SRLx: A Personalized Learner Interface for MOOCs

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Abstract. Past research in large-scale learning environments has found one of the most inhibiting factors to learners' success to be their inability to effectively self-regulate their learning efforts. In traditional small-scale learning environments, personalized feedback (on progress, content, behavior, etc.) has been found to be one of the most effective solutions to this issue, but it has not yet been evaluated at scale. In this paper we present the `Personalized SRL Support System` (`SRLx`), an interactive and scalable application that we designed and open-sourced to improve learners' self-regulated learning (SRL) behavior. `SRLx` enables learners to plan their learning on a weekly basis and view real-time feedback on the realization of those plans in the Massive Open Online Course (MOOC) platform edX. We deployed `SRLx` in a renewable energies MOOC to more than eight thousand learners and performed an exploratory analysis on our learners' SRL behavior.

Keywords: Learner Modeling, Self-Regulated Learning, Personalized Learning

1 Introduction

Large-scale learning environments open up world-class educational resources to the masses. With this unprecedented scale and reach, however, come new challenges in enabling learners of diverse backgrounds to excel given the foreign topics and unfamiliar context of the massive online classroom. Low course completion rates—dropout rates of 95% are not uncommon [16]—highlight the need for additional support in MOOCs. Past research in this space, e.g. [10,13,14,25] has explored the problems learners face when trying to succeed in these self-directed learning environments. Learners are often unable to find the time to keep up with a course, an issue related to insufficient self-regulatory abilities [10,25]. *Self-regulated learning* (SRL) is the ability to plan, monitor, and actively control one's learning process. The discipline to plan and follow a self-imposed studying regime is a skill that is learned over time and associated with a higher likelihood

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of achieving self-set course goals in MOOCs [11,18]. Learners who were exposed to such training during their studies tend to be more successful in MOOCs than learners without a tertiary education background. The latter though is a target population that is vital to keep the original vision of MOOCs alive: making higher education accessible to those that do not enter the traditional tertiary education system. Learners need tools that enable them to learn *how* to learn.

Today's MOOC platforms (such as Coursera and edX) are not designed to support learners in SRL [20]. It is not possible to explicitly plan or monitor (with the help of feedback) their learning activities. Learners are exposed to very few feedback moments to support their SRL processes.

[24] found that a single planning prompt at the start of a MOOC positively influenced learning outcomes. We have taken this concept to the next level and designed and developed `Personalized SRL Support System`[1] (`SRLx`), an interactive application for the edX platform that allows learners to explicitly express their motivation, *plan* their learning, *monitor* their progress towards their set goals at any point in time, and *reflect* on them. `SRLx`'s design was based on educational theories and findings in the SRL literature.

We deployed `SRLx` in a MOOC on renewable energies offered by a large European university and empirically evaluated the following research questions:

RQ1 What effect does explicit planning, monitoring and reflection have on MOOC learners' academic achievement, course engagement, and self-regulated learning?

RQ2 To what extent do MOOC learners adopt and take advantage of a personalized SRL support tool?

RQ3 Does `SRLx` support MOOC learners in promoting effective self-regulated learning behavior?

Along with the contribution of an open-sourced system architecture that provides SRL support at scale, we present the following key findings from our analysis of learners' SRL behaviors:

- As the course progresses, learners are able to plan their time commitment more effectively.
- Learners are predominantly intrinsically motivated.
- Learners are most conservative with the way they plan to commit time to the course compared to video and quiz activity planning.

2 Related Work

Zimmerman's [27] model of self-regulated learning comprises three cyclical phases: forethought, performance, and self-reflection. A learner first formulates a plan for their learning activities, they then carry out and act according to their plan, and finally they look back at their behavior and examine their strengths and

[1] Source code: [witheld for blind review].

areas for improvement. In this section we first examine self-regulated learning research in the classroom and then delve into SRL studies conducted within MOOCs.

2.1 Self-regulated learning in the classroom

In the traditional classroom, research on SRL is often focused on goal setting, as planning and reflection tend to be provided by the teacher or instructor.

Goal setting has been shown to be an important factor across all levels of education. Past research has investigated to what extent aspects such as who/what/when/why (who sets the goal/when are those goals set/what goals are set/why are those set) influence the effectiveness of goal setting. While these studies have been conducted across a range of education levels, they have all taken place in the traditional classroom setting.

[23] showed that engaging and teaching undergraduate students about goal setting at the beginning of their studies has a positive impact across a prolonged period of time—after one year, a 98% reduction in the gender achievement gap and a 38% reduction in the ethnicity achievement gap was observed (compared to the previous year's cohort of students).

At the secondary education level, [26] found that social-studies class students perform better (as measured by their final grade) when they set their own goals and benchmarks, than when having those imposed on them by teachers. Regularly reviewing and reflecting upon one's study goals and behaviors was found by [22] to be significantly more effective (in terms of grades and study behavior) than just setting goals in a user study with primary and middle school students. A similar result was found in [19] among 27 undergraduate students who were assigned to one of three experimental conditions while preparing for an exam: (i) continuous self-monitoring, (ii) intermittent self-monitoring, and (iii) receiving instructor feedback. In line with [22], students who performed self-monitoring exhibited higher levels of engagement and achievement than students who did not.

2.2 Self-regulated learning in MOOCs

Due to the massive nature of MOOC platforms (supporting millions of learners), a large part of the platform development effort has to be spent on continued scalability. This leaves little time and attention for advances in platforms' instructional designs. Prior research in the MOOC setting has so far focused on learner surveys (to elicit their SRL needs), pre-course SRL interventions, MOOC forum interventions, and the notion of learner feedback.

[21] and [7] surveyed MOOC learners about their experiences taking MOOCs. In [21] proper time management was found to be a major hindrance for many MOOC learners, and in [7] the concept of self-regulated learning (SRL) was investigated. The authors found varying SRL capabilities depending on learners' professional backgrounds: higher-educated learners are better able to regulate their learning (including time management) than lower-educated learners.

Providing learners with visualizations of their progress enables them to reflect upon their learning, and an emerging body of research has begun to empirically evaluate the efficacy of such feedback [1,2,5,8]. Over time, this reflection should improve learners' use of SRL strategies [3,6]. One interesting finding in [17] pertains to the timeliness of feedback and its impact on MOOC learners' final grades: feedback (in this case on in-progress assignments) received within 24 hours after submission improves learning outcomes; if the feedback is delayed beyond this point, learners do not benefit from it. According to [5], enabling learners to reflect weekly on their learning behavior in comparison to that of their successful peers led to a significant increase in passing rates. Learners with lower levels of prior education (defined as learners without a Bachelor degree or higher) did not benefit from the intervention.

To conclude, goal setting and feedback are important techniques to improve learning outcomes in the traditional classroom. In the MOOC setting, SRL interventions have so far either been restricted to pre-course interventions or feedback.

3 System Overview

The three phases of Zimmerman's model of self-regulated learning [27] (forethought, performance, and self-reflection) are integral to the design of `SRLx`, as we designed each interface within the system accordingly. We here describe the back- and front-end architecture, the real-time event tracking functionality, and the design rationale for the learner interface and experience.

Front-end The front-end of `SRLx` implements two main functionalities. It (i) tracks and persists learners' activities to the back-end such as quiz question submissions and video watch events (cf. the Measures section for an exhaustive list) and (ii) displays the interfaces for planning & feedback and persists the associated data.

To integrate the front-end with the course user interface in the edX platform, we took advantage of the RAW HTML input affordance. This feature of the edX platform allows course developers and instructors to embed and execute custom HTML, CSS, and JavaScript code in edX pages, thus allowing the creation of personalized interfaces and logic.

We created two different types of front-end components: *sensor* and *SRL interface*. A sensor component tracks and logs user progress through the course and has no visible interface. An SRL interface displays the interface of one of the four possible `SRLx` interactions: (1) **Motivation Expression**, (2) **Motivation Feedback**, (3) **Plan Formulation**, and (4) **Plan Feedback**. Both types of components (interfaces and the sensor code) exchange information in real-time with the back-end via HTTPS AJAX requests.

Capturing edX events As `SRLx` provides real-time feedback based on learners' actions on the edX platform, we had to track events such as quiz submissions and video watching events in real-time. The real-time constraint meant that we could not make use of edX's default log data setup which distributes a MOOC's daily logs in 24 hour intervals. We had to track these events ourselves. This proved to be challenging, as documentation on edX's logging infrastructure is sparse at best.

edX course components, such as videos or quizzes, are implemented via XBlocks, a component architecture based on Python, HTML, JavaScript and CSS. This allows authors to create standalone hierarchical components that may include other XBlocks. To capture user interactions, Xblocks emit and subscribe to events using an event tracking library[2]. We enable real-time event tracking which covers all necessary events used for `SRLx` by using edX's `Logger` object to subscribe to emitted events using the `listen(eventType, element, callback)` method: All Xblock fragments make use of the `Logger` object to emit events which are subsequently sent to the edX back-end via an `XMLHttpRequest`. We listen to all events of interest and forward those to our back-end.

Back-end To store and retrieve learner data in real-time, we implemented an HTTPS server in Node.js and persisted the tracked events in a MongoDB database. The server uses a RESTful API to store and retrieve learner events. It supports a JSON format for both requests and responses. Along with logging edX's learner behavior data, the `SRLx` server also logged all learner interactions with the `SRLx` interface. These processes work alongside edX's own data logging and retrieval mechanisms.

3.1 Learner Interface/Experience

As shown in Figure 1, `SRLx` has four learner-facing interfaces covering all three phases of Zimmerman's [27] SRL model: motivation expression (forethought), motivation feedback (self-reflection), plan formulation (forethought), and plan feedback (performance and self-reflection).

Motivation Expression We refer to this interface as *motivation expression* as it allows us to directly gain an understanding of learners' motivations and overall forethought for their attitude towards the course. Largely modeled after the study planning system evaluated in [23], it is shown on the top-left of Figure 1 and provides learners an open text box in which they are prompted to write about their motivation and what brought them to the course in the first place. The key question asked to learners here is *What drives you?* followed by other prompting questions to help the learner express themselves: *What brought you here?* and *What do you hope to gain from this course?* Once a learner has submitted their motivation it is persisted to our database. Learners are free to view and change their response any time.

[2] `https://github.com/edx/event-tracking`

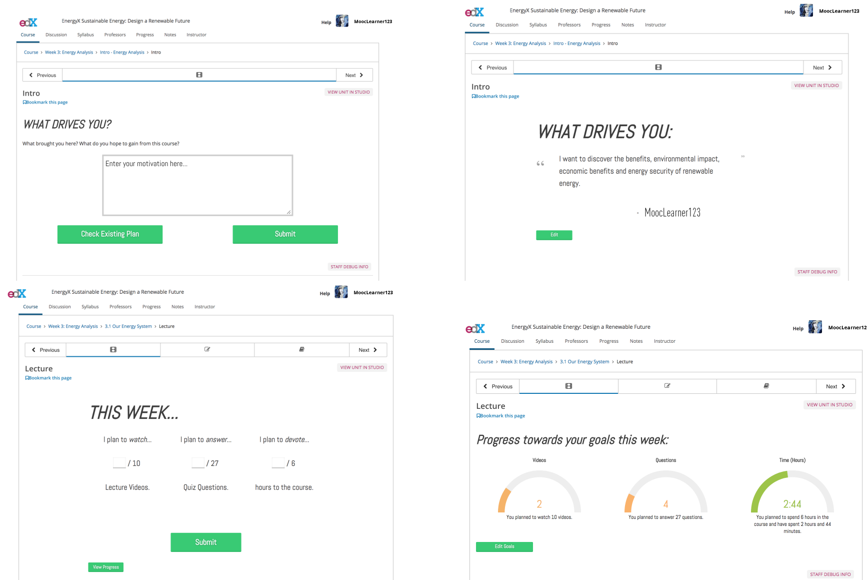

Fig. 1: The four SRLx interfaces as they appear to learners in the edX platform: motivation expression (top-left), motivation feedback (top-right), plan formulation (bottom-left), and plan feedback (bottom-right). Best viewed in color.

Motivation Expression Feedback In order to provide feedback and encourage a habit of self-reflection, we regularly make learners aware of their latest motivation response by displaying it back to them (top-right of Figure 1) throughout each course week/unit. The response is shown as a quotation by the learner underneath the *What drives you:* text. To emphasize the feel of personalization, the learner's edX username is added beneath the quote.

Plan Formulation The plan formulation view (Figure 1 bottom-left) promotes forethought in prompting learners to formulate and state their plan for the coming course week in terms of engagement with course resources. Specifically, learners are prompted to enter the number of videos they intend to watch, quiz questions they intend to answer, and hours they intend to devote to the course this week. To aid learners in their planning, we provide the total number of videos and quizzes of the week (numbers we automatically extracted from the edX course pages) as well as the recommended time to spend in the course that week (as estimated by the course instructors).

Plan Feedback To promote awareness of the learner's performance and encourage self-reflection, the planning feedback interface (Figure 1 bottom-right) consists of three gauges showing learners how well they have progressed towards the goals *they set for themselves*, removing all instructor influence.

We designed the plan feedback as a data visualization dashboard that allows learners to easily draw their own insights about their progress. Previous research in data visualization for MOOC learners found that more abstract feedback (such as the "timeliness" of the quiz submissions) only benefited learners with a higher education background [5]. Since highly educated learners already have SRL abilities, we aimed to engage those learners that lack self-regulation skills and designed the interface to be clear and straight-forward to interpret.

4 Evaluation

4.1 Participants

We deployed `SRLx` in an edX MOOC on renewable energies offered by a large European university. The course consists of 75 individual lecture videos and 295 graded quiz questions. A total of 8,057 learners enrolled in the course. The course ran on the edX.org platform and started on August 29, 2017. It concluded on November 8, 2017. We made `SRLx` available to all learners but did not provide any additional incentive for using it.

Before the course, the learners were asked to self-report their basic demographic information. 5,349 learners at least partially complied. Of these learners, 25.3% are female; the learners' median age is 26. We also collected information about their prior education level, as this has shown to have a significant impact on learning outcomes and engagement with MOOCs [5]. As is common in MOOCs, we observe a great variety in this respect with learners running the gamut from high school to PhD levels of prior education: 1% had no prior formal education, 20% held at least a high school diploma, 5% an Associate's degree, 46% a Bachelor's degree, 26% a Master's degree, and 3% a PhD. We consider learners' prior education level to be "high" when they have earned at least a Bachelor's degree, and "low"when they have not.

Given that many learners who enrolled in the course never entered the platform and logged a session (a common occurrence in MOOCs), we narrow down the sample for analysis accordingly. Of the 8,057 learners enrolled, 2,961 entered the course at least once and are therefore considered as active learners in our analyses.

4.2 Measures

To evaluate the role that `SRLx` plays in learners' achievement and course engagement, we measure a number of in-course learning behaviors that are commonly used in MOOC studies as well as a number of novel measures enabled by `SRLx` which offer different views of learners' behavior:

- Average Quiz Score $\in [0, 1]$ (proportion of attempted quiz questions answered correctly);
- Course activities, number of:
  - Video interactions (play, pause, fast-forward, rewind, scrub);

    - Quiz submissions (submissions, correctness);
    - Discussion forum posts;
    - Duration of time in course;
  - SRLx interactions:
    - Plan formulation (number of videos & quizzes and hours planned to spend in the course that week);
    - Motivation expression (submission text);
    - Editing (changing an established motivation or plan).

5 Results

In this section we present the results of our SRLx evaluation in the context of a live MOOC segmented into the following analyses aggregating data from both the edX platform and SRLx: (i) course-level learning behaviors (ii) study plan formulation tendencies, (iii) plan achievement rates, and (iv) examining the various approaches learners took with the motivation expression interface.

5.1 General Behavior Analytics

In Table 1 we present summary statistics for overall course behavior among all active learners (characterized by having logged at least one session in the course platform). Table 2 shows the number of submissions made via SRLx.

Table 1: Overview of the average behavior of active learners. In rows 2 & 3 we partition the set of active learners into "comply" (learners who formulated at least one plan and submitted at least one motivation expression) and "non-comply" (the remainder) learners.

Subset	N	Quiz Score	Session Count	Interact.	SRLx Feedback Checks	Quiz Submits	Videos Watched
Active	2,961	0.41	32.57	152.72	3.63	43.11	8.33
Comply	303	0.72	66.48	348.93	7.31	91.56	16.31
Non-Comply	2,658	0.37	28.71	130.35	3.21	37.58	7.42

As shown in Table 1, of the 2,961 active learners in the course, 872 (32%) engaged with SRLx at least one time (answering **RQ2**)—here characterized by having formulated at least one plan or submitting at least one motivation expression. While this rate of minimal engagement is substantially higher than past studies [4], the true rate of compliance (submitting both a plan and motivation) is still very low, at 10%.

While the top row in Table 1 represents all active learners in the course, the bottom two rows show the impact of self-selection in highlighting the difference in behavior between learners who did and did not engage with SRLx. We cannot claim that this difference is caused by the use of SRLx (**RQ1**); rather it is at least partially a result of the self-selection of learners who would have been highly engaged and more successful in the course regardless.

However, this trend could also be partially explained by prior research on the *doer effect*, or the "...association between the number of online interactive practice activities students do and their learning outcomes" [15]. This theory states that engagement with interactive course components (such as SRLx, discussion fora, or quiz questions) has a stronger learning effect than passive activities such as reading or watching lecture videos. So while SRLx is unlikely to be the sole cause of the increase in activity between compliers and non-compliers, theory states that it likely contributed, at least in part, to the more positive learning outcomes (namely "Avg. Score") of those who engaged with it.

Table 2: Overall submissions of motivation expressions, plan formulations, and plan/expression changes. The bottom row indicates the number of unique learners.

	Motivation Expression	**Plan Formulation**	**Edited**
Overall	679	1,997	748
Unique	396	971	338

5.2 Plan Formulation

In this analysis we focus on the plans the learners made using SRLx (answering **RQ3**)—We explore the following questions: are the learners overly ambitious with their plan formulation? Are learners able to consistently stick to their plans? Do their planning tendencies/strategies change over time? Figure 2 shows an aggregate view of all plans submitted in the course (1,997 in total).

Figure 2 (left) shows the study planning behavior of all learners who formulated and submitted at least one plan in SRLx. This illustrates that the majority of plans set were for the maximum given the week's content (in terms of time commitment, quiz submissions, and videos watched). For example, if there were 10 lecture videos in a week, and a learner planned to watch 6 of them, that would be considered a 0.6 proportion of the maximum. We find the median proportion of all plans to be 1.0. At the same time in Figure 2 (left) we observe that the goals set pertaining to the proportion of time (from the recommended six hours per week) learners plan to commit to the course is lower than that of quiz submissions and videos. A Welch Two Sample t-test ($t(3,878) = 3.72$, $p < 0.001$) indicates a significant difference between time plans ($\bar{x} = 0.838$, $\sigma = 0.34$) and video plans ($\bar{x} = 0.88$, $\sigma = 0.29$). From this finding we therefore conclude that learners are more conservative with the way they plan their time commitment to the course than the way they plan to engage with course materials.

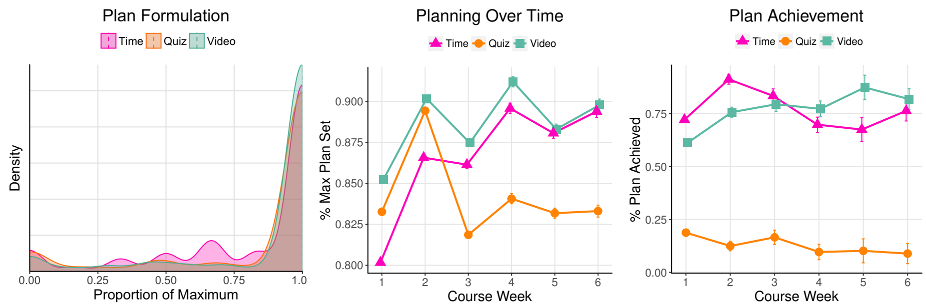

Fig. 2: Left: The proportion of learners' formulated plans set for the maximum possible value in the respective course week. Center: the proportion of the maximum plan set by learners of each activity type over the span of all course weeks. Right: plan achievement rates for each activity type by course week. Best viewed in color. Error bars show standard error.

To examine planning behavior at a more granular level, we present Figure 2 (center), which segments planning behavior by course week and illustrates change over time.

With Figure 2 (center) we are able to observe noteworthy trends particularly with time and video watching plans. Compared to the steady rate of ambition (proportion of maximum plan set) with quiz plans (overall mean of 84.7% of the maximum), learners exhibited a steady trend of increasing their ambition each week for time- and video-related plans—a 9 percentage point increase from Week 1 to Week 6 for time plans (mean of 80% to 89%) and a 5 percentage point increase for video plans (mean of 85% to 90%). While these two steady increases can be attributed to less-ambitious learners stopping out of the course, the lower rate for quiz-related plans still holds throughout the entire course.

5.3 Plan Achievement

Figure 2 (right) shows the rate with which learners achieve each aspect of their plans each course week. Whereas in the previous section we discussed how learners are conservative with their plan formulations as it pertains to time, we see in Figure 2 (right) that learners are strong at achieving their plans for time commitment and video lecture viewing with high consistency over time—an important insight given that poor time management has been identified by prior research [12,25,21,10] as one of the primary causes of attrition in MOOCs.

It is also worth noting that the consistency and success of learners' time planning achievement is not a product of less ambitious goals being set. Refer back to Figure 2 (center) to see that the opposite is actually true; learners become *more* ambitious with their time plans as the course progresses, and learners are still able to achieve their plans with high consistency by adjusting each week.

For the learners' video watching plan achievement, we observe a steady rate across all weeks with an overall mean of 63% completion. For learners' achievement of their quiz question-related plans, we observe substantially lower completion rates than those regarding time—falling from 19% in Week 1 to a mere 9% in Week 6.

We propose that these results on plan achievement are a product of the difficulty of each activity type. Though not trivial, spending time in the platform requires little more than a learner's presence. Slightly more demanding is the activity type of watching lecture videos; and most challenging of all three is answering quiz questions, which is not only dependent on the previous two activities but also requires the application of newly-acquired knowledge. In other words, the rate by which learners complete their plans is strongly related to the exigency of the respective activity type.

Prior Education Level As previous research on MOOC learners has identified achievement gaps among learners [9], we next conducted an exploratory analysis on plan completion per activity type as a function of a learner's prior education level (with "high" education learners having earned at least a Bachelors degree, accounting for 75% of learners in the course). We observe no significant difference in plan completion rates in any of the three activity types according to a Welch Two Sample t-test, thus indicating that learners are able to effectively use `SRLx` across a wide range of ability levels. This suggests that `SRLx` is equally usable and effective for learners of all prior education levels.

5.4 Motivation Expression

Among the 2,961 learners exposed to the `SRLx` interface, 396 submitted at least one motivation expression. These motivations ranged from learners working towards having better career opportunities to changing the world—the latter theme became markedly more prominent as the course progressed. The average word count is 23.9 (median 15, minimum 1, maximum 329). In Table 3 we randomly picked examples of *short* (at most ten words), *medium* length (up to 25 words) and *long* (26 words or more) submissions.

Table 3: Random sample of short, medium, and long submissions through the Motivation Expression interface.

S1	*Build up on sustainable energy knowledge*
S2	*I expect to get to know the future of energy*
M1	*I hope to learn more about sustainable ways of using and obtaining energy.*
M2	*I want a clean planet I want to be responsible for that*
L1	*As a junior architect I am interested in learning more about the relationship between energy use and building design and how intelligent design can have positive impacts on building energy use as well as occupant health and happiness.*

Replicating the methods in [24] on MOOC learner texts on course intentions, we evaluated the predictive value of the length of a learner's text submission on their (i) current grade, (ii) average quiz question score, and (iii) total time spent in the course platform and were not able to find a significant effect in any of the metrics.

The ten most frequent terms occurring among all motivations are (in desc. order): *energy*, *renewable*, *sustainable*, *knowledge*, *learn*, *future*, *course*, *hope*, *better* and *sources*. These terms speak to the motivation of many learners to use the knowledge to improve the world; interestingly, no job related term appears in this list (the term *career* occurs at rank 20), indicating that many of our learners have an intrinsic, rather than an extrinsic motivation. They are brought to the course and engage with the materials not out of need for career change or certification (as was commonly observed among MOOC learners in previous work [14]), but rather out of a desire to be able to spark positive change in the world. Given the topic of the course and its relevance to the issues facing society today, this certainly affects learner motivation in some sense, but this also demonstrates that MOOCs can be instrumental to shaping the next generation of emerging technologies in making the subject matter accessible to the masses.

6 Discussion

Based on the existing literature and theory on self-regulated learning, we designed, deployed, and evaluated a system called `SRLx` to encourage and support learners in adopting effective self-regulated learning habits in MOOCs. `SRLx` enables real-time adaptivity and personalization in the edX platform which, to this point, was not possible. MOOCs until now have required a one-size-fits all approach to learning even though they serve thousands of learners from highly heterogeneous backgrounds and skill sets. While the course in which we evaluated `SRLx` for the present study had over 8,000 learners enrolled, the potential of this technology is orders of magnitude larger—at the end of 2016, there were in excess of 10 million learners enrolled in edX courses[3]. The adaptive capabilities offered by the `SRLx` system and its infrastructure enable the delivery of personalized learning interfaces to the masses, and the more this tool is used, the more we can learn about targeted learning interventions—answering the foundational question of personalized instruction: what works for whom in which situations?

Despite the inconsistencies we observed based on previous related work, learner interactions with `SRLx` offer novel insights about the role of motivation expression and plan formulation for MOOC learners. For example, we find (i) that as the course progresses, learners are able to plan their time commitment more effectively, (ii) a strong trend of intrinsic motivation shared by learners with the motivation expression interface, and (iii) learners are most conservative with the way they plan to commit time to the course compared to video and quiz activity planning.

[3] http://blog.edx.org/year-review-edx-2016?track=blog

Given our findings on the progression of learner's planning strategies over time with `SRLx`, we are able to offer an explanation of the findings by Yeomans and Reich [24] who found that plans that were formulated about time were less likely to succeed: that intervention took place at the beginning of a course, where learners formulated time plans over the long-term—requiring the foresight of many weeks in the future; `SRLx`, on the other hand, allows learners to set a new plan at the beginning of each course week (short- to medium-term). Combined with our evidence that learner's become more effective at plan formulation over the span of the course, we conclude that time-specific plans are likely only to be ineffective when on a long-term scale; and when used on a short- to medium-term scale, they can be highly effective and attainable.

Future research should implement `SRLx` as a randomized controlled trial, or A/B test, in MOOCs to explore questions of causality—does `SRLx` directly cause learners to learn and engage more? Finally, `SRLx`, as presented here, is completely individualistic—learners only receive feedback on their own plan formulations and motivation expressions. By making `SRLx` social, or showing learners the planning behavior and performance of their peers as well as their own, this could present a promising way to leverage the scale of MOOCs and improve learner performance through increased social presence.

References

1. Bodily, R., Verbert, K.: Review of research on student-facing learning analytics dashboards and educational recommender systems. IEEE Transactions on Learning Technologies (2017)
2. Bodily, R., Verbert, K.: Trends and issues in student-facing learning analytics reporting systems research. In: LAK '17. pp. 309–318 (2017)
3. Bull, S., Kay, J.: Open learner models as drivers for metacognitive processes. In: International handbook of metacognition and learning technologies, pp. 349–365. Springer (2013)
4. Davis, D., Chen, G., Van der Zee, T., Hauff, C., Houben, G.J.: Retrieval practice and study planning in moocs: Exploring classroom-based self-regulated learning strategies at scale. In: ECTEL '16. pp. 57–71 (2016)
5. Davis, D., Jivet, I., Kizilcec, R.F., Chen, G., Hauff, C., Houben, G.J.: Follow the successful crowd: raising mooc completion rates through social comparison at scale. In: LAK '17. pp. 454–463 (2017)
6. Guerra, J., Hosseini, R., Somyurek, S., Brusilovsky, P.: An Intelligent Interface for Learning Content: Combining an Open Learner Model and Social Comparison to Support Self-Regulated Learning and Engagement. In: IUI '16. pp. 152–163 (2016)
7. Hood, N., Littlejohn, A., Milligan, C.: Context counts: How learners' Contexts Influence Learning in a MOOC. Computers & Education **91**, 83–91 (2015)
8. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness is not enough: pitfalls of learning analytics dashboards in the educational practice. In: ECTEL '17. pp. 82–96 (2017)
9. Kizilcec, R.F., Davis, G.M., Cohen, G.L.: Towards equal opportunities in moocs: Affirmation reduces gender & social-class achievement gaps in china. In: L@S '17. pp. 121–130 (2017)

10. Kizilcec, R.F., Halawa, S.: Attrition and achievement gaps in online learning. In: L@S '15. pp. 57–66 (2015)
11. Kizilcec, R.F., Pérez-Sanagustín, M., Maldonado, J.J.: Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. Computers & Education pp. 18–33 (2016)
12. Kizilcec, R.F., Pérez-Sanagustín, M., Maldonado, J.J.: Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. Computers & education **104**, 18–33 (2017)
13. Kizilcec, R.F., Piech, C., Schneider, E.: Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In: LAK '13. pp. 170–179. ACM (2013)
14. Kizilcec, R.F., Schneider, E.: Motivation as a lens to understand online learners: Toward data-driven design with the olei scale. ACM Transactions on Computer-Human Interaction (TOCHI) **22**(2), 6 (2015)
15. Koedinger, K.R., McLaughlin, E.A., Jia, J.Z., Bier, N.L.: Is the doer effect a causal relationship?: How can we tell and why it's important. In: LAK '16. pp. 388–397 (2016)
16. Koller, D., Ng, A., Do, C., Chen, Z.: Retention and Intention in Massive Open Online Courses. Educause Review **48**(3) (2013)
17. Kulkarni, C.E., Bernstein, M.S., Klemmer, S.R.: Peerstudio: Rapid peer feedback emphasizes revision and improves performance. In: L@S '15. pp. 75–84 (2015)
18. Littlejohn, A., Hood, N., Milligan, C., Mustain, P.: Learning in moocs: Motivations and self-regulated learning in moocs. The Internet and Higher Education **29**, 40–48 (2016)
19. Mahoney, M.J., Moore, B.S., Wade, T.C., Moura, N.G.: Effects of Continuous and Intermittent Self-Monitoring on Academic Behavior. Journal of Consulting and Clinical Psychology **41**(1), 65 (1973)
20. Margaryan, A., Bianco, M., Littlejohn, A.: Instructional Quality of Massive Open Online Courses (MOOCs). Computers & Education **80**, 77–83 (2015)
21. Nawrot, I., Doucet, A.: Building engagement for mooc students: introducing support for time management on online learning platforms. In: WWW '14. pp. 1077–1082 (2014)
22. Sagotsky, G., Patterson, C.J., Lepper, M.R.: Training Children's Self-Control: A Field Experiment in Self-Monitoring and Goal-Setting in the Classroom. Journal of Experimental Child Psychology **25**(2), 242–253 (1978)
23. Schippers, M.C., Scheepers, A.W., Peterson, J.B.: A Scalable Goal-Setting Intervention Closes Both the Gender and Ethnic Minority Achievement Gap. Palgrave Communications **1** (2015)
24. Yeomans, M., Reich, J.: Planning prompts increase and forecast course completion in massive open online courses. In: LAK '17. pp. 464–473 (2017)
25. Zheng, S., Rosson, M.B., Shih, P.C., Carroll, J.M.: Understanding student motivation, behaviors and perceptions in moocs. In: CSCW '15. pp. 1882–1895 (2015)
26. Zimmerman, B.J., Bandura, A., Martinez-Pons, M.: Self-Motivation for Academic Attainment: The Role of Self-Efficacy Beliefs and Personal Goal Setting. American educational research journal **29**(3), 663–676 (1992)
27. Zimmerman, B.J., et al.: A social cognitive view of self-regulated academic learning. Journal of educational psychology **81**(3), 329–339 (1989)