The Real-Time Learning Tracker

Real-Time Learner Feedback for Encouraging Self-Regulation & Metacognition in MOOCS

Maria Gatou

Master's Thesis

TU Delft Delft University of Technology

Challenge the future

The Real-Time Learning Tracker

Real-Time Learner Feedback for Encouraging Self-Regulation & Metacognition in MOOCS

by

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Abstract

Massive Open Online Courses (MOOCs) offer the opportunity to a large amount of learners worldwide having access to quality education, reaching also the most disadvantaged learners overcoming any obstacles of time and space. Nevertheless, the low completion rates which are often below 15%, is the main challenge that MOOCs face nowadays. In a MOOC environment, learners have a high degree of autonomy with limited or no pressure from teachers, highlighting the need for learners to self-regulate their learning. However, according to literature, the limited self-regulated learning skills of learners is one of the major reasons that lead them to dropout MOOCs. Besides, the vast majority of the current tools intended to help learners in the online learning environment neglect to give the help expected to the advancement of such skills.

The present work aims to investigate how self-regulated learning skills can be enhanced by encouraging metacognition and reflection in MOOC learners by means of real-time personalized learner feedback through social comparison. To this end, we have developed three versions of an interactive widget, the *Real-Time Learning Tracker* , which allows learners to visualize in real-time changes in their learning behaviour and compare it to that of previous graduates of the same MOOC. The three versions of the *Real-Time Learning Tracker* differ in the degree of complexity of the presented feedback so as to investigate how learners interpret varying visualizations of their learning behaviour and which one of them leads to more changes on their behaviour during the course. The *Real-Time Learning Tracker* was evaluated in a live TU Delft MOOC running on the edX platform while engaging nearly 2000 MOOC learners over the course of 10 weeks.

Based on our results, we argue that learners with access to one of our *Real-Time Learning Tracker* versions have higher likelihood of graduation from the MOOC, compared to learners with no access to our *Real-Time Learning Tracker* . In addition, we observed that the widget has a positive impact on learners' self-regulation whereas, we have little evidence that learners developed their engagement with the course content by the end of our experiment. Moreover, based on our findings we argue that the real-time attribute of our *Real-Time Learning Tracker* in combination with its easy access, led to a high degree of learners' widget interactions throughout the course units. In addition, our results conform with prior research proving that the provision of feedback to learners on a specific number of behavioural indicators can lead to improvements in their overall learning performance. Finally, our results reveal that the exposure of learners to the most detailed version of the widget engaged more learners and this type of feedback affected positively the learning performance and behaviour of highly educated learners.

This research highlights the significant effect of real-time feedback and self-reflection on learners' learning performance and behaviour. We suggest that future research should explore learners' intentions, goals and definitions of success and customize future iterations of the widget based on their individual needs and personalities.

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1 Introduction

Massive Open Online Courses' audience are growing steadily and their recognition as equivalent to a regular university is slowly establishing itself. They were first introduced in 2006 and emerged as a popular mode of learning in 2012 [137]. MOOCS are a current trend for creating online courses which equips learning institutions with a high quality teaching initiative with relevant visibility on the Internet [84, 132]. MOOCs refer to web platforms which allow millions of learners to have access to various instructional materials and resources without the barriers of time and place, by providing affordable learning opportunities to large number of learners, such as Coursera, Udacity and edX [110, 173]. Labelled as *the future of education* [25], MOOCS are distinguished from traditional learning environments by being open for everyone, easy to enrol, and having a heterogeneous community. MOOCs are characterized as interactive, online learning tools that support the learning of specific concepts by enhancing, amplifying, and guiding the cognitive processes of learners [9]. They are an alternative to traditional models of face-to-face education, becoming an environment that was bet on bringing revolution to higher education based on factors of their popularity, massiveness of enrolments [116], as well as by reducing the educational gap between the most privileged and the most disadvantaged learners [7, 90, 185]. By 2017, over 81 million learners worldwide registered for at least one MOOC [4]. Currently, more than 800 universities and institutions are offering over 9,400 MOOCs and these numbers are expected to rise even more [4]. Therefore, the development of MOOCs has received considerable attention from both educators and learning-technology developers.

1.1. Motivation

Regardless the rapid development and enormous gaining popularity of MOOCS, one of the main challenges MOOCS face, is the massive dropout rates of around 95% in the average MOOC [86, 91, 103]. A sharp drop in learner's participation takes place even form the first week of the course [186]. The fact that learners are able to enroll in MOOCs without any particular knowledge requirements, except for some cases in which specific previous knowledge is recommended, the MOOC registration bar is very low, leading to massive registrations. However, only a small number of learners engages in any course activity after the initial enrollment, and significant progress is made by even less. Finally, only a small proportion of those that were in some point active during the course manage to finish it.

Regarding the reasons that led learners to lose their engagement and drop out MOOCs, recent studies have shown that learners have different aims and goals when it comes to MOOCs, and completion is not the end goal for all of them when it comes to education in MOOCs [104, 121, 180]. Therefore, a gap exists between what is traditionally seen as a goal from educational providers' point of view and what learners foresee as goals. Moreover, this issue has been investigated from the learners' perspective by many studies, by collecting and analyzing MOOC learners' opinions. Lack of time or poor time management were reported by learners as the most frequent reasons for dropout [23, 79, 90, 95, 129]. In addition, low motivation in the absence of university grades or credit [106, 146], low student-teacher interaction [17, 112] and low self-efficacy [75] were reported as reasons for dropping out MOOCs.

Alternative reasons that lead learners to dropout MOOCs, as reported by many researchers, are the lack of digital learning skills or low learning skills and their poor study habits [22, 75, 161]. What defines a "successful" learner in a MOOC environment that is characterized with limited or no pressure from teachers/parents and considerably low financial obligations, is that learners should be disciplined in both the planning and following of their study habits [112]. The ability of learners to control, manage and plan their learning activity in order to complete their goals and improve their skills, is known as *self-regulated learning (SRL)* [100, 190]. This ability in combination with "the knowledge about and regulation of one's cognitive activities" which is known as *metacognition* [67], drive MOOC learners to be able to recognize the effectiveness of their learning skills. The novelty of the MOOC environment poses extra challenges for neophyte learners. While in a traditional classroom, teachers are responsible to guide students through the appropriate learning path and monitor the whole learning process [106], in MOOC environment learners need to act autonomously [134] by retaining their motivation in high levels, defining their own learning path, as well as engaging with the course material and other MOOC learners [186]. Therefore, the discipline for planning and following a self-imposed schedule does not come naturally to many learners, rather it is a learned skill [118, 122]. Moreover, the different levels of prior learning education between learners are translated also to different chances of course completion, since it has been proved that higher educated learners have also higher chances to complete a MOOC than less educated ones [74]. According to Alario-Hoyos et al. [7], the educational gap between low and high educated learners gets bigger due to the discrepancy between learning skill levels, leading to the weakening of MOOCs' potential.

However, the current design of MOOCs does not support learners to engage in self-regulating learning [115]. Therefore, several researchers recommend that MOOCs should provide learners with a metacognitive toolkit in order to boost their achievement, improve their skills and accelerate their learning process by self-regulating their learning [95, 129]. MOOC developers should therefore focus on the creation of tools that better assist learners in their learning process, instead of just being knowledge repositories. However, most of the existing MOOC platforms are not designed to support learners in developing their learning skills. As Rai and Chunrao [146] 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."

1.2. Research objective

The work presented in this thesis is a continuation of Davis et al.'s [57] and Jivet's [82] research [1], in which a personalized feedback system, the *Learning Tracker*, was developed and evaluated across four randomized controlled trials in live MOOCs on edX platform provided by DelftX. The feedback system facilitates "social comparison" with previously successful learners based on an interactive visualization of multiple behavioral indicators based on learners' activity during the course. According to social comparison theory [65], people establish their social and personal worth by comparing themselves to others. Offering learners the opportunity to compare their behavior with that of their peers promotes increased student achievement in formal learning environments [26, 81, 135]. The results of that experiment indicated that the availability of social comparison cues and this type of feedback significantly increases completion rates by a ratio of approximately 3.4%. This research functioned as an inspiration for us to continue this work by adding the following novelties in the existing research:

1. The aforementioned tool was shown to the learners every week by means of a picture incorporated in a separate section of the course content and the data was only updated in a weekly basis. Thus, in some cases, learners had to navigate through several pages in order to access the widget and the meta-level information on their behaviour was mixed with the course content. Moreover, learners could not really see where they were standing in real-time compared to the most successful class. For that reason, we set as our first goal to provide learners with real-time feedback on their learning behaviour in order to investigate if the real-time attribute of the feedback would help them make better use of a system like *Learning Tracker* than waiting a week before they see how they stand compared to successful learners. Our second goal is to offer learners easy access to our feedback system at every course page, focusing both on usability and user satisfaction.

2. A second difference compared to Davis et al.'s [57] and Jivet's [82] research is that we tried to evaluate a number of feedback interfaces, from complex to simple, in order to investigate students' interaction when the degree of complexity of the presented feedback as well as the number of study dimensions

[1] Jivet's [82] work performed in the context of a master thesis while at Delft University of Technology and Davis et al.'s [57] research used Jivet's [82] work as a baseline for further research.

varies. In that way we could test which version of our feedback system would be better for the learners in terms of engagement, self-regulation and completion rates.

3. In Davis et al.'s [57] and Jivet's [82] study, role models were built based on learners who were successful in a previous edition of the MOOC, in other words learners who managed to obtain a passing grade. In order to ensure that learners would compare themselves with slightly better performing peers, the "Average Graduate" learner model was used. We add to that by giving learners the opportunity to compare themselves also with another learner model, which is the "Most Engaged Graduate" learner model. The "Most Engaged Graduate" learner model was built based on graduate learners' degree of engagement with the course material during the course, hence the most engaged graduate was concerned the learner with the highest level of engagement. This is an indication to learners of the learning behaviour and engagement levels of the most engaged graduates of the respective course.

4. In Davis et al.'s [57] and Jivet's [82] study, the selected metrics were determined based on key aspects of successful learner behaviour and were divided into three clusters such as course material coverage, level of engagement and time management. After observing the efficiency of the selected behavioural indicators in Davis et al.'s [57] and Jivet's [82] research, we decided to borrow the metrics of the first two clusters in our *Real-Time Learning Tracker* implementation, as well as extend them with an additional engagement metric.

Initially, regarding the attainment of self-regulating learning [188], we follow the pattern proposed in Davis et al.'s [57] work, by encouraging learners' reflection on their learning behaviour and study habits as a means to promote the development of critical thinking and self-regulation skills hoping for an improvement to their success rates in MOOCs.

Moreover, we intend to utilize the vast amount of learner data that is resulted from the tracking functionality of existing MOOC platform that describes learners' online activity by means of *learning analytics*. Learning analytics is data science applied in the online learning domain and made it feasible to observe the impact of learning design on student behaviour, satisfaction and performance, enabling teachers and instructors to identify learning and teaching trends from rich data sources [147]. In that way, we are able to detect and describe cognitive activities and promote metacognitive skills such as reflection, planning and self-monitoring [135].

Since our work builds upon Davis et al.'s [57] and Jivet's [82] research, in which the feedback system can be integrated in a learner dashboard, we followed a similar path by designing and developing our feedback system as a learner dashboard destined for MOOC learners. Learning aspects like awareness, reflection, sense-making and behaviour change in online or blended learning environments[2] are encouraged with the use of learner dashboards which have been developed as effective tools to visualize data about learner activities [178].

Therefore, we developed the *Real-Time Learning Tracker* , as an interactive feedback widget in the form of a learner dashboard aimed at MOOC learners and its purpose is to provide learners with real-time and personalized feedback based on their learning activity during the MOOC. The *Real-Time Learning Tracker* offers MOOC learners the opportunity to make comparisons between their learning behaviour during the course and that of previously successful learners of the same MOOC. We followed Davis et al.'s [57] and Jivet's [82] definition of successful learners, as learners who managed to graduate from the MOOC. Similar to Davis et al.'s [57] *Learning Tracker*, the purpose of this work is to investigate the effect of real-time learner feedback through social comparison on self-regulating skills of learners by encouraging metacognition and reflection. The real-time attribute of the feedback system, offers the opportunity to learners to find out immediately if they are off-track compared to successful peers and make the appropriate changes for the better. We hope that this attribute will accelerate the learning process and will enhance learners' self-regulated behaviour by giving them the opportunity to self-monitor the changes in their learning behaviour in real-time and change their study plan accordingly. In order to support this type of intervention, both tracking learners' behavior in real-time and dynamically displaying their activities based on each learner's individual log traces, are required. Enabling real-time logging on the edX platform consists one of the major challenges of this work, since the edX platform provides a daily event log delivery to its X consortium members but does not have a real-time data API. In order to develop our widget, we first considered existing learner dashboard implementations as well as Davis et al.'s [57] work and designed three versions of the *Real-Time Learning Tracker* with different degree of granularity and study dimensions. Afterwards, in order to evaluate our *Real-Time*

[2]Blended learning is an educational approach that combines traditional classroom methods and independent study [178].

Learning Tracker , we deployed the three versions of our feedback widget in a live MOOC offered by TU Delft on the edX[3] platform during a 10-week period. Our experimental setup was based on Jivet's [82] research, in which we assigned randomly the participants into four experimental conditions, those who have no access to our learning widget and those who have access to one out of its three versions so as to perform a randomized controlled experiment (A/B testing). Finally, we compared the four conditions performing a data analysis on the log traces of the active learners enrolled in the aforementioned MOOC, in order to investigate the effectiveness of our *Real-Time Learning Tracker* and provide answers to our research questions.

Research Questions
Our work is guided by the following research questions:

RQ1 *Are learners more likely to complete the course when they can compare in real-time their behaviour to that of previous graduates and which version of the Real-Time Learning Tracker is better in terms of learners' achievement (higher completion rates[4] and final grades)?*

RQ2 *To what extent is the learners' behaviour affected by comparing themselves in real-time to previously successful learners?*

1. *Do learners become more engaged with the MOOC when they can compare in real-time their behaviour to that of successful learners and which version of the Real-Time Learning Tracker is better in terms of learners' course engagement (activity level within the MOOC environment)?*
2. *Do learners show improvement on their self-regulating skills when they compare in real-time their behaviour to that of successful learners and which version of the Real-Time Learning Tracker is better in terms of learners' self-regulation (more efficient use of time throughout the course)?*

RQ3 *Which types of learners will benefit most from the Real-Time Learning Tracker , based on their prior education level?*

Research questions 1 and 2 were also considered in Jivet's [82] prior thesis. However, in this work we investigate i) if the addition of the real-time component on learners' feedback also affects positively learners' performance, engagement and self-regulation and ii) which version of the *Real-Time Learning Tracker* , differing in the degree of complexity of the presented feedback, is better in terms of the aforementioned learning aspects.

1.3. Scientific Contribution

Our work brings several contributions to the fields of learning analytics and MOOCs. We summarize our contributions as follows:

- We introduced the design and the implementation of three versions of an interactive feedback widget, the *Real-Time Learning Tracker* , destined for learners of the edX online platform, which tracks and visualizes learners' behaviour in **real-time** for enhancing learner's engagement and self-regulatory behavior by means of reflection. Furthermore, we put additional effort to make the widget easily accessible at all times to potential users-learners, focusing both on usability and user satisfaction. We also highlighted the challenges we encountered during the design and the development of our system and its deployment on the edX platform.

- We have deployed and evaluated the *Real-Time Learning Tracker* in a real MOOC hosted on the edX platform across the duration of 10 weeks reaching nearly 2000 learners. We had access to learner data extracted from the log traces of the learners enrolled in the MOOC offered by TU Delft due to TU Delft's research partnership with the edX platform. Longitudinal studies of such magnitude are rarely encountered in the literature.

[3] `https://www.edx.org`
[4] *Completion* rate is defined as the percentage of learners that earned a certificate of completion or obtained a passing grade.

1.4. Preliminary results

The results showed the effectiveness of our widget in the MOOC under study, since learners that are exposed to the *Real-Time Learning Tracker* have higher likelihood of course completion because of alterations in their learning behaviour. Based on our results, we also argue that the mere fact of receiving real-time feedback on a limited number of learning habits could lead to changes in the overall behaviour of a learner and not only in the areas in which they received feedback.

1.5. Outline

The structure of this thesis is inspired by Jivet's [82] thesis. The organization of this document is as follows. In Chapter 2, we summarize literature related to our study and present the key ideas we adopt in our work. Chapter 3 elaborates on the design decisions and challenges involved in developing the three versions of the *Real-Time Learning Tracker* . In Chapter 4, we describe our experimental setup and elaborate the deployment of our study on a real MOOC hosted on the edX platform. In Chapter 5 we present our analysis of the data we received from our experiment. We conclude our results in Chapter 6 where we discuss the findings and limitations we observed in the results, as well as propose related future works.

2

Related Work

The structure of this chapter is inspired by Jivet's [82] thesis presenting research on the enhancement of self-regulated learning through feedback, self-monitoring and reflection, the theory of social comparison and its application to learning and the review of current learners dashboard as effective means of visualizing learning behaviour. All of the aforementioned topics are discussed in the upcoming sections reviewing the current literature and presenting the existing status of this field of study and the work that has been done on it so far. We conclude this chapter by presenting the limitations of the existing learner dashboards which we aim to attenuate in this research.

2.1. Massive Open Online Courses

The term MOOC stands for Massive Open Online Courses. Massive Online Open Courses (MOOCs) have increasingly become objects of research interest and studies, since they have afforded millions of people worldwide the opportunity to learn for little or no cost. MOOCs aim to provide a large numbers of learners with learning opportunities, being a part of a continuous trend of innovation, experimentation and use of technology [168]. Although MOOCS initially designed for the lifelong learning market [152], recently their purpose made more concrete in improving the learning experience by overcoming any geographical and time boundaries and providing more affordable learning opportunities [68].

A large number of participants are able to attend these online courses, leading to the term *massive*. MOOCs are online courses of fixed duration, following a certain pedagogy. There are no entry requirements and learners can access the content of the course and submit assignments without paying fees, hence the term *open*. They are also *online*, affording people the opportunity to access them on the Internet. In that way, learners who do not have access to traditional higher education are enabled to take advantage of other learning opportunities.

cMOOCs were the first MOOCS and they were less about presenting content and more about connecting learners [169]. They were based on the connectivist theory presented by Siemens in which learners are responsible for organizing the content of the course [170]. In that type of MOOCs, learning is seen as the process of network generation between learners as a way to create and share knowledge [60]. The connectivist component of these MOOCs led to their name as cMOOCs.

A second type of MOOC emerged in 2011, namely xMOOCs. These types of MOOCs were based on interactive media such as lectures videos and text as well as individual learning is highlighted instead of learning from peers [54] . These MOOCs offer an online, free and with no barriers entry [30]. MIT and Harvard University used the term *extension* for labeling the online version of their courses [32], leading to the x in xMOOC. Therefore, in xMOOCs the instructors define the learning objectives, the curriculum and the assessments [60].

We conduct our research only on xMOOCs since the courses provided by TU Delft are xMOOCs. To start with, in these MOOCs knowledge delivery and practice are complementary, unlike classroom lecture. The main structure of these MOOCs includes mini video-lectures of 5-10 minutes each which consists the main tool of learners for knowledge acquisition as well as several quiz questions for testing and assessing their knowledge. Another component is the forum where learners post questions that other students can answer. There are also available peer-to-peer assessments in which learners evaluate and grade themselves or their peers. Learners are also able to browse reading material, acquiring more information about the course content.

The founder and president of edX, Ananth Agarwal indicated six advantages of MOOC learning [5]. Firstly, learners do not have to sit all the time to listen to lecture in a classroom. He argues that, learning from video with short duration contributes to active learning, which has been proved to offer many benefits to MOOC learners [102]. Secondly, there is instant feedback about the assignments and answers submitted by the learners. This has been proved as the best way to learn and make progress [49]. Thirdly, learners are allowed to make many mistakes and this contributes to infinite learning or mastery-based learning. Fourthly, the learners are allowed to pause, rewind, speed up/down the video, so that they can listen more and more, which is totally impossible in real-classrooms. Fifth, there is more engagement from learners or gamification. Finally, learners learn from their peers, and with thousands of discussions and online forums.

The current paragraph describes the structure of MOOCs on the edX platform, since the present work is relied on MOOCs provided by TU Delft on the edX platform. As depicted in Figure 2.1, each course is made up of lessons and modules displayed with the form of a path below the menu bar including information about the specific course, module and lesson. Modules are usually released weekly but there is no restriction for learners to visit any material already published. Modules are divided into several sections called *learning sequences*. Each learning sequence includes either video lectures, reading materials, assessments (graded or not) and/or discussion session. A *graded assessment* can be divided into four categories. Either a peer-review assignment, a weekly problem set or a mid-term or final exam [2]. A *non-graded assessment* can be practice quiz questions for testing knowledge acquired from video lectures. However, in some cases, MOOCs are also self-paced, where everything is available at once.

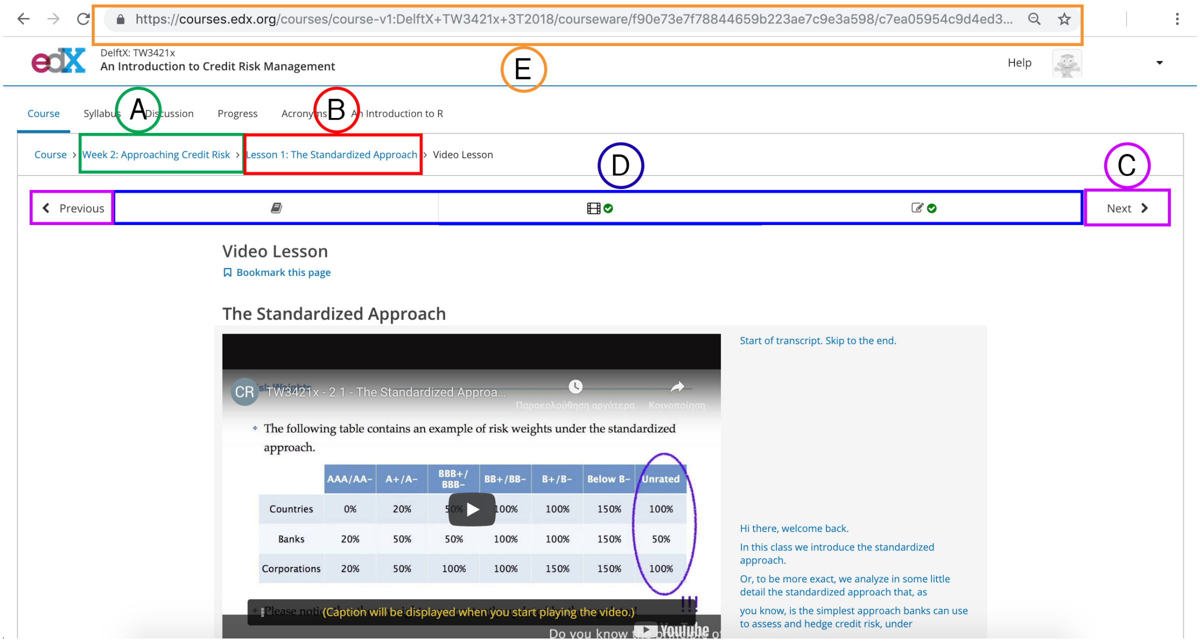

Figure 2.1: Annotated breakdown of edX interface components. A MOOC on the edX platform contains several *modules* (A), where several sections are contained in each module (B), navigation/goto buttons are illustrated in (C), each section is a part of a *learning sequence* and contains either video lectures, reading materials and/or assessment problems (D) and (E) is the page URL.

Additional information is also provided to MOOC learners of the edX platform in the form of a home section with general information relative to the course material, discussion pages, a progress page and a course syllabus with extra information about course structure and scheduling . The progress page provides learners with a simple learner dashboard which displays learners' scores of the submitted graded quizzes. Similar to Jivet's [82] *Learning Tracker*, the goal of our *Real-Time Learning Tracker* is to complement the displayed information on the progress page with a more enriched personalized learner dashboard aiming to provide learners with support throughout their learning experience in DelftX MOOCs.

2.2. Self-Regulated Learning

In this section, we introduce the importance of self-regulated learning (SRL) in the online learning environment. We also refer to prior research that aimed to promote self-regulation in MOOC learners and finally we discuss about the effectiveness of feedback as a way to trigger self-reflection and support SRL.

The ability of learners to control, manage and plan their learning activities and behavioral processes in order to reach their goals and improve their performance, is known as self-regulating learning [98, 143]. In other words, SRL can be described as the ability of learners to take control of their own learning behaviour, since SRL assumes that when students have a learning task, they autonomously create their strategic action in completing the task [47]. In self-regulated learning except from the regulation of one's learning activities, motivational, cognitive and emotional aspects are also involved [27, 28, 82, 189].

A social cognitive model of self-regulated learning was proposed by Zimmerman [188] according to which self-regulation is achieved in 3 phases consisting of *forethought*, *performance* and *self-reflection* as illustrated in Figure 2.2.

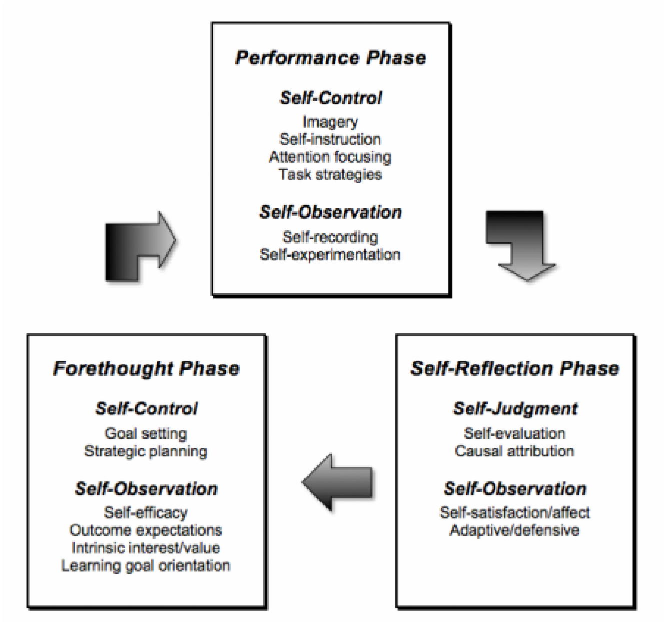

Figure 2.2: Zimmerman's [188] social cognitive model of self-regulated learning and the learning activities associated with each of the three phases.

As self-regulation skills are also considered self-teaching methods, time management and meta-cognitive evaluation of one's own understanding [189]. Moreover, Paris and Byrnes [140] claimed that the individual goal setting, the approach of tasks with confidence and positive expectations and overcoming obstacles with persistence and creative problem solving, are all considered as self-regulatory skills. Butler and Winne [45] presented that the learning outcomes, motivation and further self-regulation are recursively influenced by these skills .

Therefore, we conclude that the ability of MOOC learners to self-regulate their learning is essential for the improvement of their learning performance. Hence, in line with Jivet's [82] work we believe that MOOC designers should focus on creating interventions for learners that aim to support them advancing their self-regulated skills. Research must engage deeply with these needs of learners in order to enhance the learning opportunities that MOOCs, and future forms of open learning, provide for all learners.

2.2.1. SRL in online learning

Self-regulated learning has been acknowledged as an influential component of academic achievement in traditional classroom learning [143, 157, 191]. Recent studies demonstrated the influence of self-regulation in online learning environments [20, 131, 138]. Compared to traditional classroom learning, online learning brings more responsibilities and autonomy. Especially the flexible nature of online learning requires students to employ more self-regulatory skills [12, 29, 85, 94]. It has also been proved by several studies that learners with more self-regulatory skills are more likely to be successful in online learning environments [11, 13, 21, 80, 117, 162].

According to Azevedo et al. [15], learners with higher levels of SRL are much better at regulating their learning during the knowledge construction activity, in terms of planning their learning by creating sub-goals and activating prior knowledge, monitoring their emerging understanding, and planning their time and effort. However, the novelty of online learning environments is accompanied with the adoption of some major features like openness, flexibility and the non-existence of interaction between learners and instructors. Hence, the ability to self-regulate is becoming more essential [144, 181].

Many studies focused on the influence of self-regulation on learning outcomes such as academic achievement or performance [24, 76, 123, 164]. Moreover, several studies indicated that student achievement in the online learning environment can be boosted by SRL strategies and the learning process can be accelerated. From 12 studies, strategies like time management, metacognition, and effort regulation have been correlated with higher academic outcomes [35] and course completion [144]. All studies were required to examine the application of SRL strategies by university, college or equivalent students who enrolled in an online or web-based course, with varying number of participants. Online academic outcomes were defined as the achievement of a particular result in an online assignment, exam, subject, or degree and were expressed in terms of a numerical grade or grade point average (GPA). The majority of studies were prospective followed by experimental and cross-sectional designs. It is argued by many researchers that learners of technologically enhanced learning environments, especially of online courses, need to be supported and guided to advance their regulatory skills, so as to persist in the course [22, 95, 172]. Kizilcec et al. [100] in an attempt to provide targeted support of SRL skills to MOOC learners investigated SRL in a sample of 4831 learners across six MOOCs. The aspects that were investigated were relative to overall course achievement, interactions with course content and survey responses. The results indicated that goal setting and strategic planning were good predictors of personal course goals and help seeking was associated with lower goal accomplishment. It has also been found that learners with stronger SRL skills had a higher likelihood to revisit previously studied course materials. Nonetheless, learners in current MOOCs are provided with limited guidance in respect to this matter and there is a lot of struggle by many learners to attain the level of self-discipline required to be able to manage their own learning [129].

Despite the fact that one of the top reasons that is assumed to lead to high dropout rates is low learning skills [75], similar to Jivet [82] we believe that the need for development of SRL skills in the online environment could be seen as an opportunity to make improvements to the overall quality of learning and empower learners to seek learning that lasts.

2.2.2. Promoting SRL in MOOCS

Due to the limited personalized guidance provided by MOOC teachers, there is high likelihood that people who lack study skills and working habits drop out of MOOCs, contributing to the increase of the educational gap between high and low educated learners. According to current studies on MOOCs, course completion is directly related to time management, planning and self-monitoring skills of learners [7, 98]. However, self-regulated learning is not promoted in most of the MOOCs [118]. Therefore, many learners who do not possess some basic self-regulatory skills face major difficulties to complete the course [96].

In an attempt to encourage self-regulation on MOOC learners, several solutions have been proposed so far. Kizilcec et al. [98] after asking a group of 17 highly successful learners about their own strategies for how to succeed in a MOOC, coded their responses based on a SRL framework which afterwards led to the synthesis of seven recommendations. The evaluation in a randomized experiment of the effect of providing those recommendations to 653 learners in the same course, indicated that just urging learners with specific recommendations to engage in self-regulated learning does not increase their course achievement. Similarly Davis et al. [56], ended up in the same conclusion after the investigation in the MOOC environment of two types of instructional interventions which have been found to be effective in traditional educational environments such as study planning (elaborating on weekly study plans) and retrieval practice (i.e. strengthening course knowledge through actively recalling information).

Maldonado-Mahauad et al. [114] tried to predict learners' success in MOOC by collecting and analysing data from 2035 learners who took a self-paced MOOC in Coursera. Their indicated that they were able to predict with more accuracy learners success when students reach a certain status considering not only low level data but also their SRL strategies such as goal setting, strategic planning, elaboration, help seeking etc. In addition, Alario-Hoyos et al. [7] presented a mobile application (MyLearningMentor) that addresses the lack of support and personalized advice for MOOC learners. The architecture of this tool is designed to provide

MOOC learners with a personalized planning that facilitates them following up the MOOCs they enrol. In this tool also tips and hints were provided aiming at helping learners develop work habits and study skills, and eventually become self-learners. Nevertheless, this work is still at an early stage and needs to be implemented and evaluated with real MOOCs.

Tang and Fan [174] proposed and implemented a networked SRL platform enhanced with the Web 2.0 technology. In this design, modern web technologies are used to implement the functions or services that provide a self-planned and manages studying environment to online learners. Also integrated online learning tools are provided to learners in order to develop their self-learning capabilities. Once more this research is at an early stage and the next step is to develop a performance assessment model to measure and evaluate the outcome and the effectiveness of this tool.

Another case of a tool that scaffolds SRL in MOOCs although has not yet been evaluated, is the tool presented by the authors of [151]. Sambe et al. [151] also recognize the weakness of self-regulation skills as one of the main factors that contribute to dropout in a MOOC. For that reason, they present a conceptual framework to promote self-regulated learning in a MOOC. This framework relies on the use of a virtual companion to provide meta-cognitive prompts and a visualization of indicators. The authors of this work are confident that this system will not only improve the quality of learning on the MOOC but also will help reducing attrition.

2.2.3. Promotion of SRL through meta-cognition and feedback

Meta-cognition

As occurs from previous subsections, a learner needs to be highly self-regulated to be successful in open learning environment that provide little guidance, such as MOOCs. However, not all solutions aimed at raising learners' self-regulating levels are successful to increase learners' awareness of their skill level. According to Kizilcec and Halawa [95], only when learners own a specific level of meta-cognitive awareness, they are in a position to notice when they lack self-regulatory skills or evaluate their skill level. *"Meta-cognition is cognition about cognition, thinking about thinking, knowing about knowing, becoming aware of one's awareness and higher-order thinking skills"* [130, 136]. Pintrich [142] argued that, learners with meta-cognitive awareness own knowledge of general strategies for learning and thinking, cognitive tasks, as well as when and why to use different strategies and the self in relation to cognitive and motivational components of performance. In addition, self-regulation becomes effective only when relies on accurate self-assessment of knowledge of the conditions under which these SRL strategies might be used [156].

An important component of meta-cognitive knowledge is self-knowledge [142]. In terms of assessment, focusing on self-knowledge indicates that students should have the opportunity to assess their own strengths and weaknesses. In a physical classroom, students are able to meet individually with their teachers in order to discuss their perceptions of their own strengths and weaknesses and teachers can provide them with feedback about these perceptions. However, a MOOC environment lacks personal, face-to-face instructor guidance and attention [175]. In addition, the massive amount of learners in the course, lead course staff to struggle establishing discussions which expose meta-cognitive knowledge [39]. In the same line with Jivet's [82] research, we propose feedback as an effective tool to deal with these issues in order to raise meta-cognitive awareness in MOOCs.

Feedback

Feedback is an inherent and prime determiner of processes that constitute self-regulated learning and its role in the empowerment of learners' SRL skills is crucial [45]. Feedback is "information with which a learner can confirm, add to, overwrite, tune or restructure information in memory, whether that information is domain knowledge, meta-cognitive knowledge, beliefs about self, or cognitive tactics and strategies" [8].

Four levels of feedback have been acknowledged by Hattie and Timperley [78]. There is the task level feedback which includes feedback on how well the task is being accomplished or performed. Another feedback level is the process level feedback which is specific to the processes underline the tasks or relating and extending tasks. There is also self-regulation level feedback which is the way students' monitor, direct, regulate actions towards the learning goal. Finally, there is also self-level feedback which is a personal evaluation and effect about the learner, with limited information about the task.

According to Hattie and Timperley [78], feedback on learning strategies and feedback on self-regulation are the most effective forms of feedback. Feedback that is related to self-regulation components is powerful to the degree that it leads to further engagement or investing further effort into the task [77, 78, 165]. Therefore, if feedback is offered at the right level and structured in an appropriate way, it can assist students to comprehend, engage, or develop effective strategies to process the information intended to be learned. Feedback can be effective, when it is clear, purposeful, meaningful, and compatible with students' prior knowledge and to provide logical connections between learners' present state of learning and performance and the desired goal and standards.

In general, MOOC developers take into account all the aforementioned types of feedback [115]. Usually, MOOC platforms provide learners with the most simple type of feedback on task execution which is less effective form of feedback than the most powerful ones like feedback on self-regulation and feedback on learning strategies [101]. Feedback including self-regulation leads students to invest more effort to the task. Thus, in line with Jivet's [82] we intend to evaluate the effectiveness of the *Real-Time Learning Tracker* on self-regulation based on the amount of effort that learners invest in the MOOCs and their engagement with the MOOC.

Although teacher-facing feedback systems can offer key insights for the improvement of the course experience, they are unlikely to address the issue that many learners feel lost and isolated in MOOCs [91]. Personalized feedback promises the promotion of effective SRL behavior by facilitating self-monitoring of learning processes [87]. One of the most important lines of research which aims to provide learners with personalized feedback is that of Open Learner Models (OLM), an educational interface that gives learners insight into their current knowledge state and activity patterns, which are typically unavailable to them [43]. OLMs have been proven to work as powerful meta-cognitive feedback tools that impact learners' use of SRL strategies, by allowing learners to visualize and reflect on their own learning and achievements [41, 73].

The design of the majority of the OLM interfaces were destined for Intelligent Tutoring Systems [44]. However, in recent years new OLMs applications were designed with the purpose to support learners in large scale online learning [42]. Such application is the Khan Academy online platform[1]. After the completion of learners' pretest for a course, they are displayed an overview of their progress. The progress visualization comes alive through a skillometer for fine-grained skills and badges gained through the course [42, 55].

An OLM is generated in MOOClm [55] as well as the corresponding C and Unix MOOC learner models on the Open edX platform. In their attempt to create the OLM, the authors linked numerous events recorded in the edX activity trace logs to the achievement of learning goals. A set of "reference models" were created based on which students can perform comparisons of their own performance, based on a variety of sources for the definition of learning objectives. Similarly to Davis et al.'s [57] and Jivet's [82] work, we designed the *Real-Time Learning Tracker* as an accessible, understandable, and scrutable [88] learner model [3, 89].

2.3. Social comparison & social learning

Social comparison is the theory that drive individuals to gain accurate self-evaluations about their own attitudes, beliefs and skills by comparing themselves to the other people around them [10, 111]. People make comparisons of themselves with people who have similar abilities and opinions, when another means of evaluation is missing [61, 65]. Based on the effects of social learning and social comparison we provide learners with the opportunity to reflect on their learning behaviour.

Social learning is a theory of learning and social behaviour which proposes that new behaviours can be acquired by observing and imitating others, usually skilled practitioners [19]. Individuals externalizing their ideas, learn through teaching and engage in dialogue with others who may have different perspectives or greater expertise, are all social learning prerequisites [99]. Research has shown that learning is strongly influenced by social interactions [31]. The only chance of learners to be socially interactive in MOOCs and where social learning is promoted, is forums.

Discussion forum provides learners with the opportunity to interact with one another [99]. Learners who engage with forums are able to ask for clarifications about the course content, seek and provide help on assessments, discuss ideas relative with the course, or simply socialize with one another, creating a sense of trust among the group Brinton et al. [34], Garrison et al. [69]). Prior work has also found that more active learners with the course content are also more engaged with the course forum, reflecting a higher level of engagement with the course overall [97]. Hence, it appears that forum participation is a valuable aspect of online learning and needs to be encouraged. Nevertheless, in forums there is lack of study habits related topics. The lack of self-awareness of learners could be a possible reason for the absence of threads that cover this topic, since reflection on one's learning process demands high levels of self-awareness [82, 95].

After evaluating different types of visualizations based on social comparison in a learning environment, the results indicated that the comparison of one's behavior with their peers could raise students' motivation to

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

learn and participate in educational activities [111]. Guerra et al. [73] integrated social comparison features in the form of peer and class progress in the design of an intelligent interface for a learning management system to provide additional motivation and navigation support. This approach showed a positive effect on engagement and efficiency in two studies (N=89), but no significant effects on learner performance in terms of final grades or learning gains. In addition, Davis et al. [57] observed, that in the context of the evaluation of a personalized feedback system in live MOOCs on the edX platform, the availability of social comparison cues can significantly promote effective self-regulatory behavior and achievement in MOOC learners.

2.4. Learner dashboards

The amount of data collected using educational technologies such as Learning Management systems (LMS) and MOOCs increases with high rate in volume and complexity. Learning Analytics has emerged as a result of the growing number of online learning platforms [63] leading to the need of understanding how technology-mediated learning takes place. As suggested by Shemwell [163], visual displays are essential for sense making, as people can process large amount of data if presented in a human understandable way. Therefore, learning dashboards emerged as a means to display data through various visualizations such as graphs, gauges, dials and maps [16].

Several definitions have been proposed for learning dashboards. One of them was proposed by Yoo et al. [184] who described learning dashboards as "a display which visualizes the results of educational data mining in a useful way", whereas C. M. Steiner and Albert. [46] referred to them as "visualization of learning traces". The development of learning dashboards aims to the creation of an effective tool for raising learners awareness, reflection, sense making and behaviour change in online or blended learning [177, 178].

Several dashboards have been presented to support either teachers in traditional face to face lectures or instructors and learners in online or blended learning environments. The objective of dashboards aimed at teachers and instructors is often to support them in receiving real time feedback from students, managing group work of multiple activities and visualizing learning outcomes based on three data sources such as grades in the course so far, time on task and past performance [178]. Dashboards that are destined for *learners* offer them a visualization of their learning patterns, helping them improve their learning strategies and supporting student self-awareness. Learner dashboards should utilize social learning in ways that allow learners to make comparisons of their progress to that of their peers or prior learners who have attended the same course [135, 171]. Nevertheless, previous research indicated that most of the learner dashboards were aimed at teachers or both teachers and learners and only a few dashboards are aimed only at learners [141, 158, 177]. Recent studies [82] recognized this gap leading us to the following overview on various existing learning dashboards highlighting several dashboards aimed at learners.

2.4.1. Overview of learner dashboards

The first dashboards were destined for supporting *teachers* and *learners* on the *physical classroom*. Ruiz et al. [149] presented the TEA Model (TEAM), a visual dashboard that offers students the opportunity to track their emotions following up their evolution during the course. This dashboard aims to discover how the emotions can be displayed to promote self-reflection and affect learning performance. It was evaluated in the PresenceClick [148] [2] environment and the results indicated that students' emotions in class are related to evaluation marks indicating that students' emotions can be useful for teachers and students to improve classroom results and learning outcomes. Pulse [48] is an example of an interface in which physical activity of the students' body like speaking, moving between seats and making gestures was visualized via a video-conferencing system. The evaluation of the tool conducted via a user study where teachers used the system in a simulated class and via a student survey, finding that activity indicators are a useful record of the class and are less intrusive to students' privacy than the recording of audio or video. Another dashboard destined for university students is PADA, proposed by Mejia et al. [124]. PADA is a web-based tool facilitating descriptive visualizations for a better understanding of students about their learning model. Its aim is to increase student awareness and support reflection and self-regulation about their difficulties in reading via learning analytics on reading performance. PADA was tested with 26 students of different academic programs and levels and the results indicated that it can assist students in creating awareness, understanding their difficulties with the reading tasks, as well as establishing reflection and self-regulation in the learning process. Broos et al. [36] introduced a dashboard in order to provide students of higher education with actionable feedback on

[2] PresenceClick system records and processes the existing interactions in traditional learning sessions between students and teachers providing timely feedback.

their learning skills. Their aim was to learn about the use of this dashboard in a realistic context and test the visibility of this approach based on perceived usefulness and usability. For that reason they tested this tool in a group of students in STEM study programs. The results showed that the dashboard was perceived as clear and useful by the students. Moreover the work presented by Broos et al. [38] focused in a multi-institutional implementation and evaluation of a learning analytics dashboard aiming to provide with feedback 337 STEM students participating in a positioning test before entering the study program. Using this dashboard were able to anonymously share data with institutions. In addition active content contribution is encouraged by study advisor to enhance visual recognizability. The work presented in this study is still in a preliminary phase and more detailed analysis of the usage traces in the future may help to identify additional patterns and different behaviour of students. Finally, another learning analytics dashboard was presented by Broos et al. [37] complementing research in learning analytics with "small data". This dashboard was made available to 1905 students in 11 study programs to learn how it is been used and to gather student feedback. Preliminary findings indicated that student reacted positively to this learning analytics dashboard. However, usage and feedback differed depending on study success. Also, weaker students found to access the dashboard less highlighting future research directions of how to reach these students. Moreover, it is highlighted by the authors that more research is needed to explore the expectations of high performing students regarding LA dashboards.

On the other hand, CourseVis [119, 120] aimed at *online learning environments*. In contrast with traditional classroom, in online environments, there is a need of personalized and adaptive learning support for learners. CourseVis is a system in which tracking data from a course management system are obtained, processed, and finally graphical representations are generated that course instructors can explore and manipulate. This process helps course instructors to examine social aspects such as participation in discussion and group work, cognitive aspects such as performance and level of knowledge and behavioural aspects such as access to the course, material usage and progress of distance students. However, the tool has not been evaluated empirically on a large scale, despite the fact that the initial evaluations with small focus groups indicated promising results. PeerLA [105] was introduced as a Learning Management System plugin to support learning progress and improve students' self-regulation competency. PeerLA allows setting of long term goals, division into intermediate goals and tracking of knowledge increase or time needed. It also allows peer comparison based on the existing and the desired level of knowledge. Konert et al. [105] evaluated PeerLA with 83 in an online mathematics course over four weeks and the results showed the benefits of this tool on students' self-regulation.

Alternative dashboards destined for *learners* in *learning management systems* are GLASS [108], Moodog [187] and SAM [70]. GLASS [108] was developed as a web-based visualization platform that handles the generation of visualizations from datasets containing a large number of recorded events. The platform is targeted both to teachers and learners, providing feedback on activities and performance. GLASS is undergoing additional testing in different learning scenarios, however preliminary results obtained from user tests indicate that visualizations need to be very intuitive for both instructors and learners. Additionally, Moodog was introduced as a Moodle[3] plugin for data visualization based on activity logs. These activity logs occurred by aggregating low-level activity records into key behavioral indicators describing how students use the online course material [187]. It provides different perspectives to both learners and instructors. An easy comparison is possible between the learners' progress with that of their peers. The visualization consists of bars for each resource and each student and the usability of the plugin was tested on a group of 38 students. However, the impact of using Moodog has not yet been thoroughly evaluated and it is left to be evaluated in the future. Another dashboard is Student Activity Meter (SAM) [70] which displays information about the time learners spend on learning activities and statistics of document use. SAM was developed following a design-based research methodology and each iteration has been evaluated in a different setting. Nonetheless, SAM was evaluated based on the usability and usefulness of the different visualizations and not based on its impact on learning achievements or learning behaviours. Results indicated that the tool is useful for a variety of teacher and learner needs, involving awareness of time of resource material.

Another group of learner dashboards aimed to activate self-reflection by revealing learner behaviour. Some of these dashboards are Scheffel et al.'s [155] widget, Mastery Grids [73], INSPIREus [135], LAPA [141] and StepUp! [153]. Scheffel et al. [155] presented an activity widget into the online learning environment of a live master course, investigating the predicting power of widget indicators towards students' grades. The results compared with previous runs of the same course where the widget has not been in use. Both qualitative and a quantitative evaluation of the activity widget showed that there are predictive relations between the

[3] `https://moodle.org`

widget indicators and the grades. In Mastery Grids [73], OLM and social comparison features are combined to support learners in recognizing the most appropriate learning path. SRL aspect is also supported and learners are allowed to self-monitor their course progress. The development of Mastery Grids aimed to offer learners the opportunity to visualize their progress in comparison with the class average. Some classroom studies with semester-long duration [73, 113] indicated a positive effect on learners' engagement, efficiency, effectiveness and motivation. INSPIREus [135] was designed as a tool that supports learners' reflection by visualizing interaction behaviour, including some behavioral metrics which describe cognitive and social aspects of the interaction. The quality of the learner's individual activity with course material and integrated tools are described by the cognitive indicators, whereas communication, collaboration and cooperation between the individuals are described by social indicators. The evaluation of INSPIREus was conducted on a 50 students class aiming to investigate the way learners interpret specific visualizations of their interaction behaviour. Preliminary results provide evidence about the successful understand-ability and expressiveness of the indicators of effort, progress, working style, and the visualizations used. Park and Jo [141] presented a learning analytics dashboard destined for learners, namely LAPA (Learning Analytics for Prediction and Action), which illustrates students' online behavior patterns in a virtual learning environment of a private university. Aspects like students' time management and self-regulation are supported by LAPA with the visualization of meaningful metrics such as 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 of this tool was performed in an experimental research setting with a control group and additional surveys were conducted asking students' about perceived usefulness, conformity, level of understanding of graphs, and their behavioral changes. The results showed that the impact of LAPA on students' learning achievement was not significant, but helped learners to earn a better understanding of their learning behaviour. Santos et al. [153] presented a visualization tool of student's activity, StepUp!, which uses learning analytics technology to enable self-reflection on activities and comparison with peers . Learners get informed about the amount of time spent by receiving feedback on that metric with different tools while working for on-campus course assignments. Small groups of learners were interviewed about the usefulness and the effectiveness of StepUp! in several user-centred studies [133, 154]. StepUp! proved to be a useful tool which allows learners to better understand how themselves and peers spend their efforts. Nevertheless, users were not convinced of the added value and there was lack of motivation of using the dashboard.

2.4.2. Learner dashboards for MOOCs

In this subsection, we overview learner dashboards that have been implemented for MOOCs and are also destined for both instructors and learners.

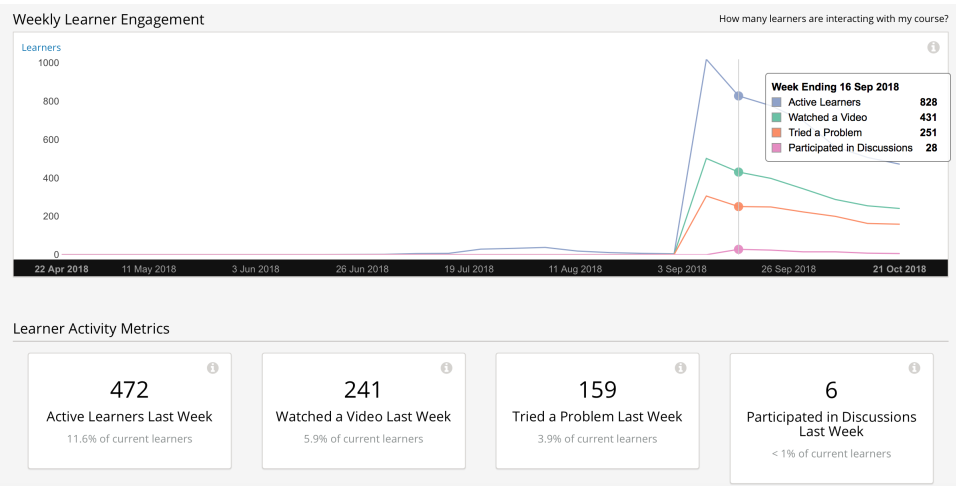

Figure 2.3: edX Insights dashboard displaying information on weekly student engagement for one DelftX MOOC deployed on the edX platform.

edX Insights[4] has been developed by edX which is a platform focused on assisting course team members by making available information about learners' activity background and performance throughout the

[4] `https://edx-insights.readthedocs.io/en/latest/index.html`

course, as depicted in Figure 2.3.

An instructor analytics module for moocRP is presented in Kia et al. [92] research, an open source open learning analytics platform. Instructors are able to investigate how students' attributes such as age, gender, location and educational background are related to their performance and achievement by proposing an interactive visualization filtering, which enables the opportunity to filter the displayed data on the dashboard. The evaluation of the tool was conducted in a preliminary qualitative user study with 5 participants and the completion of questionnaires by them after the tool demonstration. The results indicated that the dashboard needs to be augmented by more sophisticated predictive analysis, as well as more specific visualizations about learners' performance and activities informed by further user study in the future work.

León et al. [109] presented a learning analytics dashboard developed by the University of Southampton for FutureLearn platform in which analytical data are displayed to different institutional stakeholders such as learning designers, educators, facilitators, and administrators. In this dashboard student progress is visualized focusing on learners' performance and learners' social interactions. The evaluation of the usability, the impact and the validity of the tool through surveys, has been assigned as future work.

Cobos et al. [52] presented a Learning Analytics dashboard named Open-DLAs destined for the Open edX platform. It visualizes the progress of learners' activity considering navigation, social interactions and interaction with educational resources. The evaluation of this dashboard took place on the edX platform with two runs of four MOOCs created by the University Autońoma of Madrid. However, the assessment results are not publicly available. This dashboard is being improved by receiving feedback from MOOCs instructors and assistants and a new version of it will be presented to work with edX and Open edX in the future.

Le et al. [107] presented an interactive analytics interface destined for the edX platform affording MOOC instructors with the ability to communicate directly to learners based on individual predictions of three engagement analytics. These three models include (i) the opportunity to earn a certificate, (ii) the submission of enough materials to pass the course and (iii) leaving the course without returning. This interface was evaluated on a MOOC data-set of 20 courses and a variety of modeling approaches was compared in order to investigate which one had the best performance. The findings indicated that the combination of using a deep learning model such as RNN, with the ability to machine learn features from raw click-stream data, is responsible for improved performance.

The authors in [125] presented the 3S (Social, Sentiments, Skills), a learning analytics methodology for the analysis of forum interactions in MOOCs, as extracted from forum data. The proposed methodology was included in a learning analytics tool, the LAT3S destined for the edX/Open edX platform. The aforementioned tool incorporating the 3S methodology was evaluated in a MOOC on JAVA programming. The results indicated that learners increased their participation after instructors' events, and there was a decrease of positive sentiments before deadlines of open-ended assignments. Overall the results indicated the importance of such a learning analytics methodology for detecting MOOC problems.

The amount of MOOC dashboards destined for MOOC learners is even shorter. In Figures 2.4 and 2.5 the available progress dashboards for learners of two of the main MOOC platforms, edX and Coursera, are illustrated. These dashboards provide learners with feedback on their course progress in relation with the number of weekly assessments completed and their current assessment score. The visualizations are simple and easy understandable integrated with textual content and bar graphs [82].

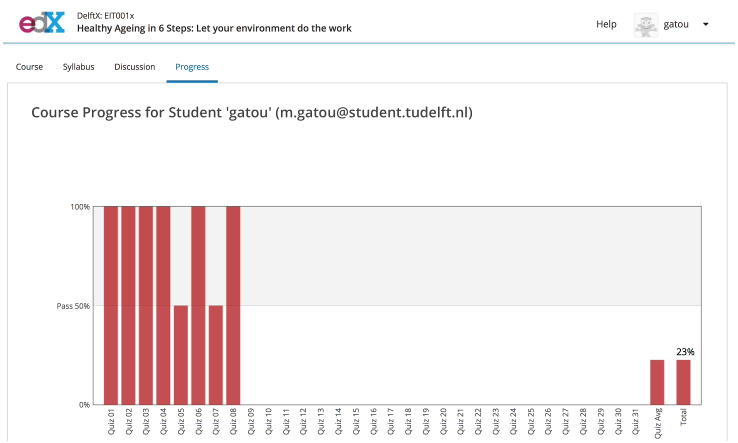

Figure 2.4: edX dashboard sample: learners able to follow their weekly and total assessment scores.

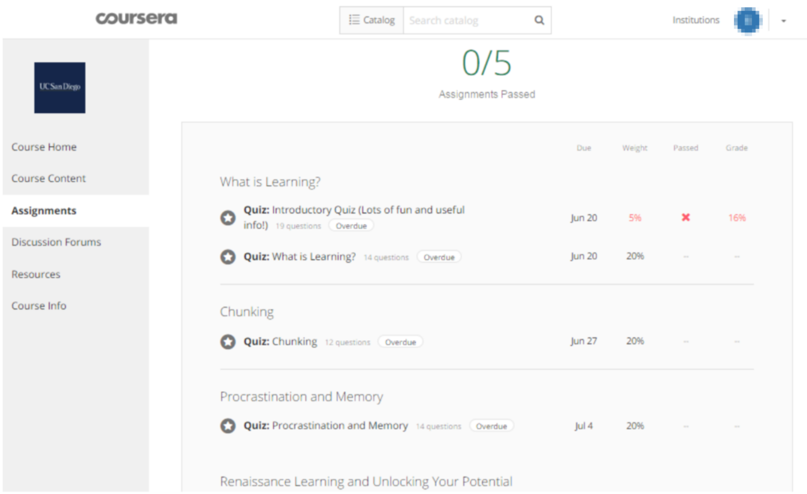

Figure 2.5: Coursera dashboard sample: learners are able to follow their grades for each quiz, whether or not they passed and the total amount of quizzes passed.

Another solution proposed for the edX MOOC platform, destined for MOOC learners and consisted the baseline and inspiration for our work in this thesis, is the development and the evaluation of the *Learning Tracker* [57, 58]. The *Learning Tracker* was developed as a personalized feedback system that facilitates social comparison with previously successful learners based on an interactive visualization of multiple behavioral indicators, as shown in Figure 2.6. This tool was evaluated across four randomized controlled trials in MOOCs (overall N = 33, 726), and the findings indicated that: (1) the availability of social comparison cues significantly increases completion rates, (2) this type of feedback benefits highly educated learners and (3) learners' cultural context plays a significant role in their course engagement and achievement.

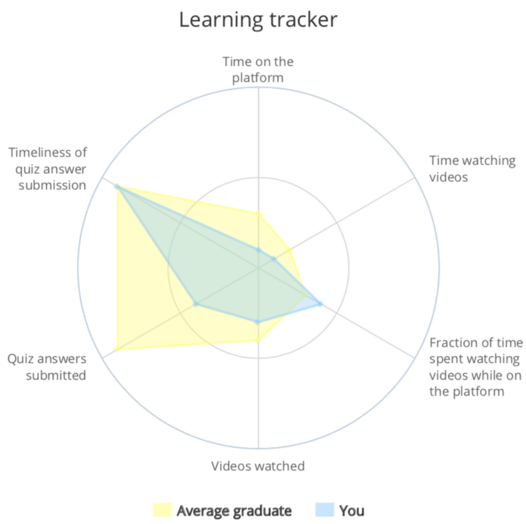

Figure 2.6: The *Learning Tracker* visual design [58, 82]. The spider chart offers a concise visualization of several metrics in a small space and it offers a simple overall evaluation of one's performance and consistency across all metrics.

Alternative solutions proposed for MOOC platforms have only been developed and rarely evaluated on a large scale. For instance, an analytics model was proposed by Vovides and Inman [179] aiming to support learners for further developing their reflective sense-making of ill-structured ethical problems. The proposed model combines activity data that describe the interaction with an online system and learning artifacts occurring from working on the online system. There is an ongoing evaluation of a prototype learner-managed dashboard which integrates the proposed model on a GeorgetownX MOOC incorporated on edX. Figure 2.7 depicts the aforementioned dashboard.

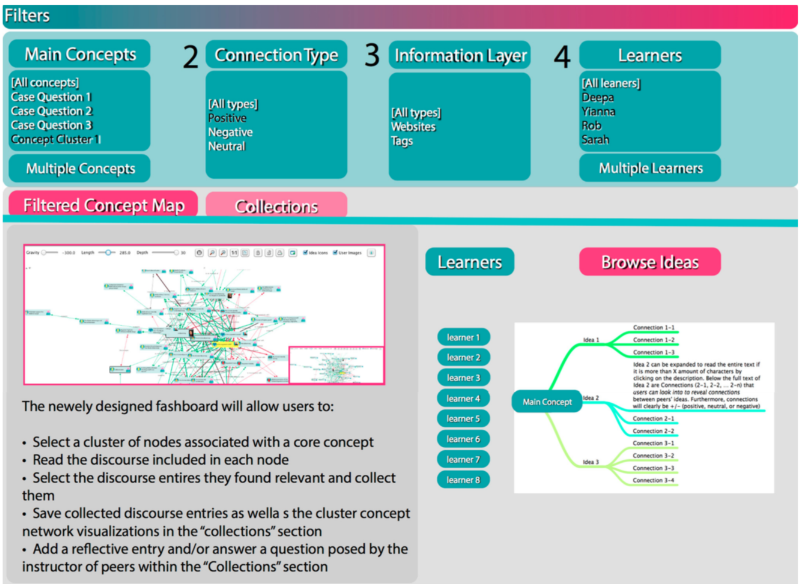

Figure 2.7: Schematic of the learner-managed dashboard that supports learners' reflective sense-making of ill-structured ethical problems [179].

An interactive widget, *SRLx*, destined for MOOC learners was also proposed by Davis [59] aiming to improve learners' self-regulated learning behaviour. *SRLx* provides learners the opportunity to plan their learning weekly and receive real-time feedback based on the realization of these plans. The widget was evaluated in a real MOOC on the edX platform through an exploratory analysis on learners' SRL behaviour. The results indicated that i) during the course progress learners were able to plan their time commitment effectively, ii) learners with the motivation expression interface had a strong intrinsic motivation and iii) learners were more generous in their plans regarding video and quiz activity compared to their plans regarding committing time to the course. Figure 2.8 depicts the four SRLx interfaces as they appear to learners of the edX platform.

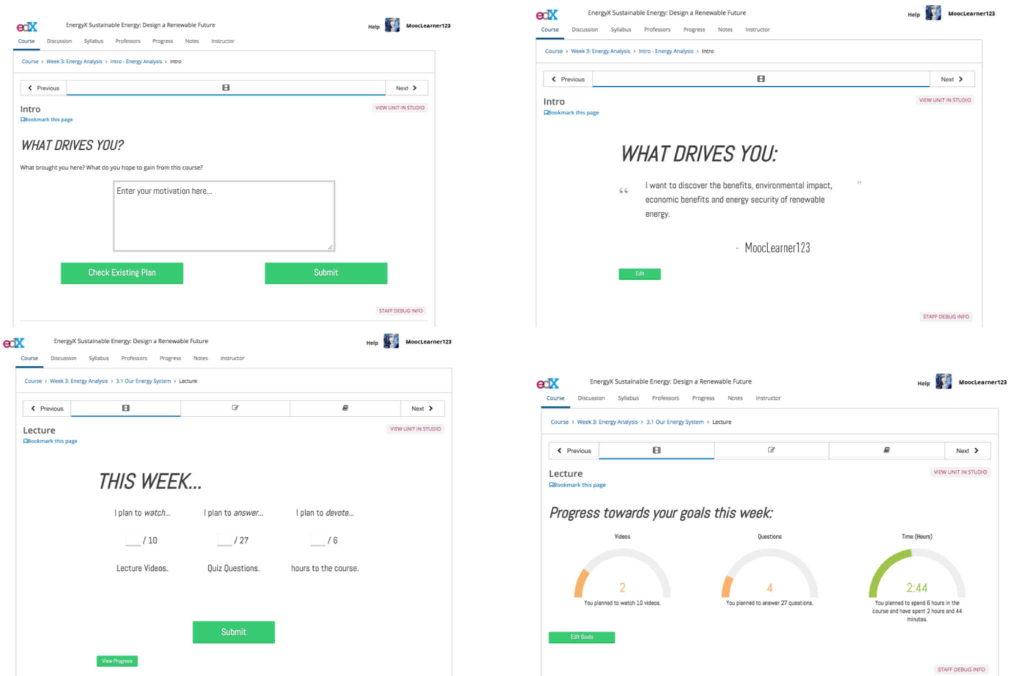

Figure 2.8: Four SRLx interfaces as they appear to learners of the edX platform [59]

Moreover, Alario-Hoyos [6] presented a mobile application, *MyLearningMentor*, that addresses the lack of support and personalized advice for learners in MOOCs. MLM provides a personalized planning to learners adapted to their profiles, preferences, priorities and previous performance. The implementation of this tool is still in progress and the purpose of a future evaluation is to assess the usefulness of MLM and the correctness of the advises provided by this tool.

Pérez-Álvarez [145] presented the design of a tool named *NoteMyProgress*, aiming to complement the current MOOC platforms and support learners' SRL strategies. The implementation of this tool followed the design based research methodology and the evaluation, just like previous studies, focused on tool's usefulness and usability without reporting results on the impact of the tool on the self-regulation of learners. Figure 2.9 depicts the interface of the aforementioned tool.

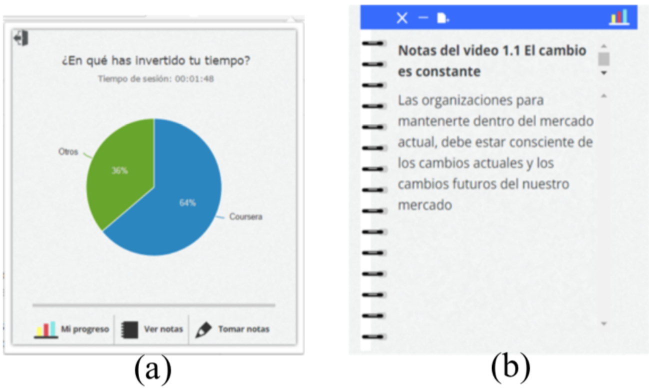

Figure 2.9: Main plugin interface and notebook of NoteMyProgress [145].

2.4.3. Existing learner dashboard limitations

So far, we recognized several gaps concerning the design and the development of existing learning dashboards, similar to the ones presented in Jivet's [82] work.

Although in recent years research on developing tools that support MOOC learners grows, the amount of learner dashboards in the existing MOOC platforms that aim to assist learners through their learning process is still limited. This comes in contrast with the number of learning analytics tools developed for supporting instructors-learners in online learning environments which has been increased in the past years. Therefore, similar to Jivet [82], we recognize the need for developing more learner dashboards that are destined to offer help and support specifically to MOOC learners. A second remark is that existing learning dashboards focus more on supporting learners with indicating actions that lead to course coverage than helping them to get engaged with the course material. Therefore, there is lack of learners' support on indicating the appropriate way to use the material of the course, the optimization of their learning strategies or the development of effective learning strategies based on self-awareness and reflection. Reviewing the literature, we noticed that in most evaluations of learner dashboards the aspects that were considered by researchers were mainly the usefulness and the usability of the proposed tools and not their actual impact on their learning performance and behaviour. In addition, the evaluation of most of the existing learning dashboards took place on small groups of learners-students and not on a large scale.

2.5. Mitigating the existing gaps

Taking into consideration the current gaps in literature and in parallel continuing Davis et al. [57] work, we designed, deployed and empirically evaluated three different versions of the *Real-Time Learning Tracker* , an interactive learning widget, that was integrated in a learner dashboard destined for MOOC learners on the edX platform. So far we have seen that self-regulated learning skills such as goal setting, time management, self-monitoring and self-evaluation have been shown to improve learning and increase learners' performance and achievement. In our work, our goal is to provide learners with support in order to develop their self-regulated learning skills by encouraging them to monitor and reflect on their behaviour. Reflection is activated by providing learners with real-time feedback on their learning strategies, as means to support SRL by increasing learners' metacognitive awareness in a MOOC environment. We believe that the positive impact of personalized feedback on learning and achievement can be complemented with the addition of a degree of immediacy, in the form of a timely intervention and recommendation for students' study strategies [49]. We assume that real-time feedback will offer the opportunity to learners to find out immediately which course aspects they have not mastered in order to be able to take appropriate corrective actions [139]. In that way it works as a just-in-time learning assistance that makes them more efficient by developing more of their own skills and mastery [176]. In the design of the *Real-Time Learning Tracker* , we also take into consideration the effects of social comparison on learners' performance, motivation and engagement and for that reason learners' behaviour can be visualized on the widget, in comparison with that of successful learners, providing them with an “ideal” model against which they can evaluate the effectiveness of their study habits. The *Real-Time Learning Tracker* is described in the following chapter.

3

The Real-Time Learning Tracker

We developed the *Real-Time Learning Tracker* as a learning widget that can be integrated in a learner dashboard, in our attempt to alleviate the existing gaps in learning support on edX platform as stated in Section 2.4.3. The *Real-Time Learning Tracker* aims to provide MOOC learners with support in becoming more efficient by developing their self-regulated learning skills. We used extracted information from learning data in the design of the widget, in order to encourage learners' self-monitoring of their activity and enhance self-reflection. Davis et al.'s [57] and Jivet's [82] research resulted in offering learners the opportunity to access easily interpretable data displayed in a human understandable way, allowing them to reflect on their behaviour and change their learning strategy accordingly, instead of being told what their next action should be.

However, the *Learning Tracker* [57] suffered some limitations that drove us to the design, the implementation and the evaluation of the *Real-Time Learning Tracker* , in our attempt to alleviate these gaps. More specifically, the lack of real-time learner feedback and the fact that the *Learning Tracker* was not easily accessible to the learners since it was placed in a specific course section, led us to the implementation of a widget that provides learners with real-time feedback based on their learning behaviour and it is easily accessible to them at all times. The *Real-Time Learning Tracker* consists of three different feedback complexity versions and each one of them uses low-level data from trace logs and converts it into behavioural indicators that describe several learning habits.

Our approach is backed by research on self-regulated learning which evidences that more knowledge is gained by learners who were encouraged to reflect on their learning [87], and by research on metacognition that demonstrates that students' metacognitive awareness of particular aspects of their learning processes could enhance their self-control [190]. In addition, the aforementioned theories have already been proved to hold in a MOOC in Davis et al.'s [57] work which we use as inspiration. In our attempt to help learners in understanding better the effectiveness of their study habits, their learning behaviour is contextualized with two models of *successful* learners such as the *Average Graduate* and the *Most Engaged Graduate*, offering an anchor point for comparison.

In this chapter we describe the basic principles that guided the design of the three versions of the *Real-Time Learning Tracker* , the design rationale and the challenges of its design. The chapter concludes with details concerning the technical implementation of the widget.

3.1. Foundations

3.1.1. Learning Tracker

The work presented in this thesis is a continuation of Davis et al.'s [57] research, in which a personalized feedback system (*Learning Tracker*) was developed and evaluated across four randomized controlled trials in live MOOCs on edX platform provided by DelftX. The feedback system facilitates "social comparison" with previously successful learners based on an interactive visualization of multiple behavioral indicators based on learners' activity during the course.

According to social comparison theory [65], people establish their social and personal worth by comparing themselves to others. Offering learners the opportunity to compare their behavior with that of their peers promotes increased student achievement in formal learning environments [26, 81, 135]. The results of that experiment indicated that the availability of social comparison cues and this type of feedback significantly increases completion rates by a ratio of approximately 3.4%. This functioned as an inspiration for us to continue this work by adding the following novelties in the existing research:

1. The aforementioned tool was shown to the learners every week by means of a picture incorporated in a separate section of the course content as it is depicted in Figure 3.1 and the data was only updated in a weekly basis. Thus, in some cases, learners had to navigate through several pages in order to access the widget and the meta-level information on their behaviour was mixed with the course content. Moreover, learners could not really see where they were standing in real-time compared to the most successful peers. For that reason, we set as our first goal to provide learners with real-time feedback on their learning behaviour in order to investigate if the real-time attribute of the feedback would help them make better use of a system like *Learning Tracker* than waiting a week before they see how they stand compared to successful learners.

2. A second difference compared to Davis et al.'s [57] research is that we try to evaluate a number of feedback interfaces, from complex to simple, in order to investigate students' interaction when the degree of complexity of the presented feedback as well as the number of study dimensions varies. In that way we are able to test which version of our feedback system would be better for the learners in terms of engagement, self-regulation and completion rates.

3. In Davis et al.'s [57] study, role models were built based on learners who were successful in a previous edition of the MOOC, in other words learners who managed to obtain a passing grade. In order not to risk de-motivation, learners are given the opportunity to compare themselves with slightly better performing peers and for that reason the "Average Graduate" learner model was used. We add to that by giving learners the opportunity to compare themselves also with another learner model, which is the "Most Engaged Graduate" learner model. The Most Engaged Graduate learner model was built based on graduate learners' degree of engagement with the course material during the course, hence the most engaged graduate was considered the learner with the highest level of engagement. This is an indication to learners of the learning behaviour and engagement levels of the most engaged graduates of the respective course.

4. In Davis et al.'s [57] study, the selected metrics were determined based on key aspects of successful learner behaviour and were divided into three clusters such as course material coverage, level of engagement and time management. After observing the efficiency of the selected behavioural indicators in Davis et al.'s [57] research, we decided to borrow the metrics of the first two clusters in our *Real-Time Learning Tracker* implementation, as well as extend them with an additional engagement metric.

A comparison of the attributes between the *Learning Tracker* and the *Real-Time Learning Tracker* is presented in the Table 3.1.

Table 3.1: Comparison table of the main attributes of the *Learning Tracker* and the *Real-Time Learning Tracker*.

	Way of feedback distribution	**Visualisation**	**Successful Learner models**	**Placement**	**Metrics**
Learning Tracker	In weekly instalments	One single feedback interface	Average Graduate	On the introduction page of each learning module	course coverage + level of engagement + time management
Real-Time Learning Tracker	In real-time	Three feedback interfaces from complex to simple	Average Graduate + Most Engaged Graduate	In every MOOC page	course coverage + level of engagement + additional engagement metric

3.1.2. Widget versions

We deployed three different versions of the *Real-Time Learning Tracker* so as to investigate how learners interpret varying visualizations of their learning behaviour and which one of them leads to more changes on their behaviour during the course. From now on we will refer to the three versions of the *Real-Time Learning Tracker* with the following names describing the complexity of the presented feedback:

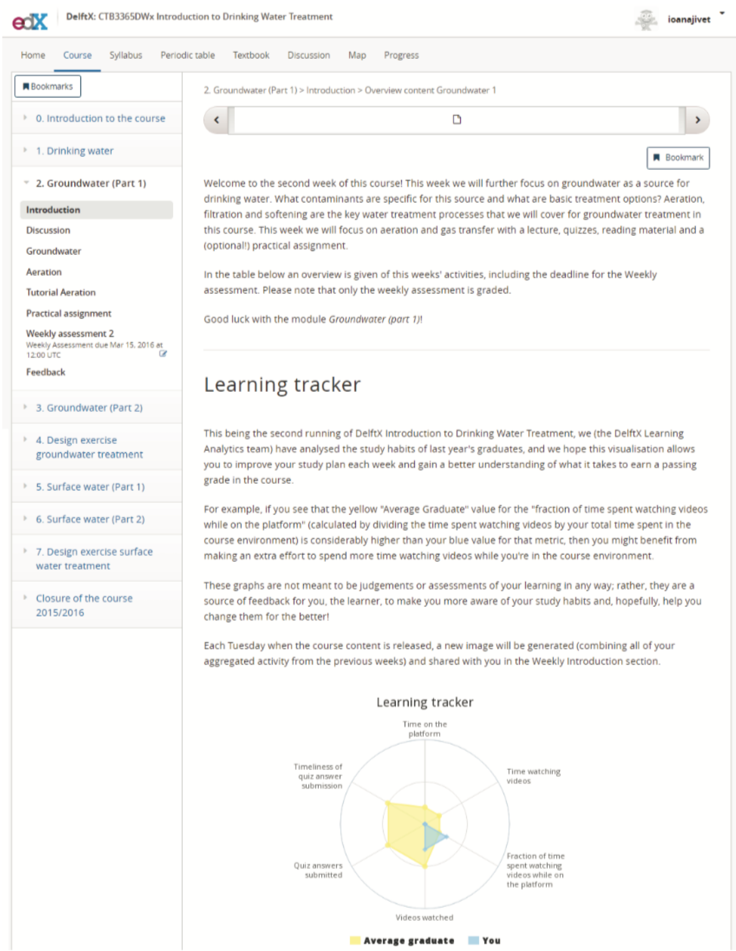

Figure 3.1: The placement of the *Learning Tracker* on the edX platform [82]. The *Learning Tracker* is placed on the course content pages, on the introduction page of each learning module.

1. Simple version – displaying one behavioural indicator
2. Intermediate version – displaying three behavioural indicators
3. Complex version – displaying six behavioural indicators

3.1.3. Assumptions

The design of the complex, the intermediate and the simple version of the *Real-Time Learning Tracker* is based on the following assumptions that we made in the context of this thesis project:

A We assume that learning behaviour can be modelled.

B We assume that effective-successful learning behaviour can be adopted by others.

3.1.4. Definitions

Moreover, the design of the *Real-Time Learning Tracker* is based on the following definitions:

A We define as successful learners, learners that complete MOOCs.

B We define as engaged learners, learners that remain active during the course and interact with the course material.

Definition of the metrics

Several behavioural indicators/metrics describe different learning habits of learners that together lead to an overall description of their learning behaviour. Learners have access to the metrics via the widget and therefore the selection of metrics should be guided by the following principles:

- The displayed information should be *easily interpretative* without the need for many additional explanations about the meaning of the metric.
- The value of each metric should be calculated based on low-level data (events, click-streams etc.) obtained from the platform logs.
- The learners should be able to reflect on their learning behaviour and change it through simple actions; e.g. if the average time a learner spends in the platform is low, they might benefit from making an effort in spending more time active on the platform.

3.1.5. Hypotheses

The work presented in this thesis is guided by the following hypotheses to our research questions (**RQs**) presented in Chapter 1, taking into consideration current findings in Davis et al.'s [57] research :

H1. In line with learning theories that consider learning as a cognitive process [72] and Bandura's theory [19] that people learn from others through observation, imitation, and modeling, as well as previous findings [49, 57, 139, 176, 189], we hypothesize that providing learners with a comparison of their own behavior to that of previously successful peers, will enhance their learning by increasing

1. learner achievement (higher completion rates) (**RQ1**)
2. course engagement (activity level within the MOOC environment) (**RQ2.1**)
3. self-regulatory behavior (**RQ2.2**)

H2. We hypothesize that the real-time attribute of the Real-Time Learning Tracker will add an extra degree of interaction and will accelerate the learning process [49, 139, 176], leading to higher performance for learners that have access to the widget (**RQ1**).

H3. We also hypothesize that the *Real-Time Learning Tracker* will serve as a triggering point for learners to become aware of their learning behaviour and use that kind of information to *self-reflect* on their learning strategies and evaluate their progress, leading to higher achievement (**RQ1**).

H4. Taking into consideration Davis et al.'s [57] findings, we hypothesize that the performance of the *Average Graduate* and the *Most Engaged Graduate* functions as a tangible target that the learners could reach and even overcome in order to increase their performance (**RQ1**).

H5. In line with previous findings [57], we expect that the Complex version of the *Real-Time Learning Tracker* will prove to be the most effective in improving

1. learners' achievement (**RQ1**)
2. course engagement (**RQ2.1**)
3. self-regulated learning (**RQ2.2**)

H6. We speculate that the Simple version of the *Real-Time Learning Tracker* is a good way to test how learners' react when they have no clear indication of the specific actions in which they should invest in order to increase their performance, since we hypothesize that the SRL aspect of learners (**RQ2.2**) will deteriorate when a less complex version of feedback is presented to them.

H7. In line with previous findings [57], we expect that the *Real-Time Learning Tracker* is more likely to help to improve the achievement(final grade) of learners who are already highly educated (learners with a Bachelors, Masters, or PhD degree) instead of learners with low prior education (learners with any degree below Bachelors) (**RQ3**).

H8. In terms of learners' engagement with the different *Real-Time Learning Tracker* versions, we speculate that the Complex and the Intermediate version of the widget will prove to be the most engaging interfaces for the learners, since they present more information to the learners and therefore, they may offer more available interactions to them.

3.1.6. Design decisions

The design of the *Real-Time Learning Tracker* is based on the following design decisions which we made using as a baseline Davis et al.'s [57] work:

A We designed the *Real-Time Learning Tracker* provided that it should look like it is a natural part of the edX platform.

B In contrast with Davis et al.'s [57] work, we do not leave the decision on how to evaluate the displayed information entirely up to the learners, but we also provide them with a short explanatory text about the displayed information

3.2. Design

During the design process of the *Real-Time Learning Tracker* , we addressed two main challenges, similar to those addressed in Jivet's [82] work: (i) the identification of meaningful information to be displayed and (ii) the devise of three visualizations differing in both granularity and the degree of complexity of the presented information which aim to support reflection.

These issues are acknowledged by Durall and Gros [62] 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, some of which we borrowed from Davis et al.'s [57] research. Afterwards, low-level activity data were used to create three types of learner profiles based on the model. Two out of three profiles described two different types of successful learners, the *Average* and the *Most Engaged* graduate respectively. The other one described each *learner currently enrolled* in the MOOC whose metric values are updated in real-time.

In all three versions of the *Real-Time Learning Tracker* the same type of visualization is used and the only varying component is the amount and the type of the displayed information. The visual design of the three versions of the *Real-Time Learning Tracker* are depicted in the Figures 3.2, 3.3, 3.4.

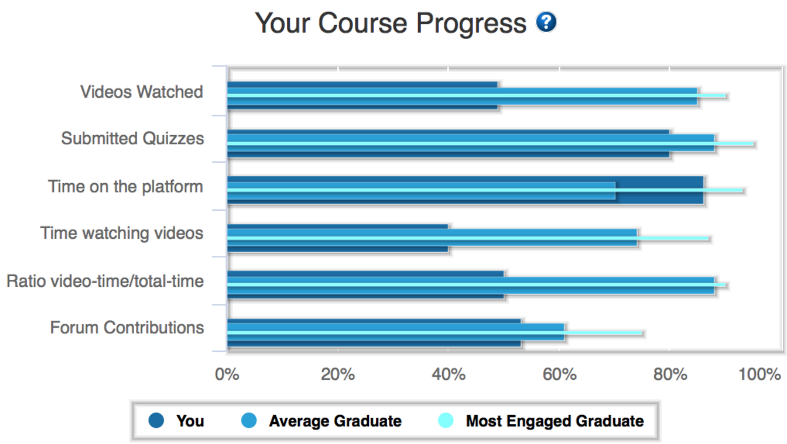

Figure 3.2: The Complex version of the *Real-Time Learning Tracker* visual design. The bar chart provides a concise visualization of six metrics in a small space and it offers a simple overall evaluation of one's performance and consistency across all metrics.

Alongside the data visualizations depicted in Figures 3.2, 3.3, 3.4, a short explanatory text was also provided by means of a tool-tip. When learners hover over a question mark tool-tip besides the title of the widget, they are get informed about the aim of this widget. The content of this explanatory text remains the same for all three widget versions:

> *This widget aims to provide you with real-time feedback on your learning behaviour in order to improve your study plan and earn a better understanding on what it takes to earn a passing grade in the course.*

In order to provide learners with a hint regarding the meaning of the displayed information, an explanatory text, containing an example of a possible interpretation of a metric, was added on an extra tool-tip inside

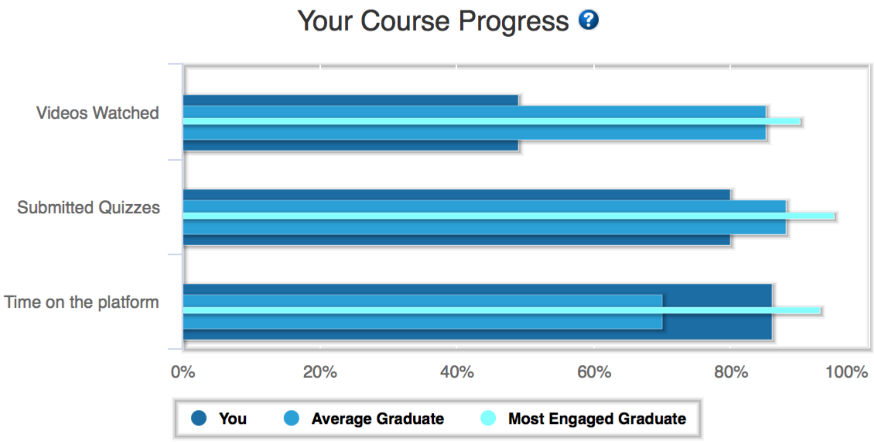

Figure 3.3: The Intermediate version of the *Real-Time Learning Tracker* visual design. The bar chart provides a concise visualization of three metrics in a small space and it offers a simple overall evaluation of one's performance and consistency across all metrics.

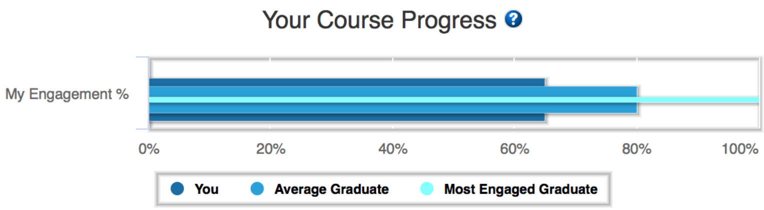

Figure 3.4: The Simple version of the *Real-Time Learning Tracker* visual design. The bar chart provides a concise visualization of one metric indicating the proportion of learners' engagement during the course, in comparison with that of the Average and Most Engaged Graduate in a previous run of that course.

the initial one. The content of this explanatory text was based on which version of the *Real-Time Learning Tracker* was displayed to the learners:

Complex version of the Real-Time Learning Tracker

> *For example, if you see the medium blue 'Average Graduate' value for the 'Ratio video-time/total-time' (calculated by dividing the time spent watching videos by your total time spent on the course environment) is considerably higher than your dark blue value for that metric, then you might benefit from making an extra effort to spend more time watching videos when you are in the course environment.*

Intermediate version of the Real-Time Learning Tracker

> *For example, if you see the medium blue 'Average Graduate' value for the 'Videos Watched' (calculated by aggregating the number of different videos watched in the course environment) is considerably higher than your dark blue value for that metric, then you might benefit from making an extra effort to spend more time watching videos when you are in the course environment.*

Simple version of the Real-Time Learning Tracker

> *Try to be engaged in more activities during the course to make your dark blue bar grow.*

3.2.1. Learner information

In the edX online learning platform, the learners' online activity is tracked by gathering low level learning data in the form of collections of user events stored in trace log files. This data amount does not deliver any particular meaning alone, but we can use it and gain insight into the learning process by transforming it into higher-level indicators [128]. The *Real-Time Learning Tracker* focuses on two aspects of effective learner behaviour:

Table 3.2: Overview of the metrics that build the learner model in each widget version, their description and their units of measurement (m for minutes).

Cluster	Metric	Description	Unit	Complex version	Intermediate version	Simple version
Course coverage	Videos Watched	Number of video lectures watched	-	x	x	
	Submitted Quizzes	Number of quiz questions submitted	-	x	x	
Engagement	Time on the platform	Amount of time spent on the course pages	m	x	x	
	Time watching videos	Amount of time spent watching video lectures	m	x		
	Ratio video-time / total-time	The ratio of time spent watching video lectures while on the course pages	%	x		
	Forum contributions	The amount of threads / responses / comments created on the course pages	-	x		
Course coverage + Engagement	My Engagement %	The ratio of learners' aggregated activity during the course computed based on all six aforementioned behavioural indicators	%			x

- course material coverage
- level of engagement

It is worth mentioning that behaviour is described by the engagement metrics, whereas learner's progress is measured by course coverage metrics. More specifically, the engagement metrics characterize the way of learners' interaction with the course material and their peers, while course coverage metrics indicate what course material the learners interacted with. Despite the fact that course coverage metric measures how far along learners are regarding the progress of the course and not how they got there, we considered this cluster has high relevance with the goal of the *Real-Time Learning Tracker* . Evidence was provided by Papanikolaou [135] that what makes learners consider how they use course resources and how useful they are in achieving specific results, is an indicator of their progress. In the upcoming paragraphs each of the clusters and their respective selected metrics are described in detail.

Overview of displayed metrics
A detailed overview of the metrics that build the learner model, their description, their units of measurement and the version of the *Real-Time Learning Tracker* that was used each time, are displayed in Table 3.2.

Course Coverage In line with Davis et al.'s [57] and Jivet's [82] work, we selected two metrics that measure course coverage: *the number of video lectures watched* and *the number of quiz questions submitted.* Based on literature findings, both metrics are good indicators of learners' success. We selected quiz questions as an appropriate metric to be displayed on the *Real-Time Learning Tracker* due to its direct impact to course completion. More specifically, the grade that learners receive from each one of their quiz submissions contribute to the overall grade in the course. This in turn leads to course completion after passing a specific threshold. According to Mukala et al. [126], successful students appear more committed in watching videos than unsuccessful students, while there is a progression for unsuccessful students in not watching videos from the 1st to the last week. Moreover, Athira et al. [14] confirmed through their experiments that students who watched maximum number of video lectures and attended higher number of quizzes, tend to pass the course. Hence, one can conclude that as the number of videos watched by learners rises, their success levels rise as well.

Course Engagement Complementing the information displayed on the *Real-Time Learning Tracker* relative to course coverage, we also displayed metrics that describe how learners spend their time on the course platform. In that way we could measure their engagement levels with the course material. Muñoz-Merino et al. [128] after several experiments argued that the total time spent on the course platform is related strongly to videos completed and exercises attempted and it is a good parameter to predict the number and quality of interactions with the platform. For that reason, we also delivered through the *Real-Time Learning Tracker* the *time spent on platform* metric, investigating **how** this time is used. Moreover, in our design similar to Santos et al. [153], Govaerts et al. [70] and Jivet [82] we report to learners how they spend their time while on the course platform, focusing more on video-lectures, since watching videos prepares learners with the necessary knowledge in order to submit the quiz questions with success. For that used metrics such *time spent watching videos*, and metrics that describe ratios e.g. *ratio video-time/total-time*. The *ratio video-time/total-time* metric indicates the proportion of time spent watching video lectures while being on the course platform. Finally, the last metric *Forum contributions* aims to provide learners with feedback concerning their forum activity and the degree of interacting with peers during the course. The aforementioned results along with the results of Davis et al.'s [57] and Jivet's [82] research, made us acknowledge these metrics as the most appropriate ones to display on our *Real-Time Learning Tracker* .

3.2.2. Graduate profiles

edX capabilities

edX is trying to enhance research on pedagogy and learning by providing a high quantity of data to researchers at edX partner institutions who exploit the edX data exports for gaining insights into their courses and learners[1]. In that way, the focus in on the improvement of education both online and on campus [82]. We extracted the low-level user activity data that we used as input data for the Average and Most Engaged Graduate profiles of the *Real-Time Learning Tracker* from the edX log traces. More specifically, comment logs, quiz results, step activity, enrolment activity and peer-review activity are types of information that is provided by these log traces. Moreover, metadata such as timestamps for each event and anonymized author identifiers are contained [1]. The log traces after the necessary processing resulted in data that describes high-level traces. Information about each session logged by the learners, the videos viewed, the quizzes submitted, the visits to the forum pages, as well as learner demographics was included in the high-level traces. The high-level trace log data used by the *Real-Time Learning Tracker* was modelled following the adapted MOOCdb[2] data model.

Metric computation

The calculation of most of the used metrics in the *Average Graduate* profile is based directly on counting or averaging values from the tables presented in the aforementioned MOOCdb data model. For instance, we calculated *time on the platform* by summing the duration field from the table *sessions* for every session logged by a learner and we operationalized *number of videos watched* as the number of entries in the *video_interaction* table containing distinct video identifiers. However, the calculation of the used metrics in the *Most Engaged Graduate* profile followed a different procedure that will be explained later in this section.

Average graduate profile

Initially, we calculated the six metric values for each graduate and after that we aggregated the data into a single value per metric. We considered that averaging across all these learners for each metric would be an

[1] `http://edx.readthedocs.io/projects/devdata/en/latest/index.html`

[2] `https://github.com/AngusGLChen/DelftX-Daily-Database`

adequate means of aggregating the data as it is an indication of the tendency of the whole group. However, we did not observe a uniform behaviour among the successful learners and a long range of values was covered by each metric. For that reason, we omitted the values falling in the top and bottom 5% of the data range for each metric, in order to avoid outliers that alter the resulting mean. The Algorithm 1 includes the basic steps of the computation of the *Average Graduate profile*.

Algorithm 1 Average Graduate Profile

```
1:  Find total graduates
2:  Compute proportion ← graduates × 0.05
3:  for each metric do
4:      Sort graduates with descending order based on the metric value
5:      Skip the first proportion of the graduates
6:      Consider the first graduates − 2 × proportion of the remaining graduates
7:      sum ← 0
8:      for each graduate do
9:          sum ← sum + metric
10:     end for
11:     Compute the average ← sum/(graduates − 2 × proportion)
12: end for
```

Most Engaged Graduate profile

The *Most Engaged Graduate* profile was defined based on the results of an *Engagement* function that was computed for each of the graduate learners from a previous run of the course. For each graduate, an engagement level was computed based on their engagement with respect to each one of the six aforementioned behavioral indicators. Consequently, the *Engagement* function aggregated the six engagement ratios for each learner, resulting in a list of learners and their engagement levels. Finally, this list was sorted in a descending order, providing all learners and their engagement ratios from the highest to lowest ones. The graduate with the highest engagement ratio was considered the *Most Engaged Graduate* and the data from the initially computed six metric values that correspond to this profile, was aggregated into a single value per metric, resulting in the *Most Engaged Graduate* profile. The Algorithm 2 includes the basic steps of the computation of the *Most Engaged Graduate profile*.

Algorithm 2 Most Engaged Graduate Profile

```
1: for each graduate do
2:     Compute the metrics
3:     Compute the Engagement ratio
4:     Engagement ← [(metric1 × 100)/max(metric1) + (metric2 × 100)/max(metric2) + (metric3 ×
       100)/max(metric3) + (metric4 × 100)/max(metric4) + (metric5 × 100)/max(metric5) + (metric6 ×
       100)/max(metric6)]/6
5: end for
6: Sort Engagement ratios with descending order
7: Choose graduate with max(Engagement) ratio
```

3.2.3. Visualization

Chart type

While reviewing the literature in order to decide which visualization type is the most appropriate for our needs, we took into consideration several options. These options involved bar charts, gauges, calendar charts and spider charts like in [66, 141, 150, 153]. However, we concluded that a bar chart is the best option for our case. Because bar graphs have been in widespread use everywhere from textbooks to newspapers, most audiences understand how to read a bar graph and can grasp the information the graph conveys. A bar displays quantitative variables with rectangular bars with heights or lengths proportional to the values that they represent. When the bars are stacked next to one another, the viewer can compare the different bars, or values, at a glance. We chose bar chart as a visualization method since it summarizes a large amount of behavioral metrics in a small space, estimates can be made quickly and accurately, the information displayed is easily interpretative to the users and comparisons among discrete categories can be made easily distinguishing each information set with different colours.

Visual appearance of the Real-Time Learning Tracker

According to our first design decision as stated in subsection 3.1.6, the *Real-Time Learning Tracker* should look like it's a natural part of the edX platform. The widget was placed in a pop-up window at the bottom right of each course page, providing to learners easy access and navigation of their progress at all times. There is also provided the opportunity to the learners to minimize/unminimize the graphs whenever they wish. Figure 3.5 depicts the placement and the format of the Complex version of the *Real-Time Learning Tracker* on the edX platform. It is presented in a way that clearly offers an interpretation of learners' *on-trackness* while making it clear that feedback is indeed personalized and unique to her.

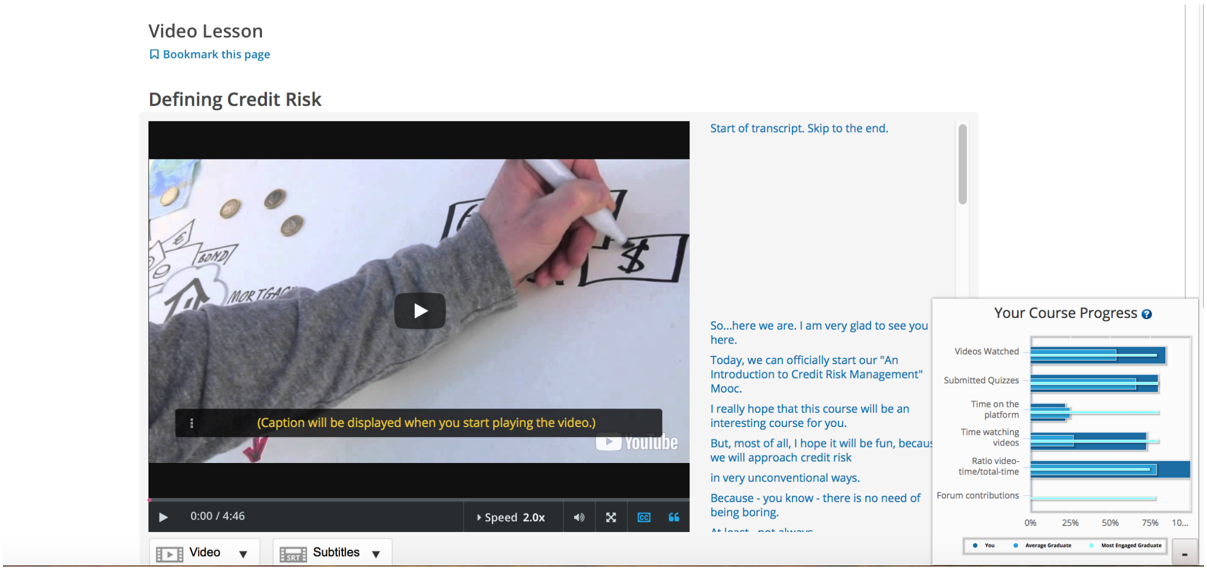

Figure 3.5: The placement of the Complex version of the *Real-Time Learning Tracker* on the edX platform. The *Real-Time Learning Tracker* is placed on a pop-up window in every course content page, offering a minimization/unminimization option to the learners.

Figures 3.6 and 3.7 provide an overview of the tool-tip explanatory texts, as presented in Section 3.2, in the Complex version of the *Real-Time Learning Tracker* .

Colour

We assigned each one of the three information sets to a specific colour. The different colour codes that were used for each one of the information sets aid learners in order to make visual correlations and comparisons of their learning behaviour to the corresponding one of last year's graduates over its different aspects. We kept the colours used in the design neutral trying also to match them with the edX format (different shades of blue), in order to constrain any judge-mental or assessment feelings occurring from the visualizations. That led to the absence of any red "danger zones" since red is implicitly linked to failure and danger and reduces motivation in the context of achievement [64]. At the other end of the scale, there is also absence of any green "safety zones" on the graph with the aim of raising awareness and encouraging growth through visualized feedback.

Interactive elements

We initially integrated the Intermediate version of the *Real-Time Learning Tracker* with interactive elements, which we used as our "basic" version, and then we extended this functionality also to the Complex and the Simple version. Figure 3.8 overviews the interactive elements of the "basic" version of the *Real-Time Learning Tracker* . Firstly, by hovering over any bar on the graph, a tool-tip is displayed with the actual values of the indicator for all the active information sets: *Learner, Average* or *Most Engaged Graduate*. As already stated in our list of hypotheses in Section 3.1.5, we argue that this additional information would allow the learners to

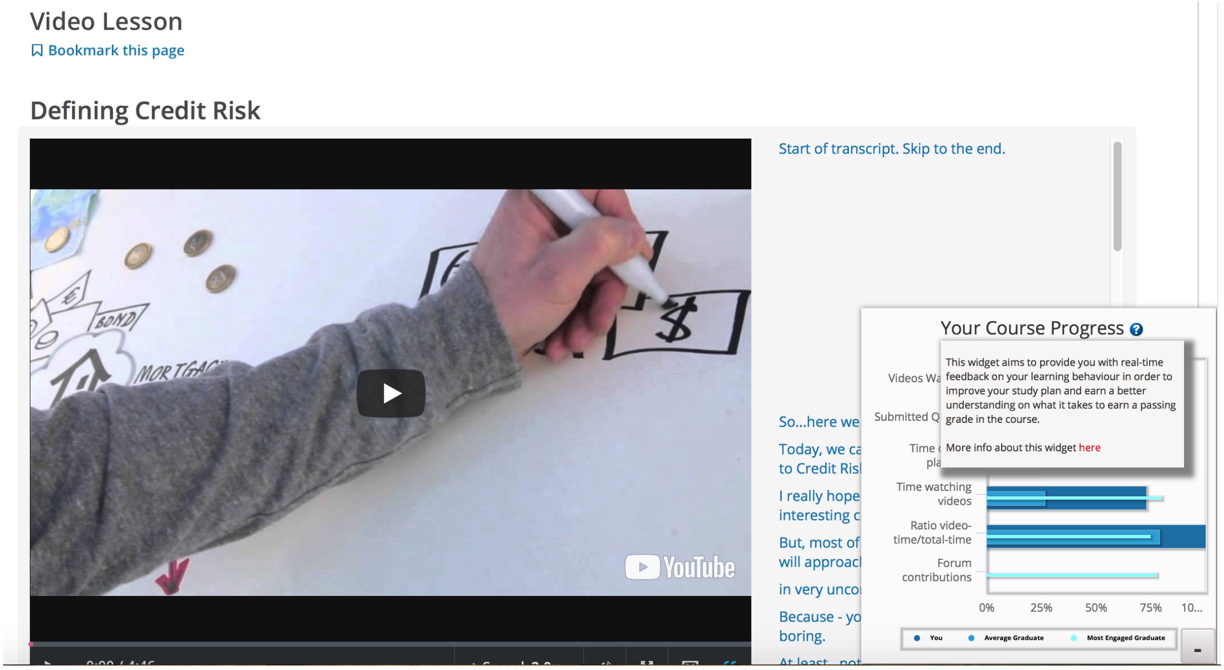

Figure 3.6: Overview of the tool-tip explanatory text in the Complex version of the *Real-Time Learning Tracker* .The content of this tool-tip text is common for all widget versions.

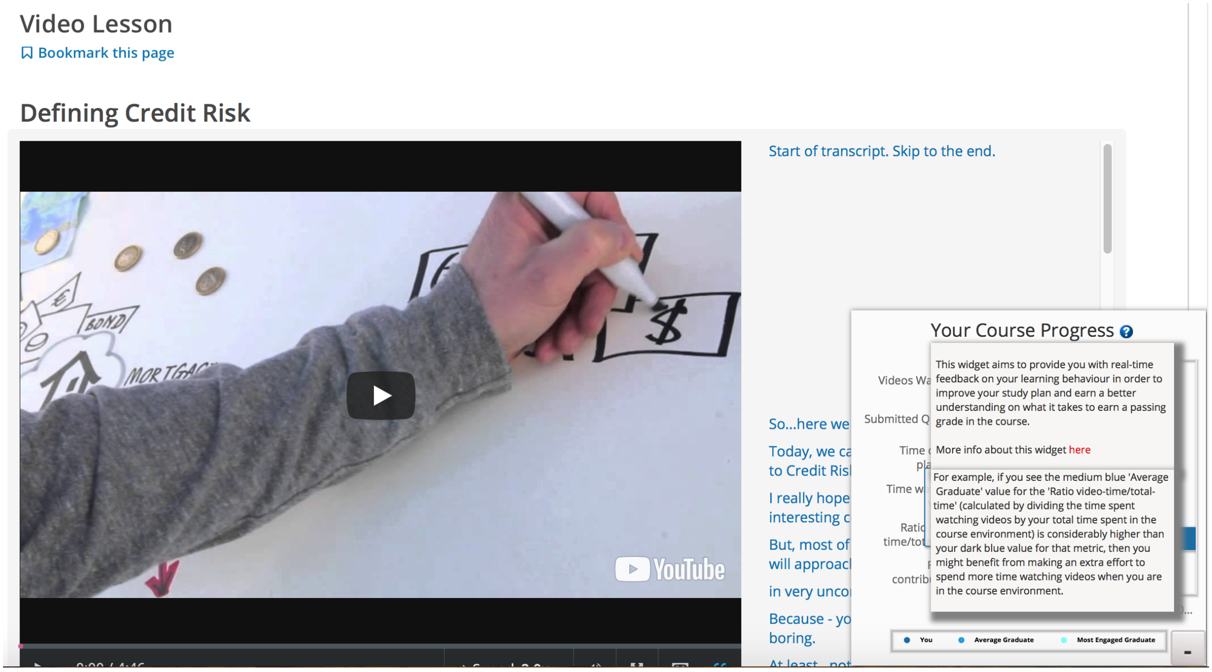

Figure 3.7: Overview of the second tool-tip explanatory text in the Complex version of the *Real-Time Learning Tracker* .The content of this tool-tip text is different for each widget version.

assess how much effort they still have to put in to reach the *Average* and *Most Engaged Graduates'* threshold. Secondly, in order to keep the graph simple for comparison, we afforded learners the opportunity to choose which information set to show or hide on the graph by clicking on the name of the corresponding set in the legend. By default, the status of all information sets are visible and learners have to actively choose to hide or display the information set of their desire.

These interactive elements offer learners the opportunity to interact with the widget, without allowing them to change the underlying model or make corrections to the displayed information. Bull [40] proved in his study that the *inspectable* learner models are more preferable to learners rather than the *editable* or the *negotiated* ones. In *inspectable* learner models learners have no control over the model data. On the other hand, in the case of *editable* learner models learners have the complete control over the model, whereas in *negotiated* ones there is joint control.

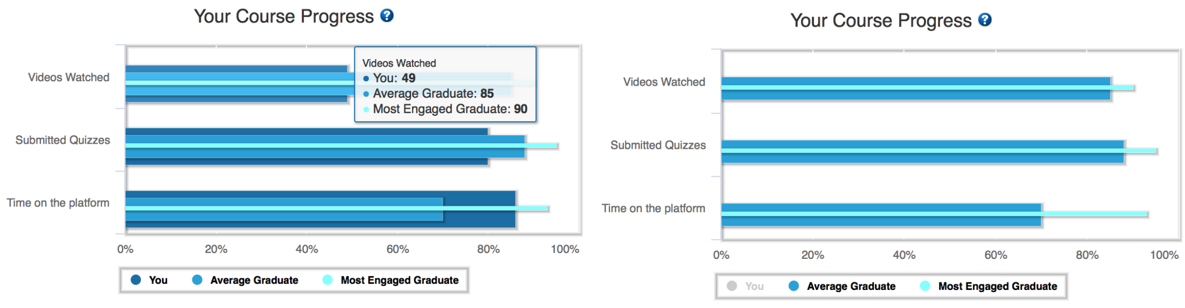

Figure 3.8: Interactive elements of the *Real-Time Learning Tracker* : additional information for bars in the form of an activated tool-tip (left) and an instance of the widget with the information set *You* hidden and the description of the two information sets such as the *Average* and *Most Engaged Graduate* depicted (right).

3.2.4. Tracking interaction with the widget

In order to investigate learners' interaction with the *Real-Time Learning Tracker* we integrated functionality that tracks the interaction with the widget. To keep the amount of data collected reasonable and limited to essentials, only four types of events were tracked:

- duration the widget was closed/open per page
- total duration the widget was closed/open during the course
- times the widget closed/opened
- times that learners showed or hid an information set - a measure of how much and in what ways the user interacts with the widget.

In addition to the type of interaction, the edX user identifier of the learner who generated the event and the timestamp of the event were also recorded. For plotting the data on the *Real-Time Learning Tracker* as presented in detail in Section 3.2.3, we used the Highcharts library which facilitated the interaction tracking with the provision of a series of event listeners for the graph and its elements. The tracking data was collected by creating new events for each one of them and hooking them to the Highcharts event listeners.The recorded event data is not shown to the learner but utilized later in our data analysis.

3.3. Technical implementation

We developed the *Real-Time Learning Tracker* for the edX platform, hence several of our design and implementation decisions were influenced by the technical possibilities offered by edX. The implementation of the *Real-Time Learning Tracker* followed five steps:

1. creating the graphic display for the three versions of the widget
2. processing the raw data from previous run of the course into successful learner profiles (*Average/Most Engaged graduates*) to be displayed on the widget
3. enabling real-time logging on the edX platform
4. processing the real-time raw data into *individual learner* profiles to be displayed on the widget
5. populating the widget with the information contained by the three aforementioned learner profiles

3.3.1. Graphic display

We generated the visualization of our widget using Highcharts[3], an external charting library. Highcharts is written in pure JavaScript and it relies only on native browser technologies allowing for an easy integration of the *Real-Time Learning Tracker* on any website. The reasons for choosing Highcharts are summarized below:

- a wide range of chart types are supported
- highly flexible design, as every element of the chart is configurable
- a simple configuration syntax for charts through a JavaScript object is offered
- external data loading is supported
- client side plugins are not required and is highly compatible with mobile and desktop browsers

Configurable chart elements range from the chart type and its aesthetics to interactive elements such as tool-tips and data loading animations.

Real-Time Learning Tracker 's client-server architecture as well as the offline computation modules are shown in Figure 3.9.

3.3.2. edX MOOC pages

We implemented all the components of the edX MOOC pages (shown in Figure 3.9) using the Javascript programming language. It consists of four functional modules. The *real-time logger* contains the code responsible for real-time logging learners' activity during the course. The edX platform provides a daily event log delivery to its X consortium members but does not have a real-time data API. In order to enable access to real-time learner event logs, we set up *real-time logger* within the xml of every page in the course gathering all kind of information from the client at every page related to learners' navigational events and click-stream data. We also queried information data such as learner's userID simply enough from Segment's analytics library used by edX, whereas we retrieved data such as the page's chapter, the page's sequential, the page's vertical etc. by parsing the browser URL. The *metrics computation* module contains the calculation of the metric values of each active learner in the course from the logged activity data. Consequently, the *individual learner profiles* are generated. In the *widget generation* module, the *real-time logger* code loads each version of the *Real-Time Learning Tracker* (one of the three JavaScript scripts) based on learner's edX id. We populated each version of the widget with data by setting the series field of the Highcharts graph object with metric values for each of the three information sets. This module uses as input the computed learner profiles that are passed as variables from the *real-time* logger code to each JavaScript script that corresponds to a widget version.

3.3.3. Back-end

We developed the back-end with the node.js[4] server environment, which directly supports asynchronous I/O operations, making it suitable for applications requiring real-time updates. It is fast and performs well under stress, facilitating a large number of simultaneous connections very well. An added benefit of node.js is its language (JavaScript)— developing both the front-end and back-end in the same language made the development more manageable for us. We chose MongoDB[5] for data storage as it uses a dynamic data schema, providing added flexibility during the development and modification of features. It also has documents stored in JSON, which makes it efficient to work with our client and server code.

The back-end is the part of the *Real-Time Learning Tracker* responsible for managing requests. Each time a new event is traced from the *real-time logger* code, an ajax POST request is sent to the Node server which in turn logs the corresponding event to Mongo database. On the other hand, during the *widget generation* step, an ajax GET request is sent to the server for acquiring the necessary logs for the learners' metric computation. In the same GET request also the already computed *Average* and *Most Engaged Graduate* profiles are retrieved.

[3] `https://www.highcharts.com`
[4] `https://nodejs.org/en/`
[5] `https://www.mongodb.com`

3.3.4. Offline computation

In this data processing step, the successful learner profiles (*Average* and *Most Engaged Graduate*) are generated by calculating the metric values from low-level activity data form a previous edition of the course and are inserted into the MongoDB database. The computation followed the metric definitions described in Section 3.2.1. The programming language that we used in this functional module is Python.

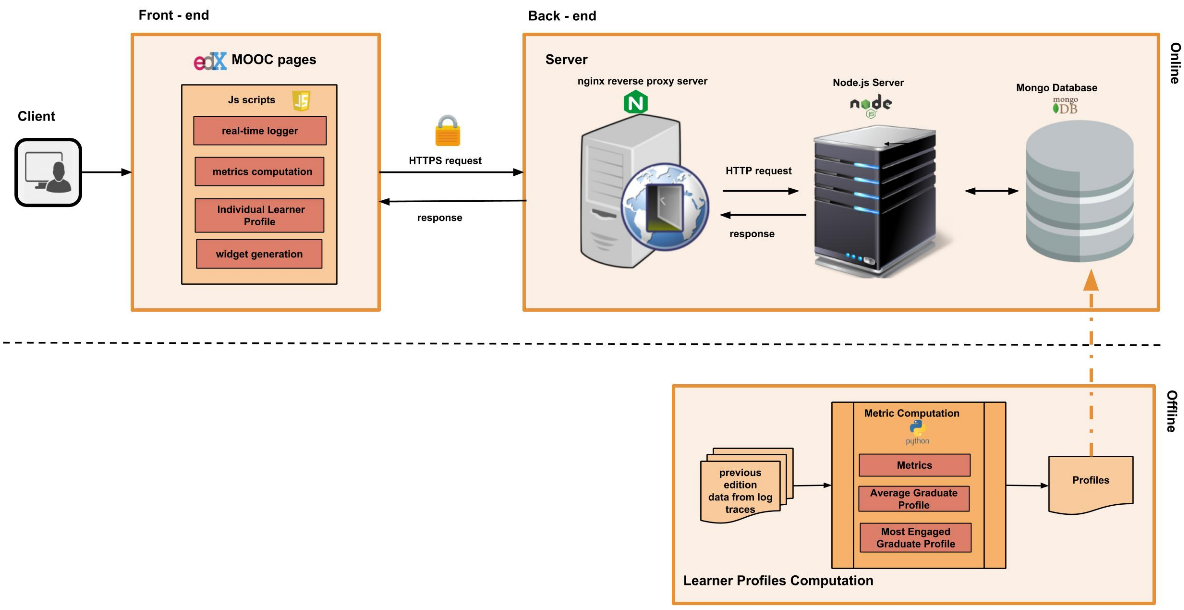

Figure 3.9: Overview on all the components of the functional architecture of the *Real-Time Learning Tracker* .

3.3.5. Integration with edX

The *Real-Time Learning Tracker* was integrated with the MOOC pages on the edX platform through an HTML snippet that was individually added on every page of every learning module as raw HTML. The snippet covered the following functionality:

- loading the *Real-Time Learning Tracker* dependencies: one Highcharts script available online
- containing the *real-time logger* code responsible for the real-time logging
- loading the three versions of the *Real-Time Learning Tracker* scripts based on learner edX identifier
- containing the widget interaction tracking code
- inserting into the page an HTML div element that defines a pop-up window in which the widget is contained.

An up-to-date version of the *Real-Time Learning Tracker* code along with a demonstration video of the widget in action is available on GitHub in the following repository:
`https://github.com/gatou92/RealTimeLearningTracker`.

4

Research Design

This chapter elaborates on the methodology to answer our research questions, as stated in Chapter 1. In order to evaluate the usefulness of the three versions of the *Real-Time Learning Tracker* in increasing learners' effectiveness and efficiency, we evaluated the widget in a live TU Delft MOOC running its third edition on the edX platform. We will first elaborate on a detailed description of the MOOC used in our experiment. We then elaborate on the experimental setup, the evaluated conditions and the evaluation metrics.

4.1. DelftX MOOC

The *Real-Time Learning Tracker* was integrated on the **DelftX *TW3421x*** MOOC during September-November 2018.

TW3421x An Introduction to Credit Risk Management[1], aims to provide learners with a rich understanding in the field of credit risk management. It provides all the necessary definitions and the implications of credit risk for banks and other financial institutions, analyzing the importance of credit risk as a very pervasive risk in our societies. In general, this MOOC provides learners an overview of credit risk management, in a gradual way combining theory with practice. This is the third edition of the course and this version is self-paced, which is available online from September 2018 until September 2019. While learners can take the course at their own pace, a weekly schedule has been created by the course instructors, so that anyone can comfortably complete it within 7 weeks. The estimated effort a learner has to invest for course completion according to course instructors, is 6 - 7 hours/week.

Table 4.1: Overview of the TU Delft MOOC in which the *Real-Time Learning Tracker* 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. A dash - indicates that this information does not exist.

	TW3421x	
	2016	2018
Start Date	Sep 15, 2016	Sep 3, 2018
End Date	Sep 15, 2017	Sep 3, 2019
Length	1 year	1 year
Experiment duration	-	10 weeks
Enrolment	11648	1837
Graduates	103 (0.9%)	58 (3.2%)

An overview of the aforementioned MOOC and its enrolment data in both editions used in the study is offered through Table 4.1 . Since we used data from both runs to generate information for the *Real-Time Learning Tracker* , the table provides information on both editions of the course. The two successful learner models were generated using data of the first edition, whereas learners from the second edition were presented with the *Real-Time Learning Tracker* . Observing the table data, we can see that the graduation ratio

[1] `https://courses.edx.org/courses/course-v1:DelftX+TW3421x+3T2018/course/`

of the second edition of the *TW3421x* MOOC in which our *Real-Time Learning Tracker* was integrated, is significantly higher than the first edition by a ratio of 2.3%. This information indicates that after the passage of only 10 weeks in the second edition of the *TW3421x* , the number of learners that graduated is higher than the half of the learners that graduated in the first edition of the *TW3421x* after the passage of a whole year. These numbers are very promising in relation with the effectiveness of our *Real-Time Learning Tracker* in terms of learners' performance, which we examine in detail in Chapter 5.

4.1.1. Course structure

The *TW3421x* MOOC is an xMOOC and its learning material of *TW3421x* is divided into seven modules, all being released in the beginning of the course. Each module consists of several sections called learning sequences. These learning sequences contain short video lectures, reading materials, non-graded practice quiz questions for deeper knowledge of the course material and help learners in understanding the most important concepts of each lecture, 4 graded home assignments that count towards the final grade with total weight of 40%, as well as one midterm exam after the end of week 4 and one final exam at the end of the course. Each one of them corresponds to 30% of the final grade. After the seven weeks, learners have a deadline until the end of the course on 3 September 2019, to complete the graded assessments. In order to receive a completion certificate, learners have to score at least 50% on the final grade. Learners are also encouraged by the course instructors to engage in forum discussions as according to them, it makes learning more interactive, increases their knowledge on the subject and allow them to be helped or to help others. All quiz questions, either non-graded practice quiz questions or graded home assignments, midterm and final exams, are multiple-choice, check-boxes, drop-down lists or require numeric answers. Learners are also provided with solutions to both practice quiz questions and graded quiz questions. In case of practice quiz questions the solutions are available to the learners at any time, whereas in the case of graded quiz questions solutions are available to the learners only after submission and grading, so that learners could receive immediate feedback on their performance. Learners have only one attempt available for answering each quiz question. The learning material available for the MOOC in terms of video-lectures, practice quiz questions and graded quiz questions contains 44 Video lectures, 73 Practice quiz questions and 31 Graded quiz questions in total.

4.2. Experimental setup

In order to provide answers to the research questions outlined in the Chapter 1, we adopted a between-group testing method (or A/B testing or Randomized Controlled Trial), which requires the division of the test population in subgroups that are exposed to different conditions. Therefore, MOOC learners were distributed into three test groups that had access randomly to one version of the *Real-Time Learning Tracker* and a control group that was not shown the *Real-Time Learning Tracker* .

- **Control group:** No widget available
- **Simple group:** Simple version of the *Real-Time Learning Tracker*
- **Intermediate group:** Intermediate version of the *Real-Time Learning Tracker*
- **Complex group:** Complex version of the *Real-Time Learning Tracker*

The learners were randomly assigned to one of the four groups based on the parity of their edX user identifier. The assignment of active learners to each group, as defined in Section 3.1.4, remained static throughout the course. Table 4.2 presents the sizes of the four groups and we can observe that approximately the same number of learners were assigned to each group, indicating that our random learners' assignment was effective.

Table 4.2: The number of active learners enrolled for the MOOC and their division in test and control groups.

	TW3421x
Simple group	375
Intermediate group	375
Complex group	381
Control group	352
Total enrolled	1483

We selected to use this experimental method in order to monitor the use of the *Real-Time Learning Tracker* in a realistic setting and to evaluate its impact by comparing the behaviour of the three test groups with that of the control group. The control group functioned as a baseline against which we could observe any change in the behaviour of any of the test groups. Therefore, we can assess the impact of the *Real-Time Learning Tracker* in terms of learners' performance by relying on recorded data as seen in Davis et al. [57] research and not on learners' subjective evaluations focused on usefulness and usability as seen in [71, 119]. The between-group experimental design is widely used as an effective experimental setup in economic, psychological, sociological and computer science experiments, but has recently been used in the learning analytics community for assessing several interventions [93, 98, 127, 141].

4.2.1. Participants

To ensure that our experiment is sensible and there are no demographics differences between the learners in the test groups and the control group, we conducted a preliminary demographics analysis. For each learner, data was available regarding their gender, age and education level. All demographic data was self-reported at the time of learners' registration in the course.

Demographics

The distribution of learners in terms of gender, age and education in the MOOC under study is illustrated in Figure 4.1. Regarding the gender distribution, we observe that half of the enrolled students are male. Regarding the age distribution, we observe that most of the learners fall in the range of 26-40 years old (40-42%) with a median age of 29. The majority of learners hold a Bachelor's or Master's degree, whereas the second highest percentage belongs to the learners with a college level education and advanced level education, similar to the results presented in [18, 33]. An extra check revealed each of the control and test groups to have a similar setup.

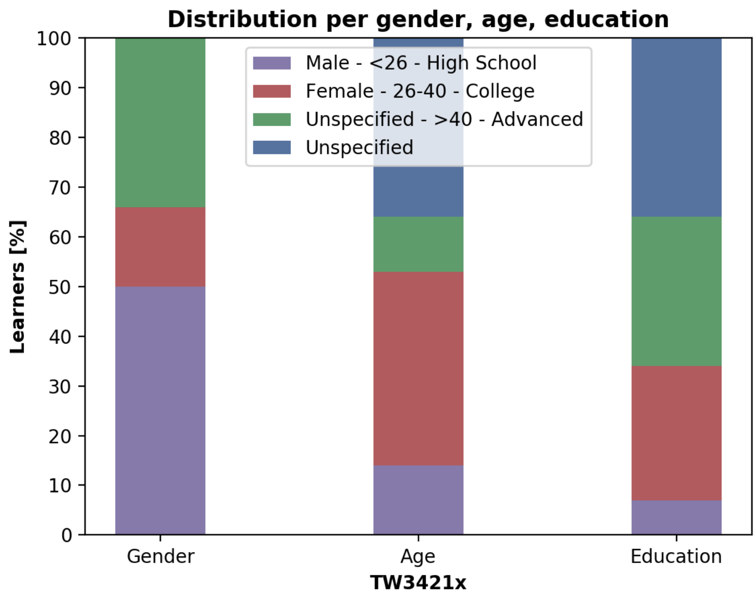

Figure 4.1: Gender, age and education distribution of the active learners in the MOOC under study.

4.2.2. edX data

We considered several data sources for the evaluation of our *Real-Time Learning Tracker* . We collected four types of information from the edX platform.

Firstly, we collected *trace logs* from which low-level user activity data were used in order to calculate the information displayed on the widget as presented in Section 3.2.1, as well as investigating changes in behaviour, engagement and motivation by processing that information into easily comparable behavioural indicators similar to the six metrics displayed on the widget.

Secondly, we also exploited *grade reports* of learners. The grade reports can be generated at any time during the MOOC and apart from the grades obtained by learners, the certificate receivers are also marked. We used this information generated at the end of the previous run of the *TW3421x* MOOC to select learners for the calculation of the *Average* and *Most Engaged Graduate's* profile and we also used the information generated at the end of our experiment (after the course of 10 weeks) of the current edition of the *TW3421x* MOOC, to compare the graduation rates between the two editions of the *TW3421x* MOOC.

Thirdly, we used *self-reported user data*. edX learners are required to complete their profile at registration with demographic data including their age, education level, gender and country of origin. We exploited this data to check the population homogeneity between the test and control groups.

Finally, we used *interaction data* describing learners' interaction with the widget which were obtained as described in Section 3.2.4, in order to get a measure of how many learners in the test groups actually used the *Real-Time Learning Tracker* and how often.

4.3. Measures & Method of Analysis

The key outcome variable we aim to affect with the design of our *Real-Time Learning Tracker* is course completion. A learner has passed and receives a certificate when she has earned the required minimum passing score based on the summative quiz questions. While individual learner intentions may vary throughout the learner population, the achievement of earning a certificate is an appropriate outcome measure, as it demonstrates sustained commitment to the course and mastery over the course material.

As stated earlier in Chapter 3, we defined as *successful* learners, those learners that managed to receive a final grade above the graduation threshold which was set by each MOOC team (50% for our MOOC). The MOOC under study is self-paced with one-year duration, meaning that the learners are able to complete the course during this one-year period. However, our experiment lasted 10 weeks and there is a great chance the *completion rates* obtained after the course of these 10 weeks, not to be representative of learners' performance. Hence, we decided to complement *completion rates* with a second performance measure in our analysis which is the *number of learners that are still active until that time in the course* considering these learners as potential graduates by the end of the course.

Our second objective is the promotion of SRL and meta-cognitive awareness. While many SRL actions are meta-cognitive and unobservable, it has been shown that some can be inferred through a learner's logged actions with the course materials [83, 100, 166, 167].

In order to test if differences between experimental conditions are statistically significant, we used the non-parametric Kruskal-Wallis test, because our measures were not normally distributed and exhibited unequal variances across conditions. For binary measures, we tested differences in proportion using a χ^2 test. We present the results of each test by each group's mean and median along with the level of statistical significance. Moreover, in order to visualize our data, we used density estimation (KDE) plots. KDE plotting is a non-parametric method to visualize the underlying distribution of a continuous variable, similar to histograms. The method does not make a normal data distribution assumption. We present the results of each test by each group's mean and median along with the level of statistical significance in Chapter 5.

5
Results

In this chapter, we present our findings with respect to the research questions described in Chapter 1. Sections 5.1 and 5.2 do not refer to any research question but they are dedicated to data preparation and the evaluation of learners' engagement with the different versions of the *Real-Time Learning Tracker* , respectively. In Section 5.3, we investigated learners' overall performance as an outcome of the learning process, as well as the effect of the *Real-Time Learning Tracker* 's different versions to their performance **(RQ1)**. In Section 5.4, we investigated learners' behaviour as means to achieve the learning outcomes, as well as the effect of the *Real-Time Learning Tracker* 's different versions to their behaviour **(RQ2)**. Finally, in Section 5.5 we investigated how the *Real-Time Learning Tracker* affects the performance of different types of learners based on their prior educational knowledge **(RQ3)**. We ran statistical tests on the edX activity data generated by the three test groups and the control group and compared the results. To identify significant differences between the four populations, we ran *Kruskal Wallis H-tests* since they do not make a normality assumption about the data distribution, common for MOOC data [53]. We set the significance level to $\alpha = .050$.

5.1. Data preparation

Since a large amount of learners do not return to the course platform after their initial enrollment (70% in case of our MOOC), we firstly prepared the data set for analysis by extracting data generated only by *active learners*. In line with Davis et al.'s [57] and Jivet's [82] work , we defined as active learners those learners that spent at least five minutes on the course platform, although in similar studies as active learners were considered learners that submitted at least one assignment [134, 160].

We considered that a five-minute period in which the learners navigate through the course pages is sufficient time for them to decide whether or not they would like to follow the course. As shown in Table 5.1, the difference in percentage of learners spending more than five, ten or twenty minutes on the course platform is not significant. In addition, a high number of learners who spent more than ten minutes on the course platform, showed the intention to revisit the course by logging several sessions on the course pages.

Table 5.1: Overview of the number of learners enrolled and assigned to the control and test groups respectively. Moreover, number of learners that spent more than 5, 10 or 20 minutes on the course for the MOOC under study. As active learners were considered those learners that spent more than 5 minutes on the course pages.

	TW3421x	**>5**	**>10**	**>20**
Enrolled	1837	1483	1385	1264
Control Group	434 (23.6%)	352 (23.7%)	334 (24.1%)	313 (24.8%)
Simple Group	470 (25.6%)	375 (25.3%)	347 (25.1%)	322 (25.5%)
Intermediate Group	466 (25.4%)	375 (25.3%)	349 (25.2%)	314 (24.8%)
Complex Group	467 (25.4%)	381 (25.7%)	355 (25.6%)	315 (24.9%)

5.2. Learners' widget interaction

We dedicated this section to the evaluation of learners' engagement with each version of the *Real-Time Learning Tracker* . In that way, we investigated whether learners devoted part of their time on the course platform to examine and interact with the *Real-Time Learning Tracker* or ignored its existence. We examined two metrics for that purpose: *time of interaction* and *amount of interactions*. We subsequently re-examined these two metrics after partitioning learners by prior education in order to investigate whether the *Real-Time Learning Tracker* affected these groups differently.

Time of interaction

We firstly investigated the percentage of time that learners had the *Real-Time Learning Tracker* open versus their total time on the course. Table 5.2 provides an overview of the mean and median values of this metric along with the results of the Kruskal Wallis test. We found significance differences between the Complex and the Simple group. We speculate that the reason why the learners of the Complex group had significantly more time the widget open compared to the learners of the Simple group is that in this version of the *Real-Time Learning Tracker* more detailed information is presented to the learners. This fact may have led them to devote more of their time on the course to examine and interact with it. However, the ratio of time that learners of the Simple group had the widget open is more than expected, considering the limited information displayed on it. This result indicates that learners devoted part of their time on the course to interact with all widget versions and no version lacked completely their interest.

Table 5.2: The mean and the median of the percentage of time that the widget was open versus the total time on the platform (%) along with the results of the Kruskal-Wallis test ($\alpha = .050$). Significant values are in bold.

Time with open widget / total-time (%)			
Comparison	*Mean*	*Median*	p-*value*
Simple	38	15	0.3
Intermediate	42	23	
Simple	38	15	**0.03**
Complex	48	32	
Intermediate	42	23	0.2
Complex	48	32	

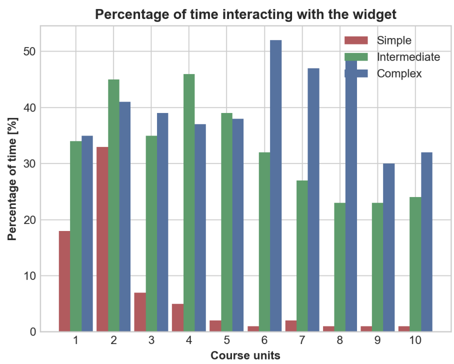

Figure 5.1: The percentage of time that active learners interacted with the widget in each course unit in relation with their total time spent in that unit.

In order to investigate how the aforementioned percentages changed throughout the course units and whether learners' interest on the *Real-Time Learning Tracker* remained until the end of the course, we evaluated the percentage of time learners interacted with the widget in each course unit in relation with the total time learners spent in that specific unit. We kept in the analysis only units containing course material, home assignments and partial exams, in which the use of the widget has more meaning. Units including surveys on learners' satisfaction with the course material were omitted. Therefore, we kept 10 out of the 12 course units in our analysis. We found significant differences in ratios between the Simple group with both the Complex and Intermediate group. Figure 5.1 suggests that in each course unit, learners from all groups dedicated part of their time to interact with all *Real-Time Learning Tracker* versions, indicating that no widget version was ignored completely by the learners. However, we can see that the ratios of the Simple group decreased significantly compared to the Intermediate and the Complex groups' ratios during the course units. An explanation on this phenomenon is that either i) the Simple interface did not manage to maintain learners' engagement throughout the course due to its simplicity and lack of detailed information, or/and ii) significantly more learners of the Simple group did not visit most of the course units, leading to zero time on the course platform for that units. On the other hand, we can see that the other two groups managed to keep learners' interest throughout the course units with significant difference compared to the Simple group, fact that once more aligns with our initial hypothesis that more detailed interfaces have the potential to engage more learners.

Amount of interactions

We also investigated the percentage of learners' interactions with the *Real-Time Learning Tracker* out of their total actions throughout the course. We consider as widget interactions all the times that learners minimized or/and unminimized the widget, as well as all the times that they showed or hid an information set on the widget. Moreover, we consider as learners' *total actions* only actions that in long term will lead learners to course completion and not their actual total clicks on the course platform. Such actions include clicks related to video watching, quiz submissions, forum participation, as well as interactions with the widget. Table 5.3 provides an overview of the mean and median values of this metric along with the results of the Kruskal Wallis test. We found significance differences between the Simple group with both the Complex and Intermediate group, indicating that learners in both the Complex and Intermediate group performed significantly more interactions with the widget compared to learners of the Simple group. We expected this finding, since it comes in line with our initial speculation, as stated in Section 3.1.5, that the Complex and the Intermediate version of the *Real-Time Learning Tracker* present more information to the learners and as a result they may offer more available interactions to them.

Table 5.3: Mean and median of the percentage of widget interactions / total actions (%) of learners throughout the course along with the results of Kruskal-Wallis test. Significant values are in bold.

Widget interactions / total actions (%)			
Comparison	*Mean*	*Median*	p-*value*
Simple	43	45	**0.009**
Intermediate	49	51	
Simple	43	45	**0.01**
Complex	49	51	
Intermediate	49	51	0.7
Complex	49	51	

5.2.1. Partitioning by Prior Education

Once more, we examined learners' widget interaction in terms of *time of interaction* and *amount of interactions*, but this time in the context of learners' prior education levels to investigate whether the *Real-Time Learning Tracker* affected these groups differently. We define high prior education learners as those with a Bachelors, Masters, or PhD degree, and low prior education learners as those with any degree below Bachelors. We gather learners' prior education levels from their edX user profile; learners who do not report their education level are ignored in this analysis. Therefore, the amount of learners that left in the analysis is 893 out of 1483 (High: 749, Low: 144).

Time of interaction

Table 5.4 provides an overview of the mean and median values of the percentage of time that high educated learners had the *Real-Time Learning Tracker* open versus their total time on the course, along with the results of the Kruskal Wallis test. This time, we observed significance differences in ratios not only between the Simple and the Complex group but also between the Simple and the Intermediate group, highlighting the fact that high-educated learners dedicated significantly more of their time on the course interacting with both the Complex and the Intermediate versions of the *Real-Time Learning Tracker* .

Table 5.5 provides an overview of the mean and median values of the percentage of time that low educated learners had the *Real-Time Learning Tracker* open versus their total time on the course, along with the results of the Kruskal Wallis test. In this case, we also observed significance differences in ratios between the Simple group with both the Complex the Intermediate groups, indicating that low-educated learners, just like the high-educated ones, dedicated more of their time on the course interacting with both the Complex and the Intermediate version of the *Real-Time Learning Tracker* . One more time the results of this analysis suggest

Table 5.4: Mean and median of the percentage of time with open widget versus the total time on the course (%) of high educated learners along with the results of Kruskal-Wallis test. Significant values are in bold.

Time with open widget / total time (%)			
Prior Education: high (749)			
Comparison	*Mean*	*Median*	p-*value*
Simple Intermediate	15 42	11 21	**0.00001**
Simple Complex	15 49	11 34	**0.0000**
Intermediate Complex	42 49	21 34	0.2

Table 5.5: Mean and median of the percentage of time interacting with the widget versus the total time on the course (%) of low educated learners along with the results of Kruskal-Wallis test. Significant values are in bold.

Time with open widget / total time (%)			
Prior Education: low (144)			
Comparison	*Mean*	*Median*	p-*value*
Simple Intermediate	16 40	10 26	**0.001**
Simple Complex	16 55	10 45	**0.00001**
Intermediate Complex	40 55	26 45	0.2

that the Simple version is the version of the *Real-Time Learning Tracker* that both high and low educated learners interacted less time with, hence the less engaging version.

Amount of interactions

Table 5.6 provides an overview of the mean and median values of the percentage of high educated learners' interactions with the *Real-Time Learning Tracker* out of their total actions in the course (as defined earlier in 5.2) along with the results of the Kruskal-Wallis test. We observed significance differences in ratios between the Simple and Complex group, indicating that high educated learners of the Complex group performed significantly more interactions with the widget compared to high educated learners of the other two groups. At the other end of the scale, we did not observe significance differences among the test groups in low educated learners. Comparing the results of the two partitions, we conclude that (i) in total both high and low educated learners of the Complex and the Intermediate groups dedicated significantly more of their time on the course platform to interact with the *Real-Time Learning Tracker* compared to learners of the Simple group and (ii) only high educated learners of the Complex group performed significantly larger amount of interactions on the widget compared to the learners of the Simple group.

Table 5.6: Mean and median of the percentage of time interacting with the widget versus the total time on the course (%) of high educated learners along with the results of Kruskal-Wallis test. Significant values are in bold.

Widget interactions / total actions (%)			
Prior education: high(749)			
Comparison	*Mean*	*Median*	p-*value*
Simple Intermediate	44 49	45 51	0.2
Simple Complex	54 51	56 52	**0.05**
Intermediate Complex	49 51	51 52	0.7

Overall, the results of this analysis indicate that learners in all test groups interacted with all *Real-Time Learning Tracker* versions, however did not remain engaged with all three of them throughout the course. The Complex and the Intermediate versions found to be the most engaging versions both in terms of time of interaction and amount of different interactions throughout the course, in contrast with the Simple version which was the less engaging one. Moreover, the Simple interface was the only one out of the three that failed to maintain learners' interest. These results come in line with our initial hypothesis (**H8**), as stated in Section 3.1.5, indicating that learners did not engage with the Simple version of the *Real-Time Learning Tracker* as much they did with the Complex and the Intermediate ones due to the limited amount of feedback presented on the Simple version, fact that consequently limited the amount of the available interactions on it. Moreover, the results of the analysis after the partition of the learners indicated that learners' different prior education did not affect their engagement with the *Real-Time Learning Tracker* in terms of time of interaction, since learners of the Complex and the Intermediate group from both partitions interacted with the widget significantly more time than learners of the Simple groups. Hence, we can conclude that both types of learners engaged with both the Complex and Intermediate versions of the *Real-Time Learning Tracker* .

After examining learners' engagement with the different versions of the *Real-Time Learning Tracker* , we continue our analysis in the upcoming sections in order to provide answers to our research questions regarding (i) the effect of the *Real-Time Learning Tracker* on learners' performance (**RQ1**), (ii) the effect of the *Real-Time Learning Tracker* on learners' behaviour (**RQ2**) and (iii) the effect of the *Real-Time Learning Tracker* on learners with different prior educational knowledge with respect to their performance (**RQ3**).

5.3. RQ1: Learners' performance

In order to answer our first research question **(RQ1)** regarding learners' performance, we evaluated whether learners become more successful when they are provided with real-time feedback on their learning behaviour and also being able to compare their behaviour to that of previously successful learners. Additionally, we evaluated which version of the *Real-Time Learning Tracker* is better in terms of learners' performance.

For this part of this analysis, using *completion rates* as a performance measure of the learners, we analyzed the grade reports available on edX on the instructor pages of the course. We collected the reports on the final day of our experiment on November 12, 2018. As presented in Table 5.7, the results in this section are based on the active learners that were still enrolled until that time in the MOOC, as learners have the possibility to unenroll from the course any time. We observed that the graduation rate is 1-3.2% higher in all test groups, detecting also significant differences in graduation ratios between the Complex and the Control group. These results support our initial intuition that the *Real-Time Learning Tracker* will increase completion rates for learners that have access to the widget, as well as that the Complex version of the widget will prove to be the most effective in improving learners' achievement, as stated in Section 3.1.5.

Table 5.7: Graduation ratios and absolute numbers among active learners in the test groups compared to the control group. Learners that obtained a final score above 50% are considered graduates. Significant differences are marked in bold.

Graduation ratios		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	2.5% (9/352) 3.7% (14/375)	0.4
Control Group Intermediate Group	2.5% (9/352) 3.5% (13/375)	0.6
Control Group Complex Group	2.5% (9/352) 5.7% (22/381)	**0.04**
Simple Group Intermediate Group	3.7% (14/375) 3.5% (13/375)	1
Simple Group Complex Group	3.7% (14/375) 5.7% (22/381)	0.2
Intermediate Group Complex Group	3.5% (13/375) 5.7% (22/381)	0.1
Overall Ratio (current edition) Overall Ratio (previous edition)	3.2% (58/1837) 0.9% (103/11648)	**0.0000**

We further investigated the distribution of final grades of the graduates per group but we did not detect any significant differences between groups. Furthermore, in order to identify if learners that completed the course, pursued also higher grades, we investigated the amount of graduates that achieved grades higher than 90 and we found that these ratios are higher in all test groups compared to the control group. We also found significant differences in ratios of learners that their final grades lie in the score interval 90-100% between the Complex and the Simple group, as presented in Table 5.8 . Figure 5.2 illustrates the distribution of the final grades of the graduates through kernel density estimation (KDE) plots. In order to better visualize the grade distribution, the plot has been cropped. The differences in density between the test and control groups are more observable in the final score interval 90-100%. In this interval, all test groups own higher density scores regarding the final grades compared to the control group, with the highest one belonging to the Complex group. These results reveal a trend that learners of the Complex group not only graduate more than learners of the Control group but also pursue higher grades.

Subsequently, using *the number of learners that are still active in the course* as a performance measure, we computed the number of learners that registered a session during the last five days before our experiment ended. Since learners are able to un-enroll from the course anytime they wish, the results in this section are based on the active learners that were still enrolled until that time in the MOOC, as presented in Table 5.9. The active learners' rate is 6.3-7.5% higher in the test groups than the control group. The differences between the control and the test groups were found to be significant, indicating a trend for occurrence of more graduates

Table 5.8: Percentages of active learners who obtained a final grade in the score interval 90-100% in the test groups compared to the control group. Significant differences are marked in bold.

Active learners' ratios with grade > 90		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	0.2% (1/352) 1.9% (7/375)	0.09
Control Group Intermediate Group	0.2% (1/352) 1.3% (5/375)	0.2
Control Group Complex Group	0.2% (1/352) 2.4% (9/381)	**0.03**
Simple Group Intermediate Group	1.9% (7/375) 1.3% (5/375)	0.7
Simple Group Complex Group	1.9% (7/375) 2.4% (9/381)	0.8
Intermediate Group Complex Group	1.3% (5/375) 2.4% (9/381)	0.4

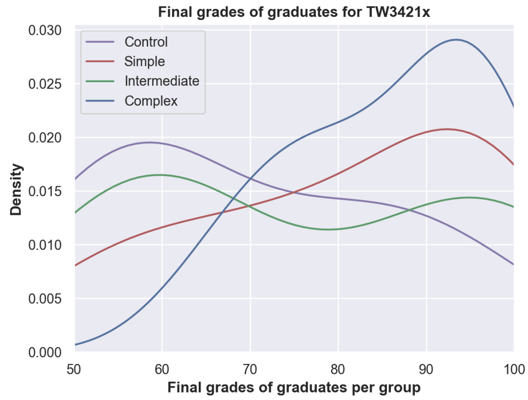

Figure 5.2: Kernel Density Estimation (Gaussian kernel) plot visualizing the distribution of final course grades of the graduates among the test and control groups. The plot has been cropped to better visualize the data distribution.

in the test groups until the end of the MOOC.

Table 5.9: Active learners' ratios and absolute numbers in the three test groups compared to the control group, along with the significance levels. Learners that registered a session during the last five days before the experiment ended are considered active learners, hence potential graduates. Learners that already completed the course until that time were omitted.

Active learners' ratios		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	7.5% (26/343) 13.9% (50/361)	**0.01**
Control Group Intermediate Group	7.5% (26/343) 14.6% (53/362)	**0.004**
Control Group Complex Group	7.5% (26/343) 15.3% (55/359)	**0.001**
Simple Group Intermediate Group	13.9% (50/361) 14.6% (53/362)	0.8
Simple Group Complex Group	13.9% (50/361) 15.3% (55/359)	0.6
Intermediate Group Complex Group	14.6% (53/362) 15.3% (55/359)	0.8

The results of the first part of this analysis using *completion rates* as a performance measure indicate that significantly more learners with access to the Complex version of the *Real-Time Learning Tracker* passed the graduation threshold until that time in the MOOC, conforming once more with our initial speculations (**H1.1**, **H2**, **H3**, **H4**, **H5.1**), as described in Section 3.1.5. Investigating further if learners that passed the graduation threshold pursued also higher grades, we detected significant differences in the final grade interval 90-100% between the graduates in the Complex and the Control group. However, the limited number of available graduates indicate that more data is needed in order to come to clear conclusions. We also observe that test groups were found to be significantly more effective compared to the control group in terms of active learners' ratios. This indicates a trend of more graduates occurring from groups with access to the *Real-Time Learning Tracker* until the end of the MOOC, highlighting the need for performing the experiment for longer period of time, ideally for the whole duration of the MOOC. In that way we could utilize more data and develop a more clear view on the effect of the *Real-Time Learning Tracker* on learners' performance.

5.4. RQ2: Learners' behaviour

In order to answer our second research question regarding learners' behaviour **(RQ2)**, we tried to understand how providing learners with real-time feedback on their learning habits affected their behaviour. For that reason, we compared the behaviour of the three test groups with that of the control group with respect to the six metrics displayed on the *Real-Time Learning Tracker* . Additionally, we evaluated which version of the *Real-Time Learning Tracker* is better in terms of learners' behaviour. More specifically, we examined extensively two aspects of learner behaviour in each MOOC: (i) *engagement* and (ii) *self-regulation* as reflected by behaviour.

5.4.1. RQ2.1: Learners' engagement

We evaluated the effect of the *Real-Time Learning Tracker* on learners' engagement **(RQ2.1)** from three perspectives:

- level of retention i.e. for how long the learners were active in the course
- course material i.e. amount of the course material learners engaged with
- forum interaction i.e. number of forum contributions (threads/responses/comments posted)

Retention

In line with Coetzee et al. [53], *retention* was operationalized as days from the start of the course until the last day that learners registered a session. The results of a Kruskal-Wallis test did not reveal a significant difference on retention among the test and the control groups. Figure 5.3 presents the kernel density estimation plot on retention registered for the learners between the four groups for *TW3421x* .

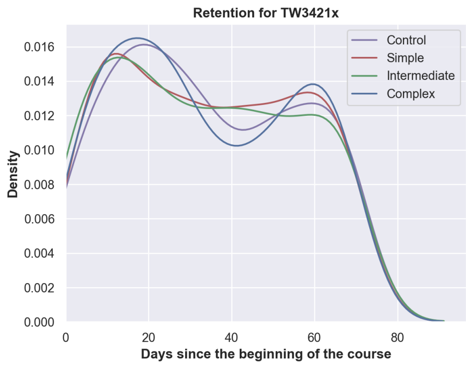

Figure 5.3: Kernel Density Estimation (Gaussian kernel) plot visualizing the retention in *TW3421x* for learners in the three test groups and the control group. Differences are not statistically significant as reported by a Kruskal-Wallis H-test with $\alpha = .050$.

We also found that the amount of learners that were still active in the course after 55 days and more, is higher in the Simple and Complex groups compared to the Control group, fact that one can also easily observe in the aforementioned figure. However, the differences on these amount of learners among the test and the control groups were not found to be significant.

Engagement with course material

We tested the level of learners' engagement with the course material in two dimensions: (i) number of videos watched and (ii) number of quiz questions submitted, including graded and non-graded quiz questions. We ran Kruskal-Wallis H tests with a 5% significance level, in order to determine any variation in the engagement of learners with the course material.

We did not find significant differences among the test groups and the control group both on the number of quiz questions submitted and the number of videos watched. Figure 5.4 visualizes the distribution of the number of quiz questions submitted for learners in each group. We observe a high density for zero quiz questions submitted. This skewness is reflective of the low engagement in MOOCs as only a few learners work towards completing the course and obtaining a certificate [51]. We cropped the plots for better visualization of the distribution of the rest of the learners. Nevertheless, the position of the four curves relative to each other in the graph suggests that more learners in the test groups submit quiz questions and this difference is more noticeable in the interval 90-104 quiz submissions. More specifically, the Complex group owns the highest density score in the aforementioned interval.

Learners that submitted quiz questions

Since we did not find significant differences on the number of quiz submissions among groups, we investigated the ratio of learners out of the active learners that submitted quiz questions per group. In that way

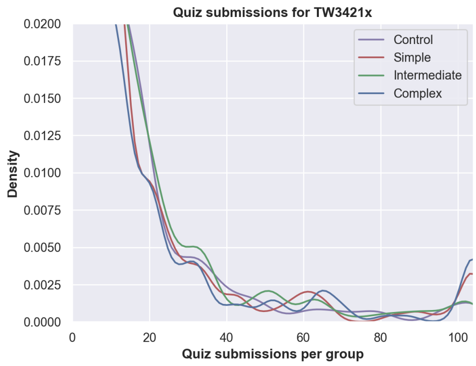

Figure 5.4: Kernel Density Estimation (Gaussian kernel) plot illustrating the distribution of the number of submitted quiz questions for learners in each group. Since many learners do not submit any assignments, there is a very high density around 0 quiz questions submitted. The plot has been cropped to better visualize the data distribution.

we can see if the *Real-Time Learning Tracker* urged more learners in the test groups to submit quiz questions. The results are summarized in Table 5.10. Once more, we did not detect significant differences in ratios between groups.

Table 5.10: The number of learners that submitted at least one quiz question out of the active learners of the MOOC under study.

	TW3421x			
	Control	**Simple**	**Intermediate**	**Complex**
>1 quiz submissions	68% (241)	69% (257)	70% (263)	71% (271)

Learners that submitted graded quiz questions

We also investigated the ratio of active learners that submitted graded quiz questions per group, since the submission of graded quiz questions leads directly to course completion. The results are summarized in Table 5.11. We can see that in all test groups the ratios of active learners that submitted graded quiz questions are higher than the control group, with the highest belonging to the Complex group. The difference in ratios between the Control and Complex group was found to be significant (**p=0.04**), indicating that more learners who have access to the Complex version of the *Real-Time Learning Tracker* submit graded quiz questions, fact that in long term may lead to higher completion rates for the learners of the Complex group.

Table 5.11: The number of learners that submitted at least one graded quiz question out of the active learners for the MOOC under study. Significant differences are marked in bold.

>1graded quiz submissions		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	7% (24/352) 8% (30/375)	0.6
Control Group Intermediate Group	7% (24/352) 9% (32/375)	0.4
Control Group Complex Group	7% (24/352) 11% (43/381)	**0.04**
Simple Group Intermediate Group	8% (30/375) 9% (32/375)	0.8
Simple Group Complex Group	8% (30/375) 11% (43/381)	0.1
Intermediate Group Complex Group	9% (32/375) 11% (43/381)	0.2

Forum Engagement

We also analyzed the engagement on the forum pages for *TW3421x* . We found that the learners' engagement on the forum was limited and no significant differences between groups with respect to the numbers of forum contributions were observed. Therefore, we subsequently examined the percentage of learners that performed at least one forum contribution out of the active learners in each group, in order to observe if the *Real-Time Learning Tracker* urged more learners in the test groups to participate in the forum. The results are summarized in Table 5.12. We can see that the ratios in both Intermediate and Complex groups are higher compared to the control group, with the Intermediate group owning the highest ratio with significant difference compared to the Simple Group. These results are unexpected considering that the *number of forum contributions* was a metric displayed only on the Complex version of the *Real-Time Learning Tracker* . We speculate that the learners' forum activity is higher in Intermediate group because either (i) the forum activity is influenced by other metrics displayed on the widget or (ii) learners in the Intermediate group have higher intrinsic forum engagement.

Table 5.12: The number of learners that performed at least one forum contribution out of the active learners for the MOOC under study. Significant differences are marked in bold.

>1 forum contributions		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	6% (21/352) 5% (17/375)	0.4
Control Group Intermediate Group	6% (21/352) 9% (33/375)	0.1
Control Group Complex Group	6% (21/352) 7% (28/381)	0.5
Simple Group Intermediate Group	5% (17/375) 9% (33/375)	**0.02**
Simple Group Complex Group	5% (17/375) 7% (28/381)	0.1
Intermediate Group Complex Group	9% (33/375) 7% (28/381)	0.5

Overall, the inspection of metrics related to learners' engagement with the course material revealed that the *Real-Time Learning Tracker* had no significant effect on most of these metrics. However, our findings also revealed the existence of a pattern in which more learners in the test groups submit graded quiz questions, highlighting the significant increase in the number of graded quiz question submitters in the Complex group compared to the Control group, conforming with our initial hypothesis (**H5.2**) in Section 3.1.5, that the Complex widget version will prove to be the most effective in improving learners' course engagement. Regarding forum engagement, the significantly higher forum participation from learners of the Intermediate group was an unexpected result suggesting that the mere fact of being exposed to real-time feedback on learners' behaviour might lead to changes in a learner's overall behaviour and not only in the areas they received feedback on. For example, learners' might pay more frequent visits to the forum while trying to obtain a higher grade and complete more graded quiz assignments. This phenomenon can be explained considering that changes to observable behaviour of learners cannot be made without having an effect on other aspects of learners' behaviour. In general, our results indicate that the development of learners' engagement with the course content is an extensive and lengthy process that requires longitudinal studies in order to come to clear conclusions. For that reason, longitudinal studies which follow learners throughout the entire duration of a MOOC or even longer periods of time covering several MOOC learners are required.

5.4.2. RQ2.2: Learners' self-regulation

To explore whether the *Real-Time Learning Tracker* had any effect on learners' self-regulating behaviour and which version affected learners' self-regulating behaviour the most **(RQ2.2)**, we ran Kruskal-Wallis H tests on the metrics that describe the *use of time* aspect of self-regulated learning. These metrics are the *total time in the course in minutes, the time spent watching videos in minutes* and *the ratio video time vs total-time in the course (%).*

We found significant differences in *time on the course* and *ratio video-time/total-time* which are presented

Table 5.13: The mean and median of the metric total time on the platform (m) along with the results of the Kruskal-Wallis test (α = .050). Significant differences are marked in bold.

Total time on the course (m)			
Comparison	*Mean*	*Median*	p-*value*
Control Simple	2781 1994	167 245	0.2
Control Intermediate	2781 15577	167 197	0.5
Control Complex	2781 5380	167 484	**0.000007**
Simple Intermediate	1994 15577	245 197	0.4
Simple Complex	1994 5380	245 484	**0.008**
Intermediate Complex	15577 5380	197 484	**0.00008**

Table 5.14: The mean and median of the metric ratio video-time / total-time (%) along with the results of the Kruskal-Wallis test (α = .050). Significant differences are marked in bold.

Ratio video time / total time (%)			
Comparison	*Mean*	*Median*	p-*value*
Control Simple	14 27	8 12	**0.004**
Control Intermediate	14 32	8 16	**0.000001**
Control Complex	14 24	8 11	**0.03**
Simple Intermediate	27 32	12 16	0.1
Simple Complex	27 24	12 11	0.4
Intermediate Complex	32 24	16 11	**0.02**

in Tables 5.13 and 5.14, respectively. Complex group differs significantly with the other groups in terms of learners' total time on the course, indicating that the learners of the Complex group spent significantly more time active on the course, taking into consideration the mean/median values of each group. Moreover, all test groups differ significantly with the control group in terms of the ratio of time that the learners watched videos versus their total time on the course. Considering the mean and the median values of Table 5.14, we observe that learners' ratios that have access to the *Real-Time Learning Tracker* are significantly higher compared to the control group. To our surprise, the Intermediate group owns the highest ratio with significance difference compared to the Complex group, although this specific metric is not displayed on that widget version. Figure 5.5 visualizes the ratio of video-time/total-time of the active learners per group. By looking at the plot, we can see that in the ratios' interval 0-5% the control group owns a high density score compared to the other groups, whereas in the highest ratios' interval 40-100% all test groups own higher density scores than the control group.

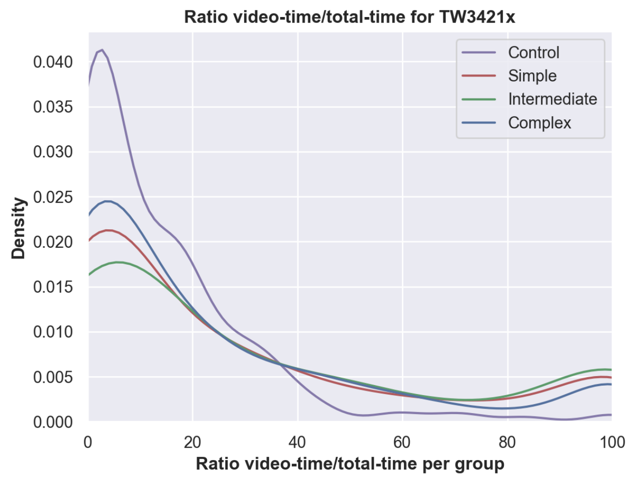

Figure 5.5: Kernel Density Estimation (Gaussian kernel) plots visualizing the ratio of video time versus the total time on the platform of the learners in *TW3421x*.

Overall, the results of this analysis indicate that the learners that have access to the *Real-Time Learning Tracker* spend more time active on the platform and are better able to self-regulate their behaviour, conforming with our initial hypothesis (**H1.3**), as presented in Section 3.1.5. The Complex and the Intermediate group were found to be the most effective groups in terms of learners' self-regulatory behaviour, fact that comes in line partially with our initial intuitions (**H5.3**, **H6**) that the most detailed interfaces will prove to be the most effective on learners' self-regulation. Nevertheless, the superiority of the Intermediate group in terms of learners' ratio of time watching videos, was once more an unexpected result, since learners in that group did not receive feedback on that metric. This result comes in line with our speculation as stated in the previous section, that the *Real-Time Learning Tracker* might have impact on several aspects of learners' behaviour, even though the widget does not provide them with direct feedback on these specific metrics. This hypothesis conforms with the theory of Wiebe et al. [182], recommending that MOOC data analysis should adopt a person-centered approach that recognizes people as "integrated wholes" by considering how many variables interact within a person. An approach like that assumes that variables used for modeling learners are interlinked and variations in one leads to changes in others.

5.5. RQ3: Who did it Benefit?

In this part of the analysis, we want to evaluate heterogeneous treatment effects, that is, we explore how the *Real-Time Learning Tracker* affects different groups of learners **(RQ3)** according to their prior education level. Hence, we next examined learner achievement in the context of learners' prior education levels to investigate whether the *Real-Time Learning Tracker* affected these groups differently. We define high prior education learners as those with a Bachelors, Masters, or PhD degree, and low prior education learners as those with any degree below Bachelors. We gather learners' prior education levels from their edX user profile; learners who do not report their education level are ignored in this analysis. This narrowed the number of active learners that were involved in the analysis from 1483 to 893 (High:749, Low:144).

We firstly investigated the graduation ratios of both high and low educated learners per group. Table 5.15 summarizes the results of this analysis regarding high educated learners. The graduation ratios of high educated learners are higher in all test groups in comparison with the control group. We also found significant differences in graduation ratios between the Complex group with both the Control and the Intermediate group, indicating that the access to the Complex version of the *Real-Time Learning Tracker* leads to higher learning performance in learners with high prior education. On the other hand, this is not the case for learners with low prior education. The total number of low educated graduates until that time in the MOOC is only three, with no graduates occurring from the Control group. Therefore, we did not find significant differences between groups.

Table 5.15: Graduation ratios and absolute numbers of high educated learners in test groups compared to control group. Learners that obtained a final score above 50% are considered graduates. Significant differences are marked in bold.

Graduation ratios		
Prior education: High (749)		
Comparison	*Ratios*	*p-value*
Control Group	4% (7/182)	0.4
Simple Group	6% (11/182)	
Control Group	4% (7/182)	1
Intermediate Group	4% (7/195)	
Control Group	4% (7/182)	**0.05**
Complex Group	9% (18/190)	
Simple Group	6% (11/182)	0.3
Intermediate Group	4% (7/195)	
Simple Group	6% (11/182)	0.2
Complex Group	9% (18/190)	
Intermediate Group	4% (7/195)	**0.03**
Complex Group	9% (18/190)	

We further investigated the final grades of high educated learners per group and we did not detect any significant differences between groups. However, we found significant differences in high educated learners' ratios who obtained a final grade lying in the highest score interval 90-100% between the Control group with both the Simple and the Complex group, as presented in Table 5.16. Figure 5.6 illustrates the distribution of the final grades of the high educated graduates through kernel density estimation (KDE) plots. In order to better visualize the grade distribution, the plot has been cropped. The differences in density between the test and control groups are more observable in the final score interval 90-100%. In this interval, all test groups own higher density scores regarding the final grades compared to the control group, highlighting the significantly higher density score of the Complex and the Simple group compared to the Control group. These results reveal a trend that high educated learners of the Complex group not only graduate more than learners of the Control group but also pursue higher grades.

Table 5.16: Percentages of high educated learners who obtained a final grade in the score interval 90-100% in the test groups compared to the control group. Significant differences are marked in bold.

Active learners' ratios with grade > 90		
Prior Education : High (749)		
Comparison	*Ratios*	*p-value*
Control Group Simple Group	0.5% (1/182) 4.4% (8/182)	**0.04**
Control Group Intermediate Group	0.5% (1/182) 2.1% (4/195)	0.3
Control Group Complex Group	0.5% (1/182) 4.2% (8/190)	**0.05**
Simple Group Intermediate Group	4.4% (8/182) 2.1% (4/195)	0.3
Simple Group Complex Group	4.4% (8/182) 4.2% (8/190)	1
Intermediate Group Complex Group	2.1% (4/195) 4.2% (8/190)	0.3

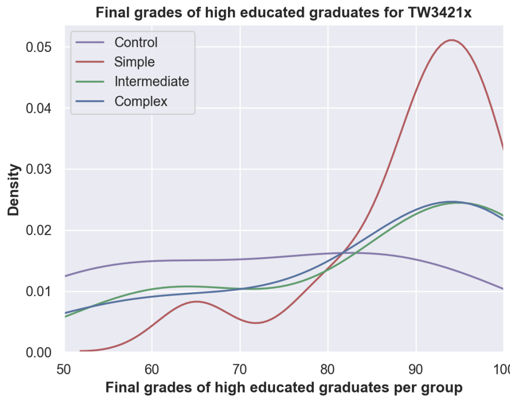

Figure 5.6: Kernel Density Estimation (Gaussian kernel) plot visualizing the distribution of final course grades of the high educated graduates among the test and control groups. The plot has been cropped to better visualize the data distribution.

This finding comes in line with Davis et al.'s [57] findings, as well as with our initial expectations (**H7**) (as presented in Section 3.1.5) and suggests two possibilities: (i) highly educated learners are better able to synthesize the information offered by the *Real-Time Learning Tracker* and translate it into positive behavior as they are already experienced learners (with at least some SRL skills) or/and (ii) lower educated learners are not concerned with obtaining a certificate, but rather focus on knowledge acquisition. Finally, while our finding that the benefits of the *Real-Time Learning Tracker* intervention are limited to learners who are already highly educated is counter to the intention and promise of MOOCs to reach the uneducated and lift people out of poverty, it exposes and highlights a new challenge for MOOC researchers and designers: designing targeted interventions that benefit learners who are not already highly educated.

6

Discussions and Conclusions

The primary goal of this research was to investigate the effect of three different versions of a real-time learner dashboard, the *Real-Time Learning Tracker* , on learners with varying levels of prior education with respect to their performance, course engagement and self-regulating behaviour. Therefore, we integrated our *Real-Time Learning Tracker* in a DelftX MOOC on the edX platform. The study followed a randomized controlled experimental design based on which the online learners were randomly assigned to one of four conditions (A/B testing) based on their edX user ID number. Thus, three quarters of the learners had access to one of the three versions of the widget and one quarter had no access to the widget. In this chapter, we reflect on the results and discuss our findings. Furthermore, we describe the limitations of our study and we underline future research directions based on our findings.

6.1. Discussions

First and foremost, we found that learners in all test groups interacted with the *Real-Time Learning Tracker* , indicating that no widget version was ignored by the learners. However, not all versions managed to maintain learners' engagement throughout the course. We detected significant differences in learners' engagement with the *Real-Time Learning Tracker* between the Simple group with both the Complex and the Intermediate groups, indicating that when learners are provided with more complex and detailed feedback on their learning behaviour devote more of their time examining and interacting with it. On the contrary, the Simple version of the *Real-Time Learning Tracker* was found to be the less engaging one for the learners, supporting our initial intuition that a less complex interface with limited amount of information presented on it, led also to limited amount of available interactions for learners. Moreover, the results of this analysis showed that the prior education of the learners did not affect their engagement levels with the *Real-Time Learning Tracker* , since both high and low educated learners interacted in a significant degree with both the Complex and Intermediate widget versions.

Regarding learners' performance, we detected significant differences in the graduation percentages between the learners with access to the Complex version of the *Real-Time Learning Tracker* and learners with no widget available. The higher graduation percentage in the Complex group indicates that significantly more learners with access to the Complex version of the *Real-Time Learning Tracker* passed the graduation threshold until that time in the MOOC. Investigating whether learners who completed the course, pursued also higher grades, we found that the percentage of learners within the higher grade range above the graduation threshold (90-100%) was significantly higher in learners belonging to the Complex group. This indicates a trend that learners with access to the *Real-Time Learning Tracker* who graduate the MOOC also pursue higher grades. On the other hand, the percentages of active learners at the end of our experiment were significantly higher in all test groups indicating a future potential of more graduates occurring from groups of learners that have access to the *Real-Time Learning Tracker* .

Investigating further the reasons behind the increased learners' performance and active learners' ratios in the test groups, data that describes learners' engagement showed that significantly more learners in the test groups attempted at least one graded quiz question and participated in the forum. Moreover, learners that were exposed to the widget attempted more quiz questions (including graded & non graded quizzes) than their counterparts, however without significant differences between groups. In addition, a closer inspection of metrics related to learners' use of time revealed that the *Real-Time Learning Tracker* had significant effect on the self-regulating behaviour of learners. This leads us to the assumption that learners' improvement in the above mentioned metrics can be associated with a general increase in self-regulated learning skills. The aforementioned observations suggest that there is a higher success ratio among learners who have access to our widget because the *Real-Time Learning Tracker* both increases the amount of learners who engage with graded material, and assists learners in better self-regulate their learning and thus performing better and obtaining higher grades. However, the need for performing the experiment for longer period of time, ideally for the whole duration of the MOOC, is imperative in order to be able to utilize more data and come to more clear conclusions in terms of learners' performance.

Our findings also indicate that the benefits of the *Real-Time Learning Tracker* were limited to learners who are already highly educated which comes in contrast with the intention and promise of MOOCs to reach the uneducated and lift people out of poverty, exposing and highlighting a new challenge for MOOC researchers and designers: designing targeted interventions that benefit learners who are not already highly educated. Taking into consideration that both types of learners (high/low educated) interacted significantly with both the Complex and the Intermediate version of the *Real-Time Learning Tracker* , we believe that the main reason why the *Real-Time Learning Tracker* benefited only the first ones, is that high educated learners are better able to synthesize the information presented on the *Real-Time Learning Tracker* and translate it into positive behaviour as they are already experienced learners (with at least some SRL skills).

In addition, our results showed that learners benefited the most by the Complex version of the *Real-Time Learning Tracker* with significant difference compared to its Simple version. These results come also in line with our learners' widget interaction findings, since the Complex version was the most engaging one for the learners. We believe that learners are better able to analyze and translate the information presented to them into positive behaviour when they have clear indication of the specific actions in which they should invest in order to increase their performance-engagement. On the other hand, we speculate that learners' SRL aspect deteriorates when a less complex version of feedback is presented to them, like in the Simple version's case.

Finally, the analysis of learners' behaviour with respect to all metrics used in the experiments revealed significant differences between the test and control groups in some metrics even though they were not displayed on all widget versions. For example, learners with access to the Intermediate version of the *Real-Time Learning Tracker* , showed a higher engagement on the forum than the learners with no widget access, without any of the tow groups pf learners having access to information relative to forum activity. In the same way, learners with access to the Intermediate version spent significantly more time watching videos while on the course pages than learners with access to the Complex version without receiving feedback on metrics related to video time. These result indicate that although learners do not get direct feedback on specific behavioural aspects through the widget the *Real-Time Learning Tracker* , however several aspects of learners' behaviour might be affected. Therefore, in line with Davis et al.'s [57] and Jivet's [82] results, we argue that 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, since changes to observable learner behaviour cannot be made without affecting other aspects of learners' behaviour.

6.2. Limitations

We acknowledge some limitations in our study that affect the reliability of the results we presented.

Experimental setup The main issue in our study was the limited duration of our experiment (10 weeks), regarding the total duration of the MOOC under study which is self-paced with one-year duration. A secondary issue is the lack of executing the experiment in different MOOCs on the edX platform that differ in both pacing and the way that release the course material. This could have affected the autonomy of the learners, since in MOOCs that a more instructor-paced approach is followed, with new course content releasing on a weekly basis, a minimal level of regulated learning is imposed by the course staff, similar to the one students are imposed by their classroom teachers [106]. In that way, the self-regulating freedom of learners is limited and therefore the potential impact of the *Real-Time Learning Tracker* . In contrast, self-regulating behaviour might be more visible in MOOCs that release the course material at once, like in our MOOC, or in 3 or more blocks. Therefore, learners have a lot more freedom in organizing their study time and more opportunities for the development of self-regulated learning skills.

6.3. Future work

There is still much room for improvements in our study to explore in future research.

- **Evaluation of the widget across different MOOCS.** In future work, we plan to expand our experiments across a number of MOOCs throughout their whole duration, that differ in both pacing and the way they release new course material, since our *Real-Time Learning Tracker* can be integrated in any type of MOOC hosted on the edX platform. Moreover, similar to Jivet [82], we believe that the exposure of cMOOC learners to feedback on their learning behaviour could benefit them. Since in cMOOCs the focus is on knowledge creation rather than on knowledge duplication like in xMOOCs, skills like SRL, learner maturity and autonomy are mandatory [23]. For that reason, we are confident that our results also hold if the *Real-Time Learning Tracker* is to be deployed in cMOOCs, even if we conducted our experiments solely on xMOOC. We backed our hypothesis on past study which proved that learning and its self-regulation have a greater potential to be fostered in cMOOCs rather than xMOOC due to the demand of a high degree of interactivity with learning objects and peers [22].

- **Design targeted interventions also for low educated learners.** Our findings indicated that the *Real-Time Learning Tracker* benefits mostly already high-educated learners, although it is counter to the intention and promise of MOOCs to reach the uneducated and lift people out of poverty. However, this exposes and highlights a new challenge for MOOC researchers and designers: designing targeted interventions that benefit learners who are not already highly educated. Hence, we suggest the conduction of extensive evaluations of different feedback visualizations targeted to low educated learners in order to identify which visualization better expresses their needs and knowledge skills. We also believe that if there is knowledge on how different demographic groups could benefit from using such a widget, we could provide learner with a further personalization of feedback. The impact of culture and learner demographics in MOOCs on use of course resources [159], completion rates [50] or engagement [97] have been already investigated by several works. In line with these findings as well as Davis et al.'s [57] recommendations, we argue that the metrics displayed on the widget, the framing of the feedback, and the visualization chosen can be adapted to the learners' skill, knowledge and cultural context (high-low cultural tightness).

- **Expand from fixed role model to different learners' personalities.** In future work, we believe that we need to move from a fixed role model in our *Real-Time Learning Tracker* to a set of different personas (e.g., high achievers vs. just-doing-enough) that learners can be identified with. In this way, we will be able to provide learners with personalized feedback according to their individual needs and learning goals and the selection of the appropriate metrics to be displayed on the widget will be more accurate and correlated to their different personalities.

- **Explore learners' intentions, goals and definitions of success.** Davis et al.'s [57] definition of a successful learner guided the design, implementation and evaluation of the *Real-Time Learning Tracker* . Most of the learners that enrol in MOOCs have quite different goals than those expected by the course developers [183]. These could be learning one or more skills and not course completion. However, we did not target these types of learners with our widget. Therefore, the investigation of how different definitions of success affect the outcomes and behaviour of learners could be a potential future research direction.

- **Encourage individual goal setting.** In line with Jivet's [82] work, we believe that in future widget iterations individual goal setting should be encouraged, as it is a central component of SRL [190]. We argue that self-regulation skills of learners would be developed even more if in the future the widget allowed them to define their own success and the related behavioural indicators that would support them in the achievement of their goals. In line with the solution proposed by Durall and Gros [62], offering learners the opportunity to choose the data they want to monitor from a flexible and extensible set of indicators would assist learners in further develop their meta-cognitive skills further and encourage them to play a more active role in LA.

6.4. Conclusion

MOOCs have afforded millions of learners worldwide with the opportunity to learn with little or no cost becoming one of the most prominent trends in higher education in recent years. Nevertheless, the very low course completion rates highlight the need for additional support in MOOCs. After reviewing the existing literature and considering the results of Davis et al.'s [57] and Jivet's [82] work, we tried to eliminate the existing gaps in tools like *Learning Tracker* that support MOOC learners through their learning process on the MOOC platforms. The main challenges that we faced through the design and implementation of our widget were (i) the provision of learners with easily accessible and meaningful feedback on their learning behaviour, (ii) the provision and update of the feedback information in real-time and (iii) the devise of easily understandable ways of visualizing it.

To this end, we designed and evaluated three versions of an interactive widget that was integrated into a learner dashboard for MOOC learners. The aim of our *Real-Time Learning Tracker* is to enhance learners' self-regulation skills by providing learners the opportunity to reflect on their learning behaviour in real-time. The *Real-Time Learning Tracker* was designed as an interactive learner dashboard and it relies on learning analytics to analyse and report in real-time learners' behaviour which is extracted from trace logs. We tested the effectiveness of our widget by deploying its three versions in a real MOOC offered by TU Delft on the edX platform. The evaluation lasted 10 weeks, reaching nearly 2000 learners. The evaluation investigated the impact of the *Real-Time Learning Tracker* on the learning process focusing on aspects like change in learners' performance, behaviour, engagement generated by the widget, effects of social comparison and the level of interaction with the widget.

Our analysis indicated that learners with access to the *Real-Time Learning Tracker* are more likely to complete the course because (i) more learners with access to the *Real-Time Learning Tracker* submit graded quiz questions and (ii) they are better able to self-regulate their learning spending more time active on the course platform. Even if our findings reveal that the *Real-Time Learning Tracker* has a positive impact on learners' self-regulation, there is limited proof that other aspects of learners' engagement were affected. However, our analysis on learners' behaviour revealed that the exposure of learners to feedback on their behaviour in real-time might drive learners alter their overall behaviour and not only aspects of their behaviour on which they received feedback. This confirms the beneficial impact of feedback and awareness of one's behaviour on learning performance [106]. The Complex version of the *Real-Time Learning Tracker* was found to be the most engaging version for learners, which also had the greatest impact on their performance and learning behaviour. Finally, our results indicate that the *Real-Time Learning Tracker* improved significantly the performance of learners with high prior education, conforming with Davis et al.'s [57] findings.

We acknowledge several research directions for future work on learner dashboards such as discovering meaningful information that should be visualized to the learners. In addition, it is essential to find out how different goals of learners can be promoted via the metrics displayed on the dashboards in order to provide learners with personalized feedback adapted to their individual needs. Secondly, adapting future interventions to assist learners based on their different personalities and learning goals, rather than insisting on a fixed role model, would lead to improving both the visualization and the selection of the data that is reported. Moreover, we recommend to expand the evaluation of future widget iterations in different live MOOCs throughout their whole duration. MOOC platforms provide researchers with integrated methods to collect a large amount of data describing the behaviour of learners to exploit it in their extensive evaluations. We believe that these evaluations should focus more on assessing dashboards' efficiency on learners' performance and behaviour and not so much on users' satisfaction and usability like most of the previous researches. Finally, we suggest future research on MOOC widgets should focus more on real-time analytics, highlighting the powerful effect of real-time feedback on learners' performance and achievement.

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