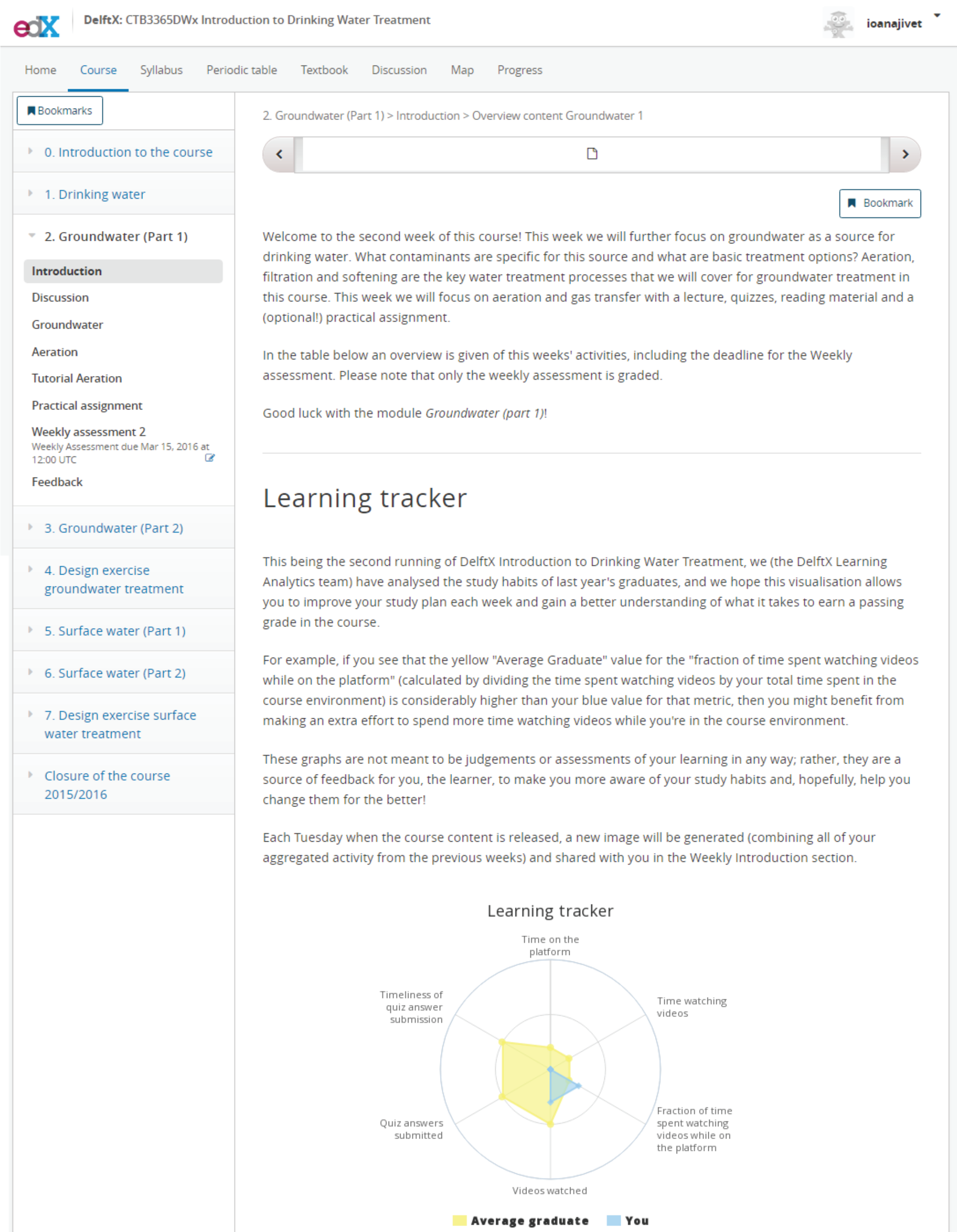

Figure 4.3: The placement of the `Learning Tracker` on the edX platform. The `Learning Tracker` is placed on the course content pages, on the introduction page of each learning module.

4.2.1 Participants

To ensure the results obtained from the three studies can be generalized and there are no demographics differences between the learners in the test group and the control group, we conducted a preliminary demographics analysis. For each student, data was available regarding their gender, age, education level and location. All demographic data was self-reported at the time of registration.

Demographics A statistical comparison between the representation of different demographic groups in the test and control group across all three courses is illustrated in Figures 4.4, 4.5, 4.6. In all three courses, two thirds of the enrolled students are male and are equally represented in the test and control group. The age distribution across the three courses is also similar, the majority of learners falling in the range of 26-40 years old (40-48%) with a median age of 28. In all courses, the majority of learners hold a Bachelor's or a Master's degree, weighing in on the high percentage of learners with a college level education and advanced level education, respectively similar to findings reported in [8, 21].

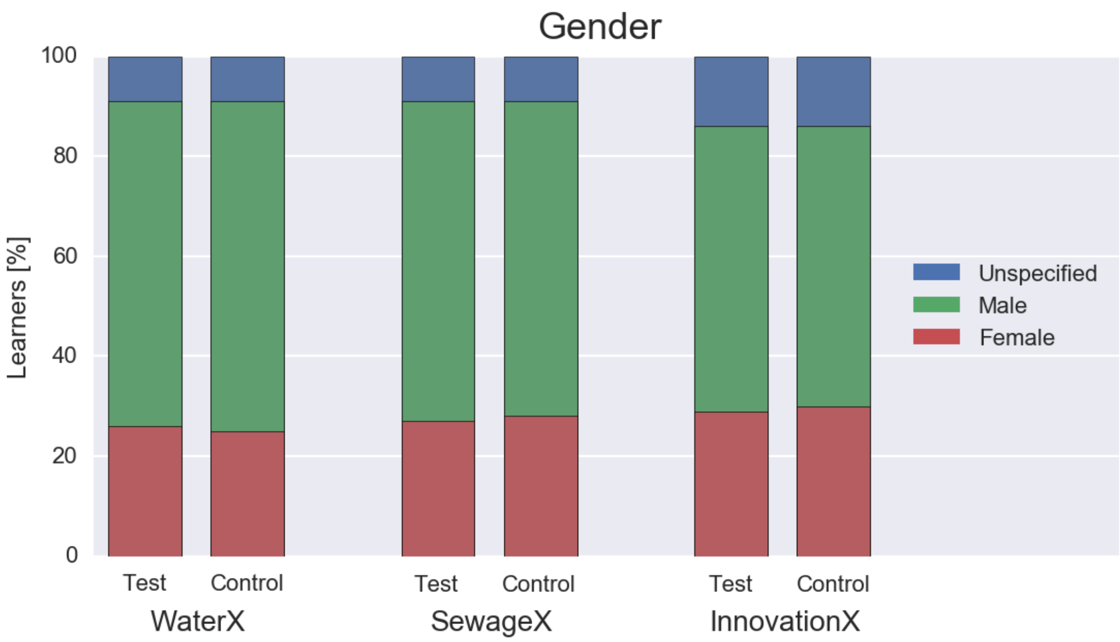

Figure 4.4: Gender distribution in the MOOCs under test in the test group versus the control group.

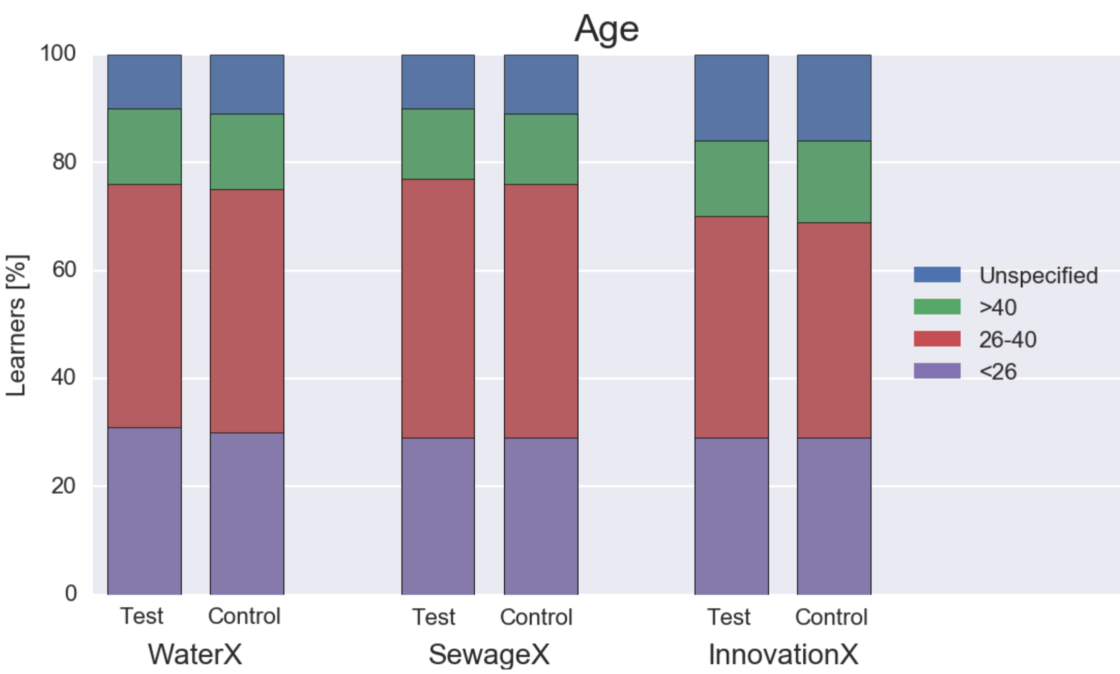

Figure 4.5: Age distribution in the MOOCs under test in the test group versus the control group.

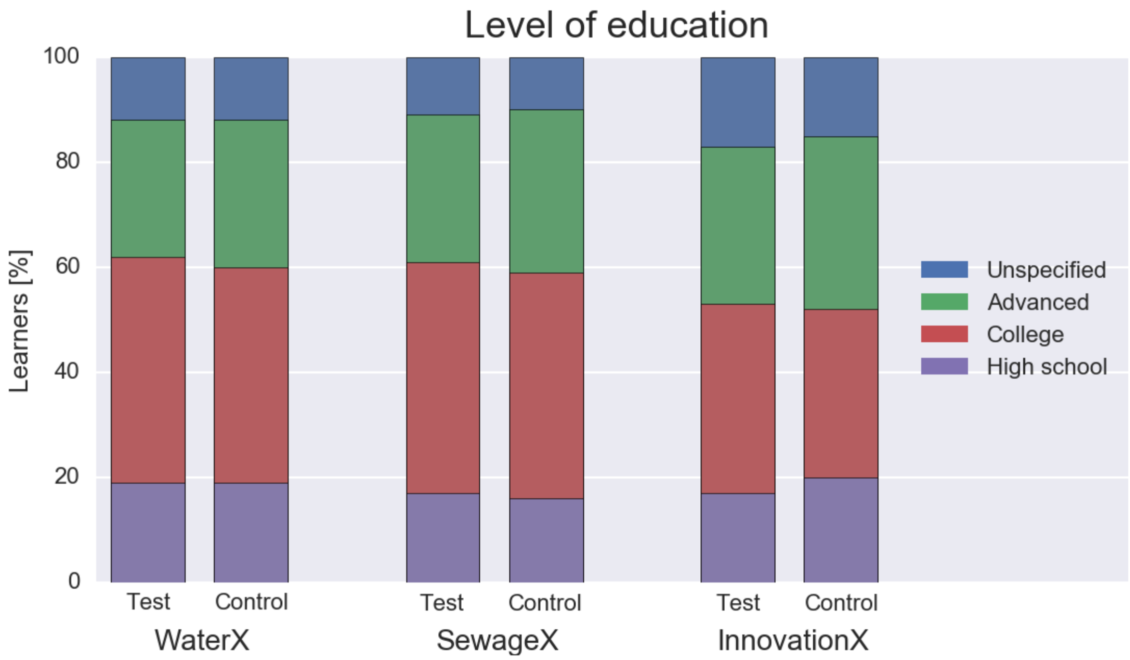

Figure 4.6: Distribution of the level of education among learner in all three MOOCs under test in the test group versus the control group.

Considering the similar distribution of gender, age and level of education, across the three courses and their subsequent test and control groups, demographic characteristics can be considered invariable in the experimental setup and they are not expected to impact the findings of the study across the three groups.

Geography We used the geographic location data to determine the geographical distribution per country of the enrolled learners. The percentage of learners for whom this data was not available was high (20-25%) and we removed them from the analysis presented in this section. The geographical distribution was further used to determine the distribution of learners over the quantiles of the Human Development Index (HDI) - a composite index developed under the United Nations Development Programme. The HDI measures average achievement in three basic dimensions of human development: a long and healthy life, knowledge and a decent standard of living [156]. Table 4.6 presents the geographical distribution of learners per country, indicating the level of country development according to the HDI values for the year 2014[4].

Across all three MOOCs, the top 15 countries are the same although with different ranking. India and the United States took the lead in every MOOC with 10.2-14.1% of the learners for which geographical data was available, followed by Brazil, Spain, Nigeria, Australia, Canada, Pakistan and United Kingdom. These numbers are in line with Nesterko's [121] evaluation of geographic data for 18 courses offered by HarvardX which listed these countries among the top 10. However, several other countries were represented in the three MOOCs: Egypt, Colombia, Mexico, Peru and France. Additionally, Netherlands is not a surprising presence, since all three courses are offered by a Dutch university.

A comparison between the development level of these countries and the topics covered by the three MOOCs brings out interesting observations. Topics like drinking water and urban sewage treatment attract more learners from countries with a lower HDI, nations where these are pressing issues, e.g. India, Egypt, Nigeria or Pakistan. On the other hand, topics that concern the long-term welfare and sustainability of the society seem to be more popular among learners from highly developed countries. The Responsible Innovation course is focused on analysis, reflection and public debate concerning the ethical principles and moral acceptability of new and emerging technologies. 7 out of the top 10 represented countries in this MOOC are socially advanced nations with a very high HDI, mostly from Europe and North America. This distinction is even more evident when we

[4]http://hdr.undp.org/en/2015-report

Table 4.6: Top 15 countries - Geographic distribution of participants in the three MOOCs and country development level based on the value of the Human Development Index in the year 2014 (green - very high, yellow - high, orange - medium, red - low).

CTB3365DWx 174 countries		CTB3365STx 161 countries		RI101x 123 countries	
India	14.1%	India	10.5%	India	10.2%
United States	11.7%	United States	7.2%	United States	8.8%
Egypt	4.1%	Colombia	3.6%	Netherlands	4.5%
Colombia	3.5%	Brazil	2.9%	Brazil	2.8%
Brazil	3.2%	Egypt	2.8%	Germany	2.6%
Nigeria	3.1%	Spain	2.7%	France	2.3%
Spain	3.0%	Mexico	2.1%	United Kingdom	2.2%
Canada	2.5%	Peru	1.9%	Spain	2.1%
Mexico	2.2%	Canada	1.8%	Pakistan	2.0%
Peru	2.1%	United Kingdom	1.7%	Canada	1.9%
Netherlands	2.1%	Nigeria	1.7%	Mexico	1.8%
Pakistan	2.1%	Netherlands	1.5%	Australia	1.7%
United Kindgom	1.9%	Australia	1.4%	Colombia	1.6%
China	1.7%	China	1.3%	Egypt	1.5%
Indonesia	1.5%	Pakistan	1.2%	Nigeria	1.5%
Unspecified	24.5%	Unspecified	21.6%	Unspecified	24.5%

probe the distribution of all enrolled learners over the quantiles of the HDI as reported in Table 4.7. `WaterX` and `SewageX` show similar distributions, but there are substantial differences with `InnovationX` where almost half of the learners are originating in countries with very high HDI compared to only a third in the other two MOOCs.

One explanation for this phenomena can be found in Maslow's hierarchy of human needs [104] when applied on a social level and not an individual one. Maslow's theory suggests that human motivation is fuelled by different levels of needs, starting with physiological needs and a need for safety, followed by love and belonging, esteem and self-actualization. Tischler [155] implies that if people throughout a society are increasingly able to trust that their basic needs will be met, they naturally shift their focus to their higher order needs. In developed countries, where economic prosperity and stability are inherent, this shift can be noticed in business, more pressing issues being related to sustainability and social responsibility of new technologies. Then, it should come as no surprise that the same societal concerns are reflected in the education learners seek, especially in an open and easily accessible learning environment like MOOCs.

Table 4.7: The distribution of enrolled learners for which demographical data is available over the quantiles of the 2014 Human Development Index for the three MOOCs used in our experiments. The values are calculated as percentage from the number of learners that have information about their country available.

	`WaterX`	`SewageX`	`InnovationX`
Very high	35.2%	34.6%	49.3%
High	24.5%	27.3%	21.0%
Medium	29.0%	28.4%	22.2%
Low	11.3%	9.7%	7.5%

4.2.2 Data sources

To ensure a more holistic evaluation for the `Learning Tracker`, several data sources were considered. The following paragraphs briefly describe the data used and its role.

edX data Focused on improving teaching and learning both online and on campus, edX is empowering research on pedagogy and learning by making available large amounts of data to researchers at edX partner institutions who use the edX data exports to gain insight into their courses and students[5]. Having access to such data, 3 types of information were collected from the edX platform:

- *trace logs* - we used the low-level user activity data to compute the information displayed on the widget as described in Section 3.2.1 and to investigate changes in behaviour, engagement and motivation by processing it in easily comparable indicators similar to the six metrics displayed on the widget.
- *self-reported user data* - at registration, edX learners are required to complete their profile with demographic data including their age, level of education, gender and country of origin. We used this data to verify the homogeneity of the population between the test and control groups across the three MOOCs.
- *grade reports* - the grade reports are generated at the end of a MOOC and apart from the grades obtained by learners, they also mark the certificate receivers. We used this information to select learners for the calculation of the average graduate's profile and to compare the graduation rates between the two editions of the MOOCs.

Interaction data The way learners use and interact with the widget was collected to get a measure of how many learners in the test population actually used the widget and how often. This data was recorded only in the evaluation of the second iteration of the widget. We gathered two types of interactions: (i) widget load events and (ii) showing/hiding an information set. Along with the type of interaction, other data recorded was the edX user identifier of the learner that generated the event, the widget the learner was interacting with since a new widget was released every week, and the timestamp of the event.

The Highcharts library, used for plotting the data on the widget as detailed in Section 3.2.2, facilitated the interaction tracking by providing a series of event listeners for the chart and its elements. The tracking data was collected using Google Analytics and their feature for event tracking[6] by hooking it to the Highchart event listeners. With the built-in data export feature, the interaction data can easily be extracted from the Google Analytics in a more convenient CSV format.

However, due to technical issues the tracking data recorded before May 9, 2016 is not reliable. Thus, the tracking data covers the courses only starting with week 5. Although the collected data shows the usage of the widget by learners that continue to be engaged with the course even after the initial weeks, we discarded the interaction data from the analysis because it does not provide complete information for all the participants in the study.

[5]http://edx.readthedocs.io/projects/devdata/en/latest/index.html
[6]https://developers.google.com/analytics/devguides/collection/analyticsjs/events

Chapter 5

Results

In this chapter, we present our findings with respect to the research questions described at the beginning of Chapter 4. We investigated learners' overall performance as an outcome of the learning process (**RQ1**) and their behaviour as means to achieve the learning outcomes (**RQ2**) by running statistical tests on the edX activity data generated by the test group and the control group and comparing the results. To identify significant differences between the two populations, we ran Mann-Whitney U tests as they do not assume a normal distribution of the data which is common for MOOC data [40]. The significance level was set to $\alpha = .050$.

5.1 Data preparation

As a high number of learners do not return to the course after they enrolled (65-74% for our three MOOCs), we prepared the dataset for analysis by extracting data generated only by *active* learners to obtain more accurate results. Although similar studies considered as active learners those that submitted at least one assignment [143, 123], we defined active learners by having spent at least five minutes of the platform for two reasons.

Firstly, we considered that a five minute period in which the learners browse through the course pages is enough for them to make a decision whether they wish to follow the course or not. As Table 5.1 shows, the difference in percentage between the learners that spent more than 5, 10 or 20 minutes on the platform is not substantial. Additionally, a large majority of learners that spent more than 10 minutes on the platform logged several sessions on the platform showing the intention to revisit the course.

Secondly, we wish to analyse the data generated also by learners that are *auditing* (watch most videos, but completed assignments rarely, if at all) or *sampling* (explored course videos) as defined by [86] in order to observe if the `Learning Tracker` succeeds in increasing the retention rate.

Table 5.1: Number of learners that spent more than 5, 10 or 20 minutes on the platform for each of the MOOCs under study. The differences between the percentages are sensible. We consider *active* learners those that spent more than 5 minutes on the platform.

	`WaterX`		`SewageX`		`InnovationX`	
	Test	Control	Test	Control	Test	Control
> 5 min	29.8% (1626)	29.1% (1595)	24.1% (975)	24.1% (988)	21.2% (250)	21.5% (251)
> 10 min	27.3% (1489)	26.8% (1471)	22.3% (899)	21.9% (896)	19.0% (225)	18.6% (218)
> 20 min	23.9% (1306)	23.7% (1302)	19.8% (801)	19.2% (786)	17.2% (203)	16.2% (190)

5.2 Learners' performance

We evaluated whether learners become more successful when they can compare their behaviour to that of previously successful learners (**RQ1**). As defined earlier in Chapter 3, we consider learners *successful* if they obtain a final score above the graduation threshold set by each MOOC team (60% in the case of our MOOCs).

For this analysis we used the grade reports available on edX on the course instructor pages. The reports were collected on the final day of each MOOC. Since learners have the possibility to unenrol from the course, the results in this section are based on the active students that were still enrolled at the end of the MOOC as presented in Table 5.2. Figure 5.1 visualises the graduation percentages in each group for each MOOC under study. In all three experiments, the graduation rate is 2-3% higher in the test group.

Table 5.2: Graduation ratios and absolute numbers among active learners in test groups compared to control groups. Learners that obtained a final score above 60% are considered graduates.

	WaterX	SewageX	InnovationX
Test	13.1% (188/1440)	18.1% (165/911)	25.2% (54/214)
Control	11.2% (160/1429)	15.1% (137/907)	22.4% (47/210)

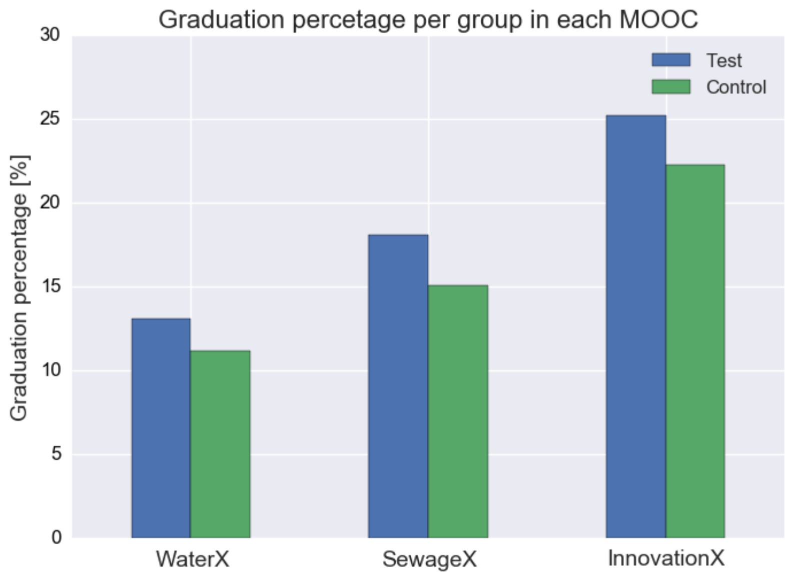

Figure 5.1: Graduation ratios among active learners in test groups compared to control groups in the studied MOOCs. In all three studies, graduation percentages are higher among learners in the test groups i.e. learners that had access to the `Learning Tracker`.

We further investigated the distribution of final grades among the learners in each group as shown in Figure 5.2 through kernel density estimation (KDE) plots. Similar to histograms, KDE plotting is a non-parametric technique for visualizing the underlying distribution of a continuous variable. The method does not assume a normal distribution of data.

The plot shows a high density around a final score of 0. However, in order to better visualise the grade distribution, the plot has been cropped. This skewness is reflective of the low engagement in MOOCs as only a few learners work towards completing the course and obtaining a certificate [38]. In all three courses, there are notable differences in density between the test and control group for the final score interval 60-80%. This indicates that more learners with access to the `Learning Tracker` passed the graduation threshold, but they did not pursue higher grades. The Mann-Whitney U tests did not detect any significant differences in performance between the test group and the control group. The test results are listed in Table 5.3.

Table 5.3: The mean±SD (standard deviation) of final grades obtained by active learners in each MOOC along with the results of the Mann-Whitney U tests. The significance level is set to $\alpha = .050$. The maximum grade is 100.

	WaterX	SewageX	InnovationX
Test	14±27	19±32	26±32
Control	13±25	16±31	22±30
p-value	.052	.115	.062

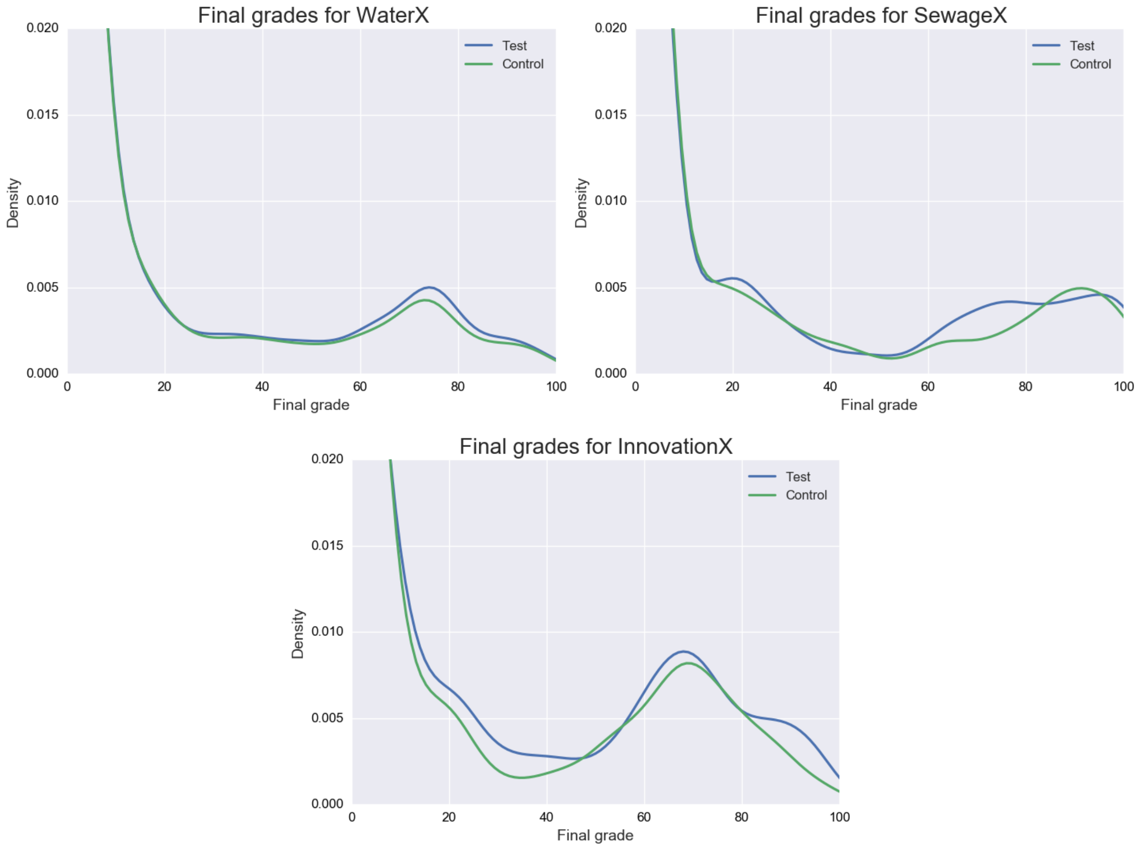

Figure 5.2: Kernel Density Estimation (Gaussian kernel) plot visualising the distribution of final course grades between the test and control groups in all three courses. None of the differences between groups are significant as reported by a Mann-Whitney U-test with a significance level α = .050. There is a very high density around a final score of 0 and the plot has been cropped to better visualize the data distribution.

5.3 Learners' behaviour

In order to understand how providing learners with feedback on their learning habits affected their behaviour (**RQ2**), we first compared the behaviour of the test group with that of the control group with respect to the six metrics displayed on the widget. Table 5.4 gives an overview on the results of the Mann-Whitney U tests run to identify significant differences between the two groups.

Table 5.4: The two-sided Mann-Whitney statistical test results for all the three course over the six metrics displayed on the respective version of the widget. The significance level is $\alpha = 0.05$. The metrics that exhibit significant differences between the test group and the control group are shown in bold.

Cluster	Metric	CTB3365DWx	CTB3365STx	RI101x
Progress	number of quiz questions attempted	**.036**	.114	**.044**
	number of videos accessed	.910	-	-
Use of time	time on the platform	.660	-	-
	time spent watching videos	.880	-	-
	ratio video/total time	.730	-	-
	time-on-task	-	-	.476
SRL time management	sessions/week	-	.156	.078
	average length of a session	-	.758	.601
	average time between sessions	-	.827	.257
	timeliness of submission	.055	.113	**.039**
Interaction	number of forum sessions	-	.095	-

We identified statistically significant differences for a significance level $\alpha = 0.05$ in two metrics: *number of graded quiz questions attempted* and *timeliness of quiz submissions*. However, the results are not consistent across all three MOOCs and they do not offer a holistic view on learners' behaviour. Therefore, we examined extensively three aspects of learner behaviour in each MOOC: (i) engagement, (ii) self-regulation and (iii) motivation as reflected by behaviour.

5.3.1 Learners' engagement

We evaluated the effect of the `Learning Tracker` on learners' engagement (**RQ 2.1**) from three perspectives:

- level of activity and retention i.e. for how long into the course were the learners active
- course material i.e. how much of the course material learners engaged with
- forum interaction i.e. how much did learners visit the forum

Retention and activity

We operationalized *retention* as days from the beginning of the course until the last day on which the learners registered a session, similar to [40]. We quantified the *level of activity* through the number of sessions learners registered on the platform. The results of a Mann-Whitney test revealed a significant difference on retention between the two groups only in `SewageX` ($p = .027$). We also found a significantly higher level of activity among the test group learners for `InnovationX` ($p = .032$). The results are summarized in Table 5.5. Figure 5.3 presents the kernel density estimation plot on retention and sessions registered for the learners between the two groups for `SewageX`.

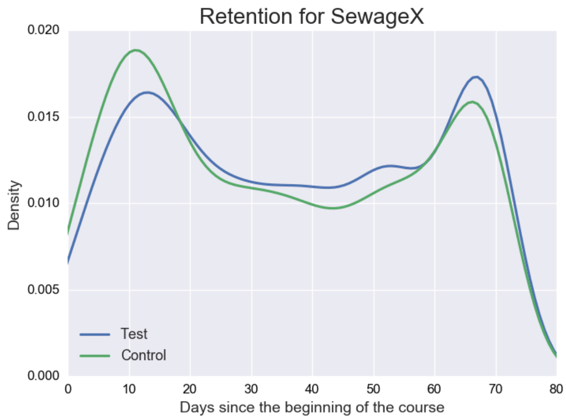

Figure 5.3: Kernel Density Estimation (Gaussian kernel) plot visualising the retention in `SewageX` for learners in the test group and control group. Differences are statistically significant as reported by a Mann-Whitney U-test with $\alpha = .050$.

Table 5.5: The mean±SD (standard deviation) of retention (days since the beginning of the course until the last day on which the learner registered a session) and activity (number of registered session) performed by learners in each MOOC along with the results of the Mann-Whitney U tests ($\alpha = .050$). Significant differences are marked in bold.

	`WaterX`			`SewageX`			`InnovationX`		
	Test	Control	p-value	Test	Control	p-value	Test	Control	p-value
Retention	32±22	32±22	.995	37±23	35±23	**.027**	34±20	31±21	.128
Sessions	9.8±15	9.6±15	.928	40±58	39±60	.080	46±76	35±51	**.032**

Engagement with course material

We investigated learners' engagement with the course material along three dimensions: (i) number of videos accessed, (ii) number of graded quiz questions attempted and (iii) number of practice (non-graded) quiz questions attempted. Although the learners did not receive any feedback on the number of practice quiz questions attempted, we included this metric in the analysis to identify if there are any changes in learners' engagement with other types of learning material on which they do not receive feedback. To determine any variation in the engagement of learners with the course material, we ran Mann-Whitney U tests with a significance level of 5%. The results are summarized in Table 5.6.

Table 5.6: The mean±SD (standard deviation) of engagement with course material variables obtained by learners in each MOOC along with the results of the Mann-Whitney U tests ($\alpha = .050$). Significant differences are marked in bold. The star (*) next to the p-values indicates that the metric was displayed on the widget in the respective course.

	`WaterX`			`SewageX`			`InnovationX`		
	Test	Control	p-value	Test	Control	p-value	Test	Control	p-value
Videos accessed	7±9	7±9	.910*	8±12	8±13	**.030**	9±12	8±12	.292
Graded quizzes	5±9	4±8	**.036***	7±11	6±11	.114*	25±31	21±31	**.044***
Practice quizzes	9±17	9±16	.512	35±62	32±60	.071	-	-	-

We found significant differences between the test group and the control group on the *number of videos accessed* only for one course (p=.030). The variable *number of graded quiz questions attempted* showed significant differences between the two groups in two studies (p=.036 and p=.044). However, there are no significant differences on the number of *practice quiz questions attempted*. This suggests that test group learners were directing their efforts on solving the graded questions rather than trying the practice assignments. However, the learners did not receive feedback on this metric through the widget in any of the experiments.

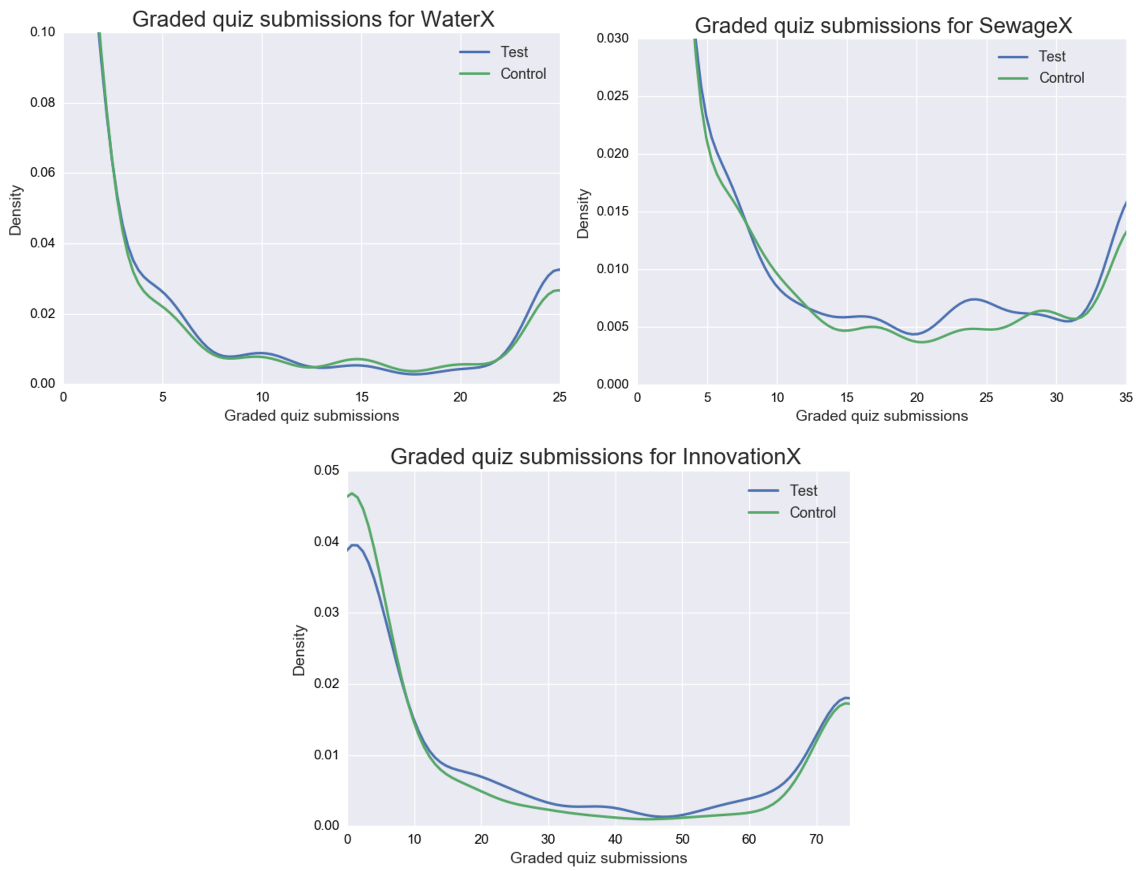

Figure 5.4: Kernel Density Estimation (Gaussian kernel) plots illustrating the distribution of the number of attempted graded quiz questions for learners in each group. Differences are significant as reported by a Mann-Whitney U-test with $\alpha = .050$ for `WaterX` and `InnovationX`. There is a very high density around 0 quiz questions attempted as many learners do not submit any assignments. The plot has been cropped to better visualize the data distribution.

Across all three studies, learners in the test group attempt more graded quiz questions as shown by the mean values presented in Table 5.6. Figure 5.4 visualises the distribution of the number of graded quiz questions attempted for learners in each group. All three plots show similar distribution patterns with peaks at the extremes of the range of available questions. We observe a high density for 0 quiz questions submitted, similar to the distribution curve of final grades presented in Figure 5.2 as fewer learners attempt quiz questions. The plots were cropped to better visualize the distribution for the rest of the learners. However, the density curve for both the test group and the control group in `InnovationX` is not highly skewed around 0 quiz questions attempted in comparison with the other two courses. This indicates that overall, more learners engaged with the course material in `InnovationX`. Across all three courses, the position of the two curves relative to each other in each graph suggests that more learners in the test group attempt graded quiz questions.

Learners that attempted graded quiz questions In Figure 5.5 we show the progression of both groups through each course with respect to the number of learners that attempted at least one graded quiz question. As each course progresses, a larger number of learners in the test group submit graded quiz answers. The difference between the groups becomes visible between weeks 2 and 3 in all three courses, a week after the first `Learning Tracker` widget was introduced to the *test* group. Although in `InnovationX` the difference is visible starting with week 1, the gap increases in favour of the test group starting with week 3. Table 5.7 presents the percentage of learners out of active learners that attempted at least one graded quiz questions by the end of the course.

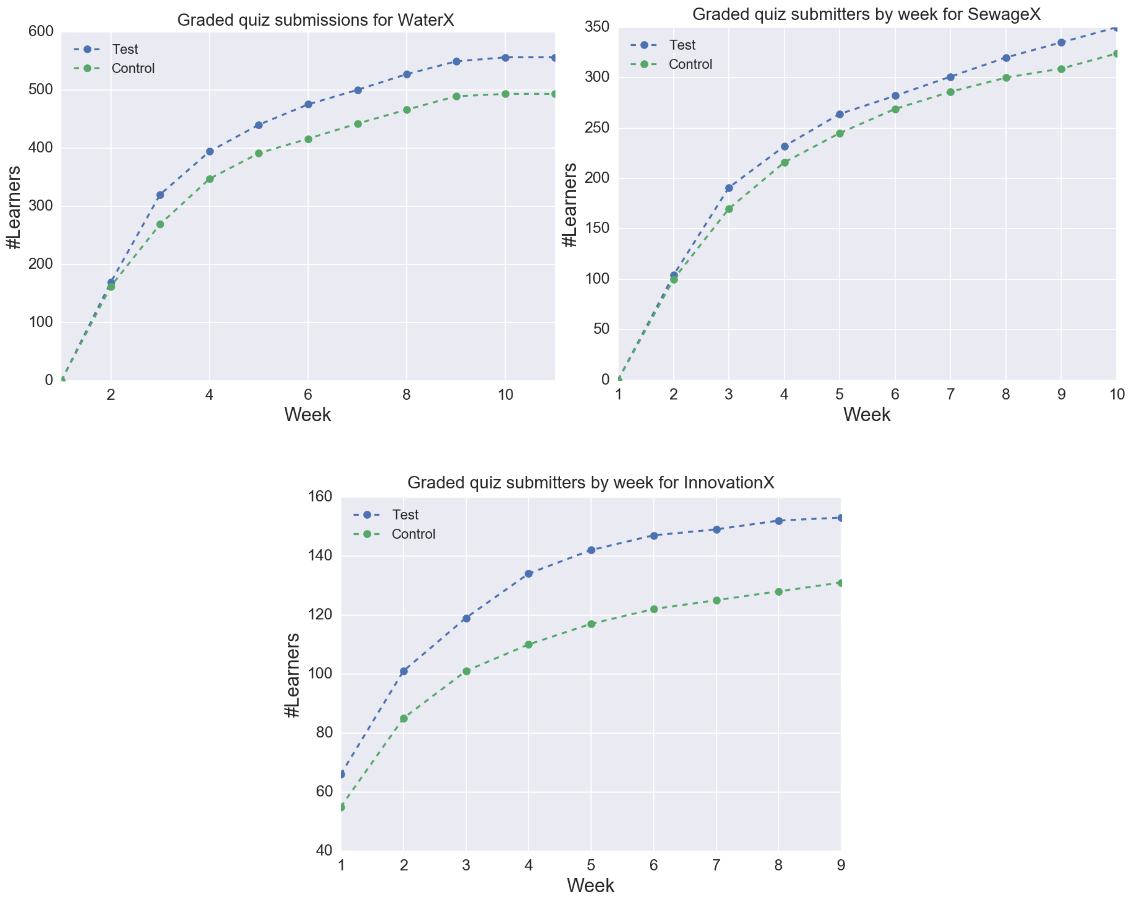

Figure 5.5: The number of learners that attempted at least one quiz question by each course week. The values on the Y-axis have been adjusted for a better visualisation according to the sizes of each plotted group. As explained in Section 4.2.1, we ensure that the populations were randomized sufficiently for the results to be valid.

Table 5.7: The number of learners that attempted at least one graded quiz submission out of the active learners for each of the MOOCs under study. The values are higher for the test group in all cases.

	WaterX		SewageX		InnovationX	
	Test	Control	Test	Control	Test	Control
> 1 graded quiz	34% (553)	31% (487)	36% (351)	33% (324)	60% (151)	50% (126)

Forum engagement

We analysed the engagement on the forum pages for `SewageX` and `InnovationX`. We found that the learners' engagement on the forum differed significantly with respect to the numbers of forum visits only in `InnovationX`, as shown in Table 5.8. The percentage of learners that visit the forum in each group differs slightly (49.9% in the test group and 46.4% in the control group for `SewageX`) but the contrast is higher for `InnovationX` (44.8% in the test group and 37.8% in the control group). These results are unexpected considering that the *number of forum visits* was a metric displayed on the `Learning Tracker` only in `SewageX`. We speculate that the test learners' forum activity in `InnovationX` is significantly higher because either (i) the forum activity is influenced by other metrics displayed on the widget, (ii) learners in the test group have higher intrinsic forum engagement or (iii) the nature of the MOOC encourages learners to be active on the forum.

Table 5.8: The mean±SD (standard deviation) of forum visits made by learners along with the results of the Mann-Whitney U tests. There are significant differences for `InnovationX` for a significance level $\alpha = .050$. Significant differences are marked in bold. The star (*) next to the p-value indicates that the metric was displayed on the widget in the respective course.

	WaterX			SewageX			InnovationX		
	Test	Control	p-value	Test	Control	p-value	Test	Control	p-value
Forum visits	-	-	-	3.0±7.9	2.7±7.6	.095*	3.2±9.5	1.9±6.1	**.048**

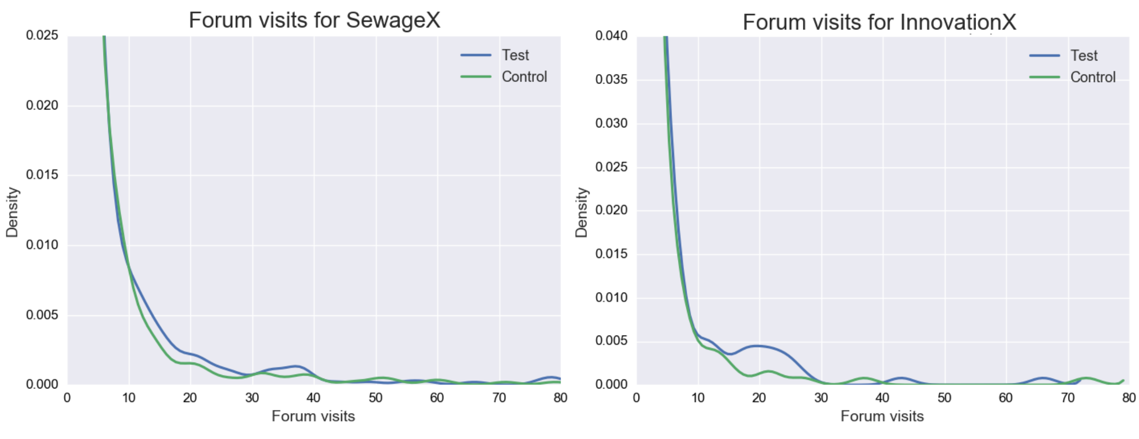

Figure 5.6: Kernel Density Estimation (Gaussian kernel) plot visualising the number of forum visits distribution for learners in the test group and control group. Differences are statistically significant as reported by a Mann-Whitney U-test with $\alpha = .050$ for `InnovationX`.

5.3.2 Learners's self-regulation

To explore whether the `Learning Tracker` had any effect on self-regulating behaviour (**RQ 2.2**), we ran Mann-Whitney U tests on the metrics that describe the *use of time* and the *time management* aspect of self-regulated learning. The results of these tests are presented in Table 5.9.

We found significant differences in *timeliness of quiz answer submission* only in `WaterX`. However, across all the courses, the mean values for each group show that learners in the *test* group submit quiz answer 3 hours earlier on average (see Table 5.10). We speculated that the lack of

Table 5.9: The Mann-Whitney statistical test results with a significance level $\alpha = .050$ on the metrics that quantify *use of time* and *SRL aspects* for all the three course. Significant differences are marked in bold. The star (*) next to the p-value indicates that the metric was displayed on the widget in the respective course.

Cluster	Metric	CTB3365DWx	CTB3365STx	RI101x
Use of time	time on the platform	.659*	.067	.055
	time spent watching videos	.880*	.083	.390
	ratio video/total time	.727*	.362	.992
	time-on-task	-	-	.510*
SRL time management	sessions/week	.585	.156*	.078*
	average length of a session	.175	.758*	.601*
	average time between sessions	.086	.827*	.257*
	timeliness of submission (h)	.055*	.113*	**.039***

significant differences in the other two studies might be influenced by the fact that the *timeliness of quiz answer submission* metric was calculated based on a very short recommended deadline (1-2 weeks) compared to the actual submission deadline. Therefore, we investigated timeliness of submission also with respect to the actual deadlines as illustrated in Figure 4.1.

In this case, the differences become significant for `WaterX` with p=.040 and for `InnovationX` with p=.035. In figure 5.7 we present the timeliness of the two groups for `InnovationX` with respect to the recommended deadline (left) and the actual deadline (right). The results of the statistical test along with Figure 5.7 show that the test group is better able to self-regulate their behaviour and reduce their procrastination with respect to the actual submission deadlines. In the test group, many learners submit their work well before the actual deadline.

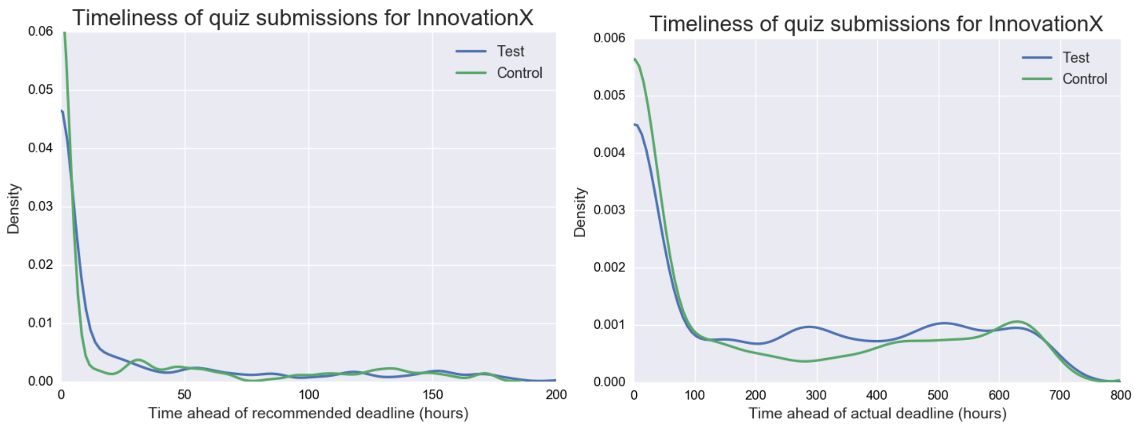

Figure 5.7: Kernel Density Estimation (Gaussian kernel) plots visualising how far ahead of the recommended deadline (left) and actual deadline (right) learners in `InnovationX` attempted weekly quiz questions. The left side of the plot is indicative of procrastinating behaviour, whereas the right indicates proactivity. Mann-Whitney tests ($\alpha = .050$) indicate significant differences when the timeliness is calculated based on the actual submission deadline This suggest that the timeliness metric impacts learners' procrastination, encouraging them to submit their work earlier.

Table 5.10: The mean±SD (standard deviation) of timeliness metrics against recommended and actual deadline along with the results of the Mann-Whitney test ($\alpha = .050$). Significant differences are marked in bold.

	`WaterX`			`SewageX`			`InnovationX`		
	Test	Control	p-value	Test	Control	p-value	Test	Control	p-value
Timeliness (h) (recommended)	24±47	22±45	.055	32±76	28±71	.113	100±151	90±146	**.039**
Timeliness (h) (actual)	260±417	232±404	**.040**	285±455	260±437	.145	217±241	178±242	**.035**

However, there was no distinguishable difference with respect to the other metrics for *SRL time management*. Furthermore, the statistical tests did not reveal any significant differences for the metrics that describe learners' *use of time*.

5.4 Learners' on-trackness

We define *on-trackness* as the similarity between one's behaviour and that of successful learners. We investigate whether the `Learning Tracker` influences learners' on-trackness and the extent to which the widget motivates learners to reach a similar behaviour to that of previously successful learners (**RQ2.3**). In literature, learners' motivation is usually evaluated via a post-course survey in which learners have to report their levels of motivation. However, well-known issues with post-surveys are that (i) very few people complete them [78, 35] and (ii) the reporting is done at a later point in time, when learners have passed the moment and their recollections are influenced by the overall feelings of accomplishment at the end of the course [13].

To tackle these issues, we identify changes in motivation by detecting changes in behaviour and the level of activity in the course as envisioned by [124]. To this end, we adopt a method similar to that used in [53, 154] by grouping learners based on their behaviour patterns using k-means clustering algorithm [100]. However, instead of calculating an engagement score based on learner's interaction with the content, assessments and forum discussions like in [53], we use an *on-trackness* score that reflects how similar is the learner's behaviour to that of the average graduate displayed on the widget. The clustering algorithm is applied on learners' *on-trackness profiles* which are built as a vector containing the on-trackness score of each week.

The score is computed based on the six metrics displayed on the `Learning Tracker`. To ensure coherency across the values that contribute to the score, we use the scaled values of the metrics. We define *metric deviation* the difference between the learner's scaled value of the metric and the average graduate's value. In order to calculate the score, three methods were considered: (i) the sum of the metric deviations, (ii) an arithmetic method that computes a weighted sum of the six metric deviations, and (iii) a geometric approach that calculates the overlap between areas on the widget generated by the information sets belonging to the learner and the average graduate.

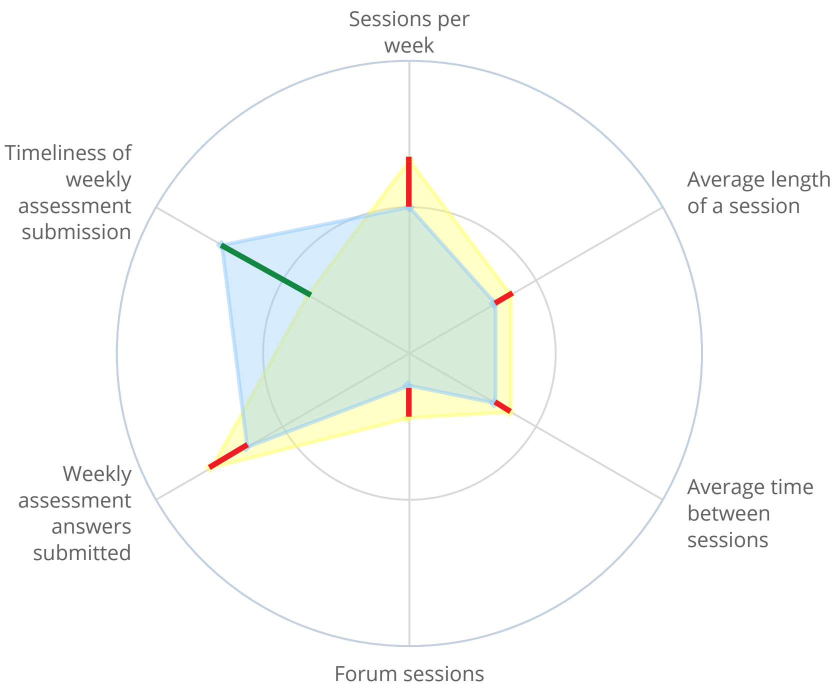

Figure 5.8: The widget of a learner that is doing well in one metric and is behind in the other five. The positive metric deviation is marked with green and the others with red. By simply summing the deviations, the *on-trackness score* is 0 and the learner is classified as *on-track*. By following the proposed arithmetic approach as a weighted sum, the score is negative and the learner is *behind*.

The solution we opted for was the arithmetic method because it accounts for the cases in which a learner performs really well in one metric, but below average in the other five metrics. Such an example is illustrated in Figure 5.8. To account for these cases, the weights are inversely proportional with the amplitude of the deviation of the metric. This way the weights are calculated dynamically with each score computation.

Similar to [154] we choose a threshold value for the on-trackness score according to which the learners are classified into categories. For score values higher than 0.75 learners are considered to be *ahead*, performing better than the average graduate. If the score is lower than -0.75, we classify them as *behind*, performing worse than the average graduate. Learners whose score falls in the interval -0.75 and 0.75 are *on track* with a similar behaviour to that of previously successful learners. The closer the score is to 0, the similar the behaviours are. Figure 5.9 displays the widgets generated by sample learners from each of the three categories.

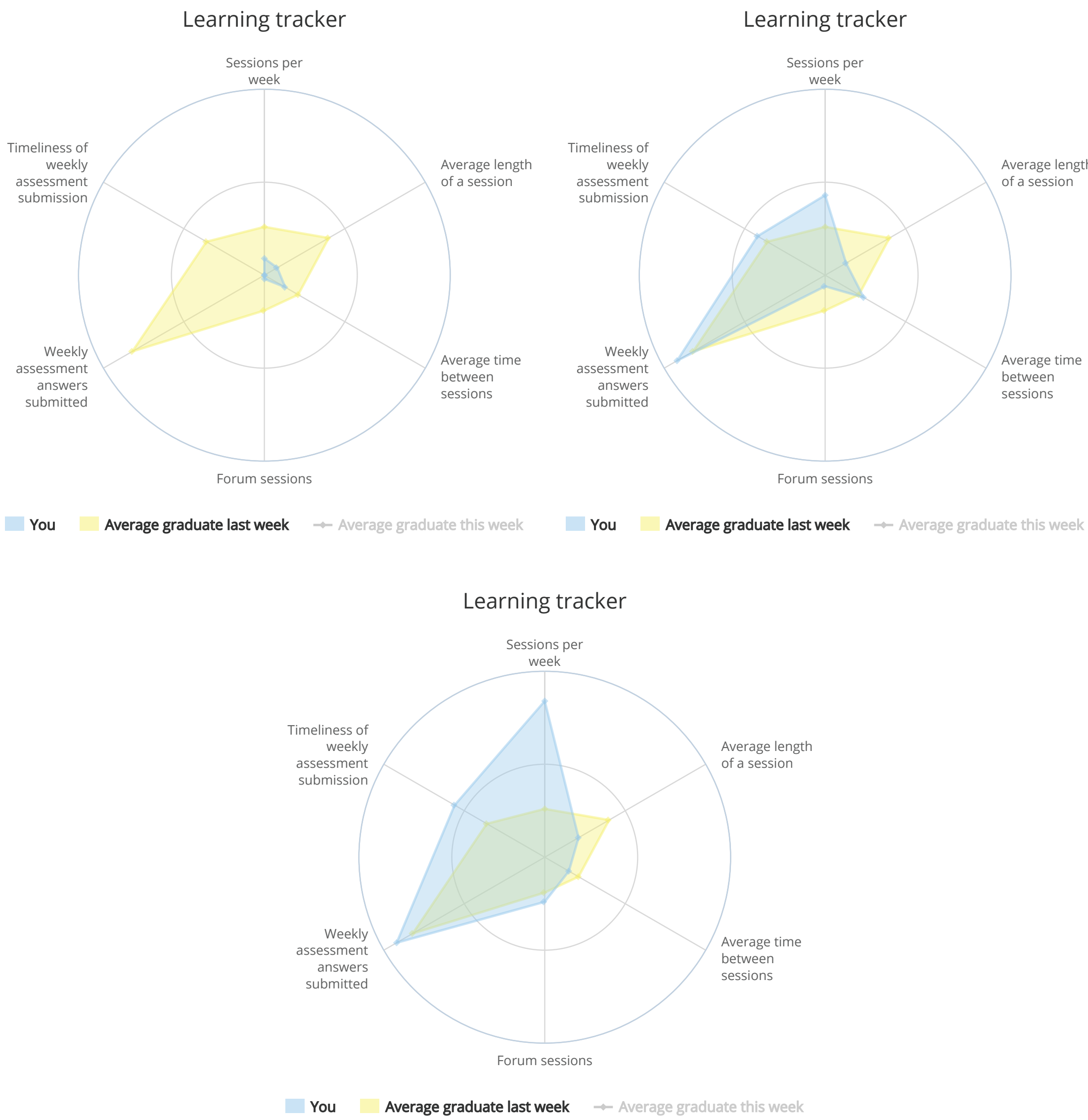

Figure 5.9: Three versions of our widget with data from week 10 of `SewageX`, showing a learner that is *behind* (top left), one that is *on-track* (top right) and one who is *highly engaged* with the course (bottom).

In order to apply the k-means clustering algorithm, the number of cluster has to be predefined. We identified this number by using the elbow method on the within-cluster variance. The elbow method a heuristic approach that identifies the point where adding another cluster does not improve the modelling of the data [90]. Figure 5.10 illustrates the applied method for `InnovationX`. The number of clusters for each course identified in this manner is 4.

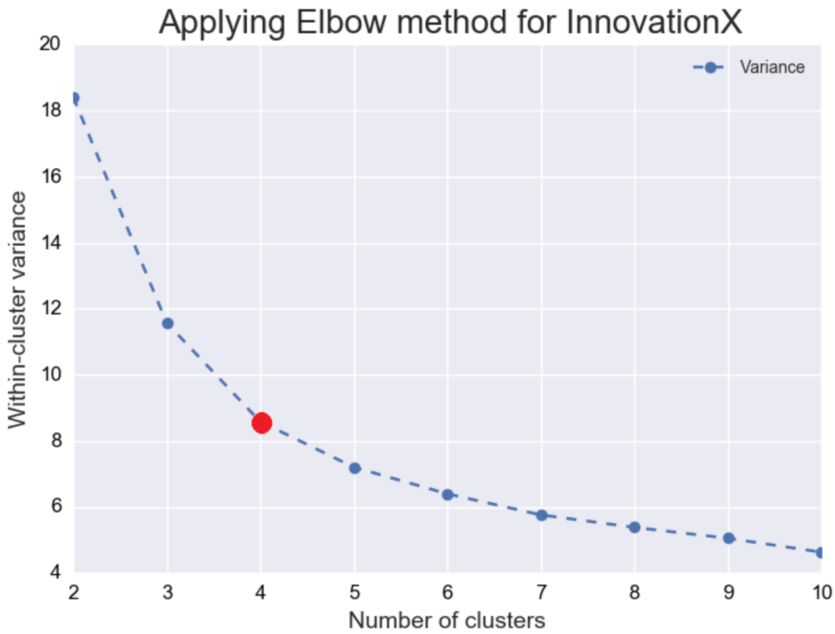

Figure 5.10: The elbow method for identifying the number of clusters for k-means clustering algorithm. The graph draws the within-cluster variance for an increasing number of clusters for `InnovationX`. Once the steepness of the curve reduces, adding another cluster would not affect the modelling of the data. In this case, the number of optimal clusters is 4.

Figure 5.11 visualises the centroids for each cluster identified by applying the k-means clustering algorithm. The golden line represents the minimum on-trackness score for each week i.e. the score's value for a learners that has no activity since the beginning of the course. The learners exhibit similar behaviour patterns in all three courses. Out of the four patterns, two (Cluster 1 and Cluster 2) show a steady progress, while the other two exhibit a decrease in on-trackness over time (Cluster 3 and Cluster 4). The decrease in on-trackness score reflects drop-outs or very low activity. Plots in Figure 5.11 show that learners' score are mostly negative, most learners' being categorised as *behind* in every week.

Cluster 1 includes learners that are *on-track* and have a behaviour similar to that of average graduates throughout the whole period of the course. Their level of engagement is constantly high. This cluster accounts for 14-19% of the learners. Cluster 2 are learners that are *behind, but keeping up with the course* and they represent 15-19% of active learners. Learners in cluster 3 are *behind and with initial activity*, totalling up to 17-37%. Their level of engagement is high in the beginning of the course, but it reduces after a few weeks. However, the majority of active learners (34-45%) belongs to cluster 4. They are *behind and with very limited or no activity* from the beginning of the course.

Table 5.11 presents details regarding the composition of each cluster. Across all three courses, the majority of learners belong to Cluster 3 and 4. This is not surprising, considering that the retention rate of all three MOOCs is low and many learners drop-out early in the course as shown in Section 5.1. Additionally, the data shows that 93-100% of the graduates are in Clusters 1 and 2. However, we assume that the few graduates in clusters 3 and 4 completed the required assignments to obtain a graduation score while having a limited interaction with the platform. The distribution of test learners in each cluster is balanced (46-54%), although a bit higher in clusters 1 and 2. However, `InnovationX` is an exception with almost the whole composition of Cluster 1 being learners from the test group.

Table 5.11: Overview on the four clusters in each course, summarizing the size of each group, the percentage of test learners present in each group and the distribution of graduates among the four clusters.

	WaterX			SewageX			InnovationX		
	Size	Test learners	Graduates in group	Size	Test learners	Graduates in group	Size	Test learners	Graduates in group
Cluster 1	505	53%	68%	284	54%	56%	93	99%	48.5%
Cluster 2	499	53%	30%	296	53%	37%	97	19%	51.5%
Cluster 3	1057	49%	1%	720	46%	3%	86	70%	0%
Cluster 4	1160	50%	1%	663	50%	4%	225	36%	0%

Figure 5.12 illustrates the widgets of the central learner (i.e. closest to the cluster centroid) from Cluster 1 (left) and Cluster 2 (right) for weeks 3 (top), 6 (middle) and 9 (bottom) in `SewageX`.

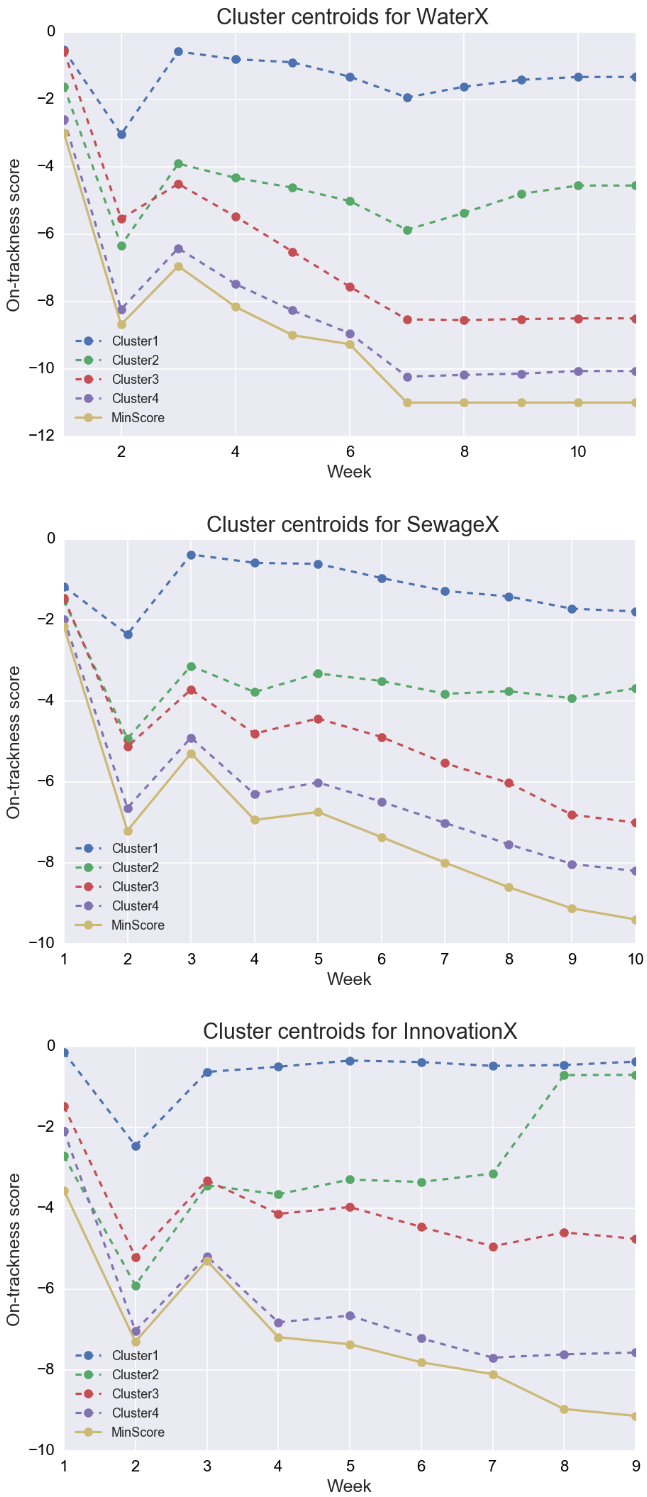

Figure 5.11: The centroids for each cluster identified through the k-means clustering algorithm. The golden line represents the minimum *on-trackness* score for each week. Learners from all three courses present similar on-trackness patterns: (1) on-track; (2) behind, but keeping up; (3) behind with middle-course drop-out; (4) behind with limited or no activity.

Figure 5.12: The widgets of the central learner (i.e. closest to the cluster centroid) from Cluster 1 (left) and Cluster 2 (right) for weeks 3 (top), 6 (middle) and 9 (bottom) in `SewageX`. Both learners obtained a graduation score.

Chapter 6

Discussion

The main goal of this research was to investigate the effect of a learner dashboard on learners' performance and self-regulating behaviour. To this end, we deployed our `Learning Tracker` in three MOOCs offered by TU Delft on the edX platform. The studies followed a between-group design with only half of the learners having access to the widget. The results will be discussed in the following sections. We further present the limitations of our study and highlight directions for future research in the field of learner dashboards that encourage self-regulation.

6.1 Findings

To start with, we observed a higher graduation percentage among the learners that had access to the `Learning Tracker`. Investigating further the reasons behind the increased success rate, we did not detect any significant difference on the final grades between the learners in the two groups. However, data that describes the learners' engagement showed that more learners in the test group attempted at least one graded quiz question. Moreover, learners that were exposed to the widget attempted more graded quiz questions than their counterparts. The percentage of learners within the grade range right above the graduation threshold (60-80%) was higher among the learners that had access to the `Learning Tracker`, suggesting they aimed to graduate the MOOC, but did not pursue higher grades. All these observations indicate that there is a higher success rate among learners that have access to the widget because the `Learning Tracker` increases the share of learners that engage with graded material, rather than assisting learners in performing better and thus obtaining higher grades.

Secondly, when comparing the behaviour of learners from the test group and the control group with respect to the six metrics displayed on each widget we did not obtain consistent results across all three courses. Although we did not explicitly state our definition of a successful learner to participating learners, we observed significant responses in the two metrics directly associated with graduation requirements: (i) number of graded quiz questions attempted and (ii) timeliness of their submission. Similar findings were reported in [62, 143]. Guerra et al. [62] showed that students that had access to an interface for online content management that combines OLM and social comparison explored and solved more distinct problems. Sharma et al. [143] reported that successful learners engage more, put more effort into assignments and don't procrastinate as much as their peers. These two metrics have a direct impact on the *learners' success*, as we defined it for the purpose of this work i.e. learners graduate if they submit enough graded assignment before the deadline.

A closer inspection of metrics related to learners' use of time and time management revealed that the `Learning Tracker` had no significant effect on the self-regulating behaviour of learners apart from timeliness of submission. This leads us to the assumption that learners' improvement in the above mentioned metrics can not be associated with a general increase in self-regulated learning skills. However, we observed that the effect of self-regulation on procrastination becomes evident when we inspect learners' timeliness over the whole duration of the course and not with respect to our recommended submission deadlines. Our findings indicate that the acquisition and development of self-regulated learning skills is a extensive and lengthy process that requires learners to practice and refine various learning strategies and study habits over longer periods of time as also indicated by Kornell [93]. Thus, we conclude that in order to investigate the full extent of learners' self-regulation, longitudinal studies that follow learners across the whole duration of a MOOC or even longer periods of time which cover several MOOCs learners undertake are mandatory.

Thirdly, the analysis of learners' behaviour with respect to all metrics used in the experiments revealed significant differences between the test and control group in some metrics even though they were not displayed on the widget. For example, learners with widget access in `InnovationX` showed a higher engagement on the forum than their counterparts, although neither group had access to information related to forum activity. Similarly, test learners in `SewageX` accessed more lecture-videos than the control group without receiving feedback on video related metrics.

This indicates that the `Learning Tracker` might affect several aspects of learners behaviour, although learners do not get direct feedback on them through the widget. Thus, we argue that the mere fact of having feedback on a limited number of behaviour metrics could trigger self-reflection in learners and lead to both unexpected and unforeseen changes in behaviour. For example, in the attempt to get a higher grade and completing more graded quiz assignments, the learners' might visit the forum more often. One explanation for this phenomena is that changes to observable learner behaviour cannot be made without affecting other aspects of learners behaviour. We hypothesize that learners' behaviour can be broken down into specific study habits (e.g. visiting the forum before submitting assignments, submitting assignments early, spacing the study sessions etc.) that are interconnected and influence each other. Thus, attempts to change one study habit lead to changes in other learning habits.

This hypothesis is in line with the theory proposed by Wiebe et al. [162]. They suggest that MOOC data analysis has to take a person-centred approach that acknowledges people as "integrated wholes" by considering how a large number of variables interact within a person. Such an approach does not assume that variables used to model learners have a linear effect, but rather are interconnected and variations in one lead to changes in others.

Fourthly, we believe that cMOOC learners could also benefit from being exposed to feedback on their learning behaviour. As cMOOCs focus on knowledge creation rather than knowledge duplication like xMOOCs, SRL, learner maturity and autonomy are highly required skills [12]. Although our experiments were conducted only on xMOOC, we are confident that our results also hold if the `Learning Tracker` is to be deployed in cMOOCs. We based this hypothesis on previous research which showed that cMOOCs have a greater potential to foster learning and its self-regulation than xMOOC because they require a higher degree of interactivity with learning objects and peers. [10].

Nonetheless, we consider that the metric selection should account for the type of MOOC the widget is integrated in. Thus, metrics that describe interaction, forum engagement and use of communication tools might be a lot more relevant in cMOOCs, due to the constructivist concept behind their development [147]. In contrast, xMOOC are more similar to repositories of knowledge. Therefore, learners would benefit more from feedback on their level of engagement with course material and performance [115]. This would give them the freedom to identify and adopt learning strategies that would increase their engagement levels and the usage of available learning material.

Finally, by clustering learners based on the evolution of their on-trackness score over the period of the course, we identified four patterns of behaviour. After investigating the composition of each cluster, we can trace correlations between the levels of engagement exhibited by learners and their on-trackness score evolution. Learners in the two clusters that include the majority of graduates (i.e. *on-track* and *behind, but keeping up with the course*) present a steady evolution of the on-trackness score, with similar score values each week. However, learners from one cluster showed a higher overall score, suggesting higher values in the metrics that reflect increased levels of activity. On the other hand, the on-trackness score of learners that present low to no activity showed decreasing values for the on-trackness score each week.

According to our definition, on-trackness scores close to 0 indicate similarity between the reported behaviour of current learners and the average graduate. An unexpected observation which can be derived from Figure 5.11 is that the *on-trackness* score presented negative values, even for learners belonging to the first two clusters. Thus, very few learners were classified as "on-track" or "ahead", even among graduates which are by definition *successful learners*. Additionally, as shown in Figure 5.12, typical learners from two clusters do not show behaviour similar to that of the average graduate. We identify several reasons for the extremely low scores. Firstly, *mathematical average* might not be an optimal way of aggregating the metrics of the *average graduate* even after removing outliers. The average metric values that resulted from this calculation seem to be too ambitious for learners. Secondly, the calculation of the *on-trackness score* might not be robust enough to accurately quantify how similar two learners are in terms of behaviour. Thirdly, the metrics displayed might not be representative enough to describe a holistic view of learners behaviour and do not account for all changes in behaviour.

To our knowledge, this is the first work that classifies learners into "behind", "on-track" and "ahead" based on their similarity to the learning behaviour of successful learners. Previous studies calculated the *on-trackness* of learners' based on their progress throughout the course and amount of course material that was accessed [117]. Based on our results, we argue that in order to aid learners throughout the learning process, effective learner dashboards or other learner-managed systems should report learners' on-trackness by taking into account learners' behaviour in context (e.g. by comparing it with that of a standard model [124]) along with learners' course progress while evaluating and reporting learner data.

6.2 Limitations

We acknowledge a number of limitations that affect the reliability of the results presented in this study.

Design of the widget First and foremost, the learners had access to only six metrics on the widget which limited the number of aspects they get feedback on. Consequently, the relevance of these metrics is critical. Secondly, for each metric, we reported the behaviour of successful learners through a single value instead of a range like in [11]. This limitation arose due to the type of the chosen visualisation because representing a range on a spiderchart would have cluttered the graph.

Experimental setup One major limitation related to the experimental setup is the placement of the `Learning Tracker`. As the widget did not have a designated position on the edX platform, its placement was influenced by the course structure. Thus, in some cases, learners had to navigate through several pages in order to access the widget. Due to the widget's placement, the meta-level information on their behaviour was mixed with the course content. In future, this issue can be resolved by better integrating the `Learning Tracker` with edX e.g. by placing it on the "Progress" page of each course.

The secondary issue is that the pacing of the courses differed between the three MOOCs and could have affected the autonomy of the learners. `WaterX` and `SewageX` followed a more instructor-paced approach, with new course content released on a weekly basis. In this situation, the course staff imposes a minimal level of regulated learning, similar to the one classroom teachers manage for their students [93], limiting the self-regulating freedom of learners and therefore the potential impact of the `Learning Tracker`. In contrast, self-regulating behaviour might be more visible in `InnovationX` as the course material was published in 3 blocks. Therefore, learners had a lot more freedom in scheduling their study time and more opportunities for developing self-regulated learning skills.

6.3 Future work

The design, implementation and evaluation of the `Learning Tracker` was guided by our definition of what makes a learner successful. As many learners enrol in MOOCs with other goals than those expected by the course developers [163], e.g. learning one or more skills and not finishing the course, these learners were not targeted by the widget. Selecting metrics that do not account for a variety of learner goals reduce the range of definitions for success as also suggested by Bentley et al. [14]. Therefore, a potential research direction would be investigating how different definitions of success impact the outcomes and behaviour of learners.

Moreover, as individual goal setting is a central component of SRL [171], we believe learners would be able to develop their self-regulation skills even more if future iterations of the widget could include extensive personalisation, allowing learners to define their own success and the related metrics that would support them in achieving their goals. Allowing learners to select the data they want to monitor from a flexible and extendible set of indicators would support learners in developing their metacognitive skills further and encourage them to take a more active role in LA, in line with the solution proposed by Durall et al. [50].

Another line of future research should investigate how users interpret visualisations of their learning experience and how well developed their feedback literacy is. For example, in `WaterX` we reported total time on the platform, while in the subsequent two studies we provided feedback on the average length of a session. Learners' understanding of metrics based on how they are reported (e.g absolute numbers or averages) is a valuable insight for the design of learner dashboards that illustrate learners' behaviour.

As the `Learning Tracker` uses social comparison to contextualize one's learning behaviour, social effects like behaviour uniformization among learners [62] and the extent to which comparing one's self to other affects learners' motivation are vital points in its future development. Forms of social comparisons could put pressure on learners that are "too far behind", leading them to give up the course instead of encouraging them to pursue their goals. At the other extreme, very active learners might be discouraged because they are "too far ahead" [70]. Moreover, according to Festinger's social comparison theory [54], the bigger the difference between one's abilities and the ones they are comparing themselves to, the less likely they are to use it as a comparison further.

Finally, we believe that further personalisation of learner feedback can be delivered to learners if there is knowledge on how different demographic groups benefit from the use of a widget. Several works already investigated the impact of culture and learner demographics in MOOCs on resource use [142], completion rates [36] or engagement [86]. Building on these findings, the metrics displayed on the widget, the framing of the feedback, and the visualisation chosen can be customized to the learners' skill, knowledge and cultural background.

Chapter 7

Conclusions

MOOCs are a promising online environment that attracted the attention of both higher education institutions and avid knowledge seekers. However, the major challenge MOOC providers are still struggling with is the high drop-out rates. Taking into account the existing literature and the results of this work, we consider that the lack of tools that support MOOC learners through their learning process on the MOOC platforms is a gap that needs to be addressed in order to allow for MOOCs to achieve the potential envisioned by Billsberry [15]. Our widget tackles the two challenges outlined by Baker in [7]: providing meaningful information for learners and devising easily understandable ways of visualising it.

In order to address these challenges, we designed and evaluated a widget that could be integrated into a learner dashboard for MOOC learners. Our widget aims to develop learners' self-regulation skills by encouraging learners to reflect on their learning behaviour. The `Learning Tracker` was designed as an open learner model and it relies on learning analytics to analyse and report learners' behaviour which is extracted from trace logs. The widget was developed in two iterations, each iteration being evaluated in live MOOCs. We evaluated the widget through an empirical long-term evaluation throughout three MOOCs offered by TU Delft on the edX platform, reaching 20.000 learners. The evaluation is less focused on usability and user satisfaction as common in literature, but rather on the impact of the `Learning Tracker` on the learning process and learning. The analysis also covers change in behaviour, the engagement generated by the widget, the effects of social comparison and the level of interaction with the widget.

Our main results reveal that when exposed to the `Learning Tracker` learners are more likely to complete the course with a graduation mark because (i) learners attempt more quiz questions and (ii) they submit their work earlier. Although our results indicate that the `Learning Tracker` impact learners' engagement and reduces procrastination, there is little evidence that other aspects of learners' self-regulation were influenced. Nonetheless, a deeper analysis on learners' behaviour showed that being exposed to feedback on their behaviour might lead to changes in a learners' overall behaviour and not only in the areas they received feedback on. This underlines the powerful effect feedback and awareness of one's behaviour has on learning performance as discussed by [93].

We recognize directions for future research for learner dashboards, similar to the ones outlined by [7]. Firstly, future work should focus on identifying meaningful information that should be reported to the learners. Moreover, in order to provide personalized dashboards which cater to the needs of their users, it is critical to comprehend how learners' different goals can be supported through the metrics displayed on the dashboards. Secondly, understanding how learners perceive and interpret different types of visualisations would lead to improving the graphical solutions through which data is reported. Finally, we believe that dashboard designs proposed for MOOC environments should be accompanied by extensive evaluations in live MOOCs. MOOC platforms provide a diversity of learners in terms of demographics and learning goals and integrated ways of collecting a large amount of data which describes learners' behaviour. Moreover, these evaluations should focus on assessing the impact such dashboards have on learners' performance, motivation and the way they manage their learning processes.

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