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**Article**

# Self-Regulated Learning User Interface (SRLUI) Design Principles and Experimental Findings in MOOCs

**Shu-Yi Hsu [1,*], Yoo Kyung Chang [1], Vivienne Shaw [2]**

[1] Teachers College, Columbia University, USA;
[2] Columbia University, USA;
* Correspondence: sh3146@tc.columbia.edu

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**Abstract:** There have been many attempts to support learners in massive open online courses (MOOCs) with retention and self-regulated learning (SRL) with limited and mixed findings. This paper presents a design of integrated SRL support called SRLUI developed from a review of SRL support and empirical findings. The results from implementing SRLUI for 808 learners in eight MOOCs are also presented. The finding indicates that SRLUI has a high compliance rate (80%), and increases learning outcomes for a high-performance group. There is no direct evidence indicating SRLUI has an impact on learner persistence. Future studies are suggested to investigate the potential typologies of MOOC learners and differentiate SRL supports into subgroups.

**Keywords:** Self-regulated learning, MOOCs, Learning analytics, Online Learning, Instructional design, User interface

## 1. Introduction

### *1.1 What are MOOCs?*

A massive open online course (MOOC) is a type of online course available to the public and often taught on a large scale (Pheatt, 2017). Without the hassles of the traditional school application process and tuition, a learner can take a course from a renowned university through internet access and a valid MOOC platform account (Reich, 2020). With a small fee, learners can also access graded assessments and potentially earn a certificate upon completion of the course. MOOCs have gained huge popularity since 2011 because of their easy accessibility, low financial commitments, and contribution by world-renowned universities, which were typically considered difficult to access. Until November of 2020, class central reported 180 million learners enrolled in MOOCs (Shah, 2020). MOOCs started to become a vehicle for people to enhance their academic or professional profile either as a pathway to access educational programs or to attract future employers. However, due to there being little or no consequences for dropping out, some research has shown MOOCs have high dropout rates and poor learning outcomes (Stein and Allione, 2014).

With the growing offerings and increasing enrollment of MOOCs, a number of researchers and educators have investigated the learning challenges and opportunities associated with MOOCs. MOOCs were first offered by Stanford University as free classes to the public in 2011 (Ng and Widom, 2014). MOOC pedagogy focuses on student-content interaction and delivers through a series of short videos, multiple choice quizzes, auto-graded coding assignments, fast-forward playback, subtitles, and discussion forums (Reich, 2020). To complete a MOOC course, a learner has to be able to plan a learning schedule, gather course information and materials, watch lectures and complete the assignments within the timeline. MOOC learning at scale model presents students with heavy responsibilities to regulate their learning. The rare teaching fellow presence coupled with limited personal feedback and social interactions with peers may result in high dropout and low completion rates in MOOC learning environments (Zhang et al., 2021).

### *1.2 What are Challenges in MOOC Research?*

MOOC research identified prior knowledge, experience with online learning, and self-regulated learning skills as strong predictors of learning outcomes (Kizilcec and Halawa, 2015). Several studies attempted to support MOOC learners by manifesting self-regulated learning behaviors (Ceron et al., 2021; Alonso-Mencia et al., 2020). However, there was still scarce empirical evidence of SRL interventions on learning outcomes (Jansen et al., 2020). Three research challenges in MOOCs were identified: (1) Most of the studies have a low compliance rate (10–30%) of the SRL interventions due to high dropout rates, which makes it hard to produce conclusive outcomes. (2) The concerns for data privacy and ethics make it difficult for researchers to get access to the learner data (Joksimović et al., 2018). (3) MOOCs have various pedagogies in course length, delivery mode (i.e. instructor-paced or student-paced), and submission due dates. It is difficult to compare the efficacy of SRL interventions across different studies to produce generalized findings (Quintana and Tan, 2019).

*1.3 Goal of This Paper*

This paper provides design principles to support SRL in MOOCs by synthesizing prior studies and showcases the design and implementation of a self-regulated learning user interface (SRLUI). The results from implementing SRLUI across eight credential-based MOOCs with 808 participants are presented. The research questions explore the efficacy of the SRLUI by examining the compliance rate and the impact on learning persistence and learning outcomes.

## 2. Literature Review

*2.1 What is Self-Regulated Learning?*

Zimmerman (2000) describes SRL as a series of thoughts, feelings, and behaviors generated by students to achieve their goals. Zimmerman (2000) hypothesizes SRL as a cyclical model in which learners undergo repeated phases of learning from forethought, performance, and self-reflection to attain their learning goals. In the forethought phase, a learner sets learning goals and conducts strategic planning. In the performance phase, a learner utilizes time management, help-seeking, and environment structure to execute learning tasks. In the self-reflection phase, a learner processes his performance and adjusts the strategies to attain the learning goals.

Zimmerman carried out several empirical studies to inspect self-regulated development processes and the validity of the cyclical model in the context of academic training (Kitsantas, Zimmerman, and Cleary, 2000) and athletic skills (Zimmerman and Kitsantas, 2002). These studies yielded the following conclusions: (1) Goal setting is the key to goal attainment, (2) SRL is more than a concept or attitude. It is a set of “mentally and physically demanding activities" (Zimmerman, 2013, p141), (3) SRL training is more effective when the three phases are taught together, and (4) Computer-mediated learning environments can be used to scaffold SRL development and provide immediate feedback.

*2.2. SRL Research in MOOCs?*

In the past decade, researchers have attempted to establish the positive correlation between a student’s SRL ability and learning outcomes in MOOCs (Al-Freih, 2017; Kizilcec et al., 2016; Kizilcec et al., 2017b; Reich, 2014). Numerous studies also examine SRL interventions and their influence on learning outcomes in MOOCs (Yeomans and Reich 2017; Davis et al., 2018; Jansen et al., 2020; Pérez-Álvarez et al., 2018; Alonso-Mencia et al., 2019). However, many of them could not produce statistically significant or robust results due to low compliance rates or small sample sizes (Ceron et al., 2021). The following section presents the prior SRL interventions and the analysis of the potential design challenges and opportunities in MOOCs. Next, a design and implementation of an SRL intervention, the self-regulated learning user interface (SRLUI), are presented to explore its impact on the compliance rate, learner persistence, and learning outcomes.

*2.3. Design of SRL Supports in MOOCs*

Prior SRL interventions were designed in several formats with a combination of survey, information-computer mediated technology (ICT), and video training. Prior research utilized a survey as a prompt to initiate learner SRL abilities because it was an economic and quick way to set an experimental design (Yeomans and Reich, 2017; Kizilcec et al., 2017a). Yeomans and Reich (2017) explored the impact of goal setting in relationship with MOOC completion rates and the number of certificates purchased by using a pre-course survey study. Their results suggested long-term goal planning could increase completion rates, yet this positive association was most apparent with a subgroup of students who were affiliated with schools. Following the same line of research, Kizilcec et al. (2017a) also employed a pre-course survey prompting learners to consider the values created upon completing the course. The study was a randomized experiment and the value affirmation process was found to improve grades, persistence, and completion rates among a specific subgroup of learners - lower class men (Kizilcec et al., 2017a). Kizilcec et al. (2020) later replicated previous long-term planning (Yeomans and Reich, 2017) and the value-relevance affirmation study (Kizilcec et al., 2017a) with 20,000 users in MOOCs. However, they concluded that these one-time only and short-term intervention (less than 10 minutes) effects diminished quickly; continued intervention with context-specific support was needed to facilitate SRL skill development (Kizilcec et al., 2020).

Unlike previous studies focusing on the partial phase of SRL support, Jansen et al. (2020) designed an experimental study to support full SRL phases ability using lecture videos and surveys. However, due to high dropout rates, only a small number of learners interacted with the artifacts, and no conclusive results were produced.

Another way to facilitate SRL is to provide information communication technology (ICT)-based tools to help learners monitor their learning behaviors. Several SRL artifacts featured personalized learning analytic dashboards such as SRLx (Davis et al., 2018), Chromeger (Alonso-Macia et al., 2019), and NoteMyProgress (2017, 2020). Davis et al. (2018) designed a user interface, SRLx, embedded in a MOOC to prompt learners to make short-term learning goals. Learners were provided with visual feedback based on their learning goals in comparison to what they have completed (i.e. number of videos). However, this research was not set up as a randomized experimental study and the compliance rate of the tool was low (30%). Davis and his colleagues (2018) recommended that future studies should integrate randomized experimental design to yield a casual relationship between the intervention and the results.

NoteMyProgress (Pérez-Álvarez et al., 2018; Pérez-Sanagustín et al., 2020) and MOOCnager (Alonso-Mencia et al., 2019) were web applications designed to support learner's SRL activities in MOOCs. NoteMyProgress focused on time-management and note-taking (organization) abilities. Once downloaded and installed in the app, NoteMyProgress produces a visualization of the learning behaviors by tracking the learners' time spent in the course (i.e. videos, assessments, and forums). This study also reported low compliance rates which limited any significant findings. Pérez-Álvarez and his colleagues recommended future research could build interactive visualizations to enhance learner engagement with the artifact.

MOOCnager, underpinned by Zimmerman's SRL models, was designed to support three phases of SRL activities (Pérez-Álvarez et al., 2018). MOOCnager featured an interactive user interface to allow learners to engage in goal setting, time management, and self-assessments. Learners were prompted to enter weekly learning goals and evaluate their progress and their feelings. There was a reminder feature informing learners about approaching due dates. Unfortunately, the study was unable to produce any significant results because of low compliance rates. They also suggest SRL tool could be built on the course platform rather than an external tool (Pérez-Álvarez et al., 2018).

Given the aforementioned research challenges in MOOCs, there are a few design implications for future SRL intervention design.

(1) SRL interventions would be more effective if supporting the entire SRL process rather than partial ones (Zimmerman, 2000).
(2) An interactive visualization could increase learner interaction with the SRL interventions (Pérez-Álvarez et al., 2018).
(3) The SRL interventions should be content-specific and embedded into MOOC platforms (Alonso-Mencia et al., 2019; Kizilcec et al., 2020).
(4) Utilizing learning analytics to provide adaptive feedback (Winne, 2017).
(5) Developing SRL skills requires time (Zimmerman, 2000). A longitudinal and repeated support would yield better results than one-time-only, short-term artifacts (Kizilcec et al., 2020).

### *2.4. SRLUI*

Based on the design implications, SRLUI was created to support all three phases of SRL behaviors based on Zimmerman's cyclical model (2000). SRLUI consists of three pages: course progress page, study planning, and study tips. SRLUI is created as a standalone module titled "Weekly Reflection" (Fig. 1) at the beginning of weekly content.

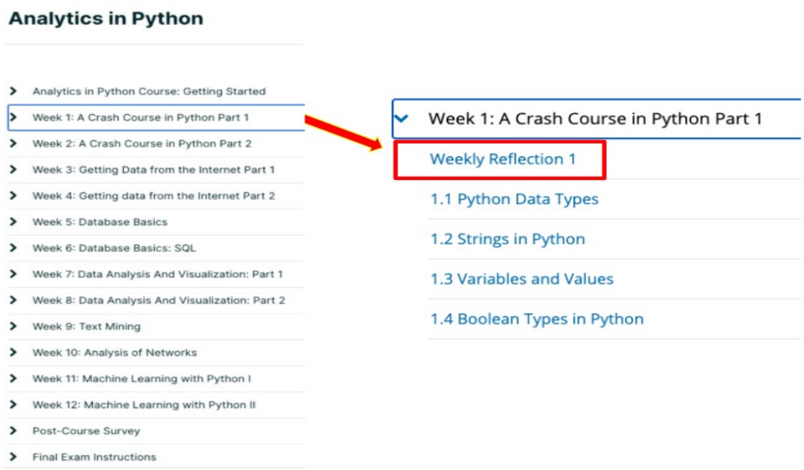


**Fig. 1.** Intervention, SRLUI, appears as Weekly Reflection, embedded in the first unit of the weekly content as part of the learning materials.

On the course progress page, a dashboard of learning behaviors with weekly and historical views is provided to initiate self-evaluation and reflection. In the treatment group, learners have a chance to interact with SRLUI by evaluating the completion rate of the study plan on a scale from 0–100% (Fig. 2) whereas the control group is only provided with the learning analytics information but no options to conduct self-evaluation (Fig. 3).

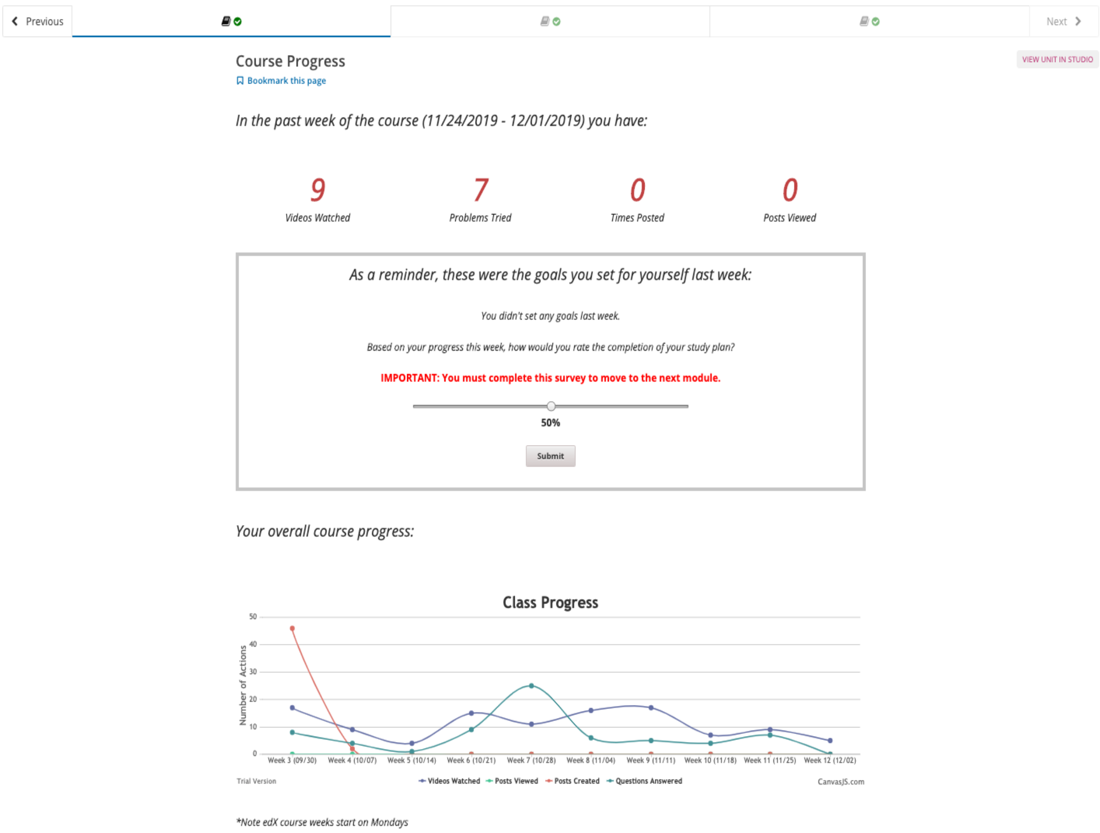


**Fig. 2.** Curse progress page for the treatment group.

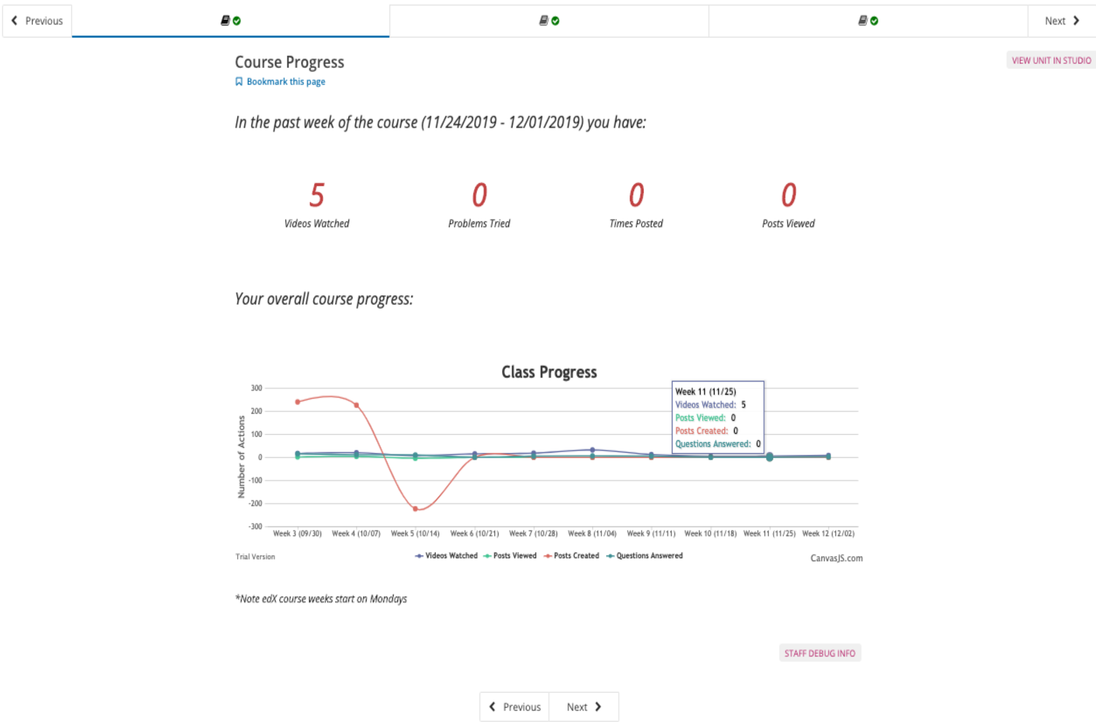


**Fig. 3.** Course progress page for the control group.

On the study planning page, the treatment group is prompted to set learning goals and then plan the learning tasks using what users see is what they schedule email notifications as reminders (Figs. 4 and 5). Whereas the control group is provided with the topics of the upcoming week (Fig. 6). On the study tips page, both the treatment and the control groups are provided with general learning tips with a comic to help them better plan their studies (Fig. 7). SRLUI is available for learners to use as they see fit. Detailed SRLUI architecture information can be found in the paper of Hsu (2021).

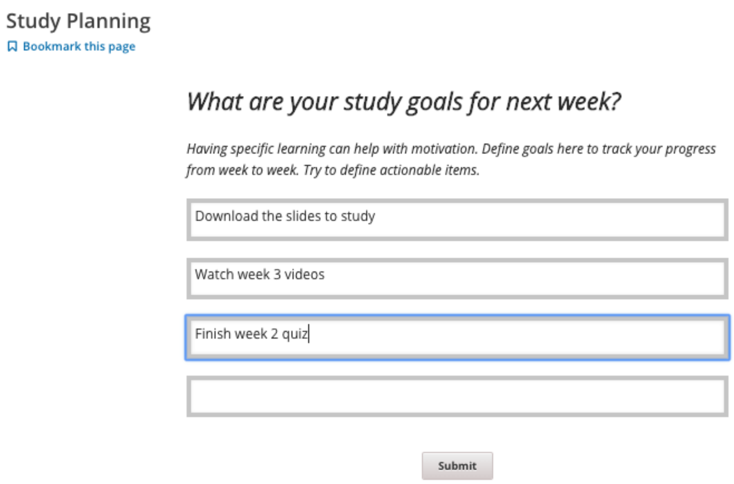


**Fig. 4.** Study planning page: it prompts the treatment group to set studying goals for next week.

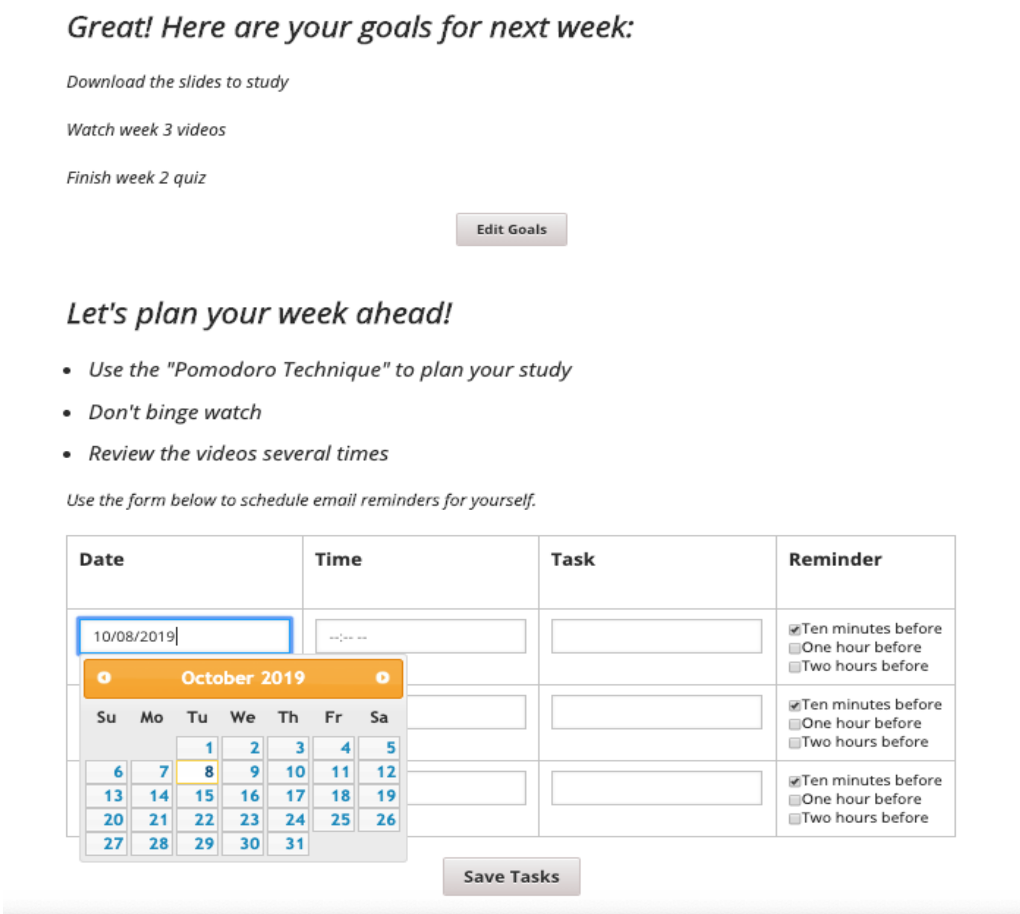


**Fig. 5.** Study plan page (continued). After setting the goals, learners in the treatment group are prompted to plan the study tasks by putting down the time and items to study. A reminder email is sent out based on each learning task to the email associated with the learner's edX account.

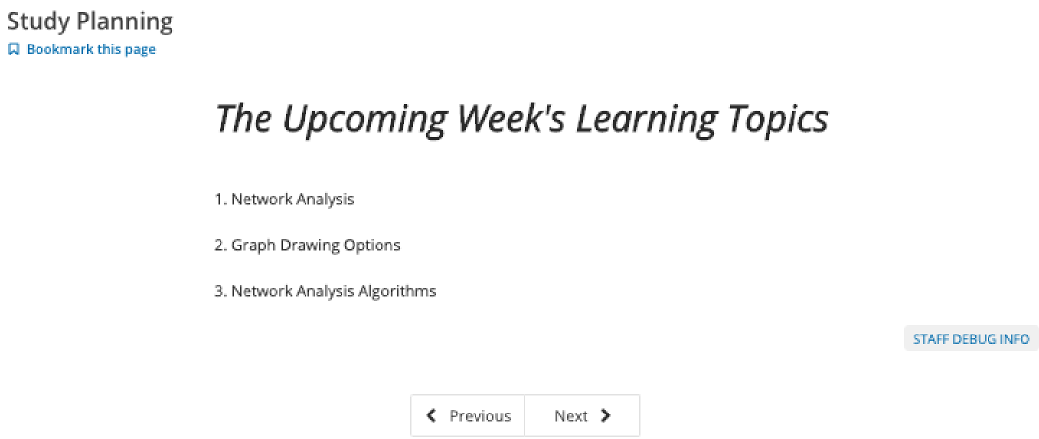


**Fig. 6.** Study planning page for the control group. Learners are provided with next week's learning topics.

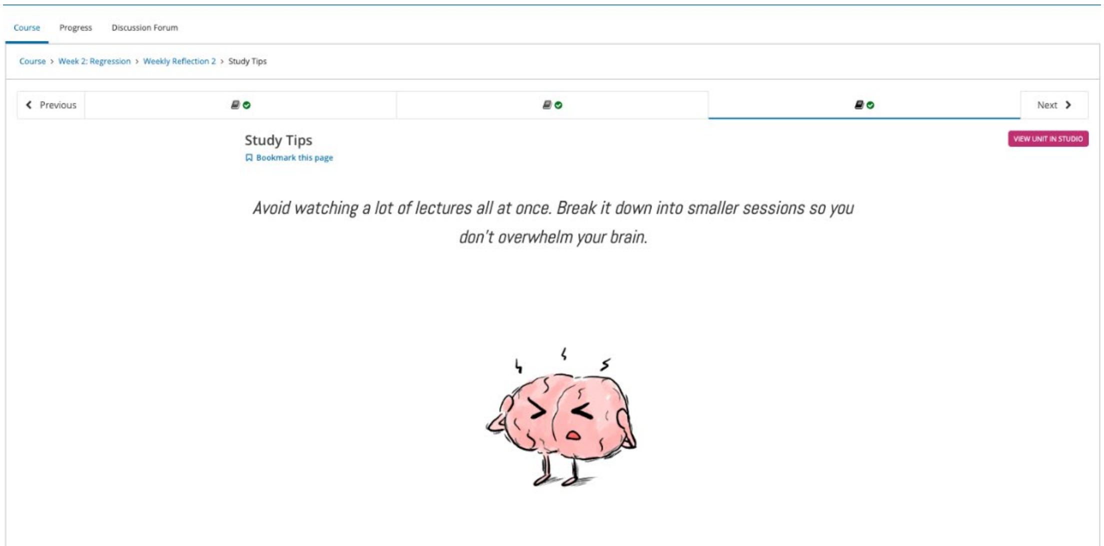


**Fig. 7.** Study tips. This page provides general study tips for both the treatment group and the control group.

## 3. Materials and Methods

### *3.1 Current Study*

To examine the relationship between SRL support, learner interaction with the support, and its impact on learning persistence and outcomes, SRLUI was built into eight credential-based MOOCs. Learners were randomly assigned to the treatment and control groups. SRLUI featured a personalized, longitudinal, and interactive interface to allow learners to use it as they see fit. The control group was designed with a similar process but with no interactive functionalities.

The previous MOOC SRL research lacks empirical evidence to pin the association between SRL interventions and learning outcomes. In the past literature, learner usage of SRL artifacts was low (10–30%). Thus, research question 1 (RQ1) is "What is the compliance rate of SRLUI?". The following research questions explore the effectiveness of SRLUI on learner persistence and learning outcomes. Research question 2 (RQ2) is "What is the impact of SRLUI on learning persistence?, and research question 3 (RQ3) is "What is the impact of SRLUI on learning outcomes?".

### *3.2 Participants*

Data were collected from eight MOOCs on edX. Only the verified track learners (n=1,314) were eligible for the study because only paid learners could access the graded assignments. Since the intervention was administered from the 5th week of the courses, learners who left the course by week four were excluded. That yielded a total of 808 participants to be included in the data. Learners were randomly assigned to the treatment group or the control group based on their user identification number. There were 430 participants in the treatment group and 378 in the control group. Among the self-identified survey, 46% of participants were male and 11% were female. More than 50% of the participants had undergraduate degrees or above and only 6% of learners had a high school diploma or below. (Table 1)

**Table 1.** Descriptive data of demographic information (n=808)

| Variable | *N* | *Mean* | *SD* | *Min* | *Max* |
|---|---|---|---|---|---|
| *Gender* | | | | | |
| male | 372 | 0. 46 | 0.5 | 0 | 1 |
| female | 94 | 0.11 | 0.32 | 0 | 1 |
| *Age* | 499 | 33.74 | 9.66 | 11 | 68 |

**Table 1.** *cont.*

| | | | | | |
|---|---|---|---|---|---|
| *Education* | | | | | |
| high school or under | 50 | 0.06 | 0.24 | 0 | 1 |
| undergraduate | 224 | 0.28 | 0.45 | 0 | 1 |
| post graduate | 184 | 0.23 | 0.42 | 0 | 1 |
| Treatment Group | 430 | | | | |
| Control Group | 378 | | | | |
| Class | 8 | | | | |

### *3.3 Context*

The experiment included eight credential-based MOOCs enlisted as two MicroMasters programs offered by an Ivy-league university on edX. The computer science MicroMasters program includes artificial intelligence, machine learning, robotics, and animation and CGI motions. The business analytics MicroMasters program includes business analytics in python, data models and decisions in business analytics, demand and supply analytics, and market analytics. These MOOCs were instructor-led courses with the same start and end dates. Each course was 14 weeks, including 12 weeks of the course and two weeks of final exams. Upon registration to the verified track, all the course materials and graded assessments such as quizzes and coding projects were available for access. No submissions were allowed after the due dates. If a learner achieved 60% or above for the total grades and attended the final exam, he or she could be awarded a certificate upon completion.

### *3.4 Data Sources*

Three types of data were collected for data analysis: learning outcome data, behavioral data, and demographic data. All the data were collected while learners engaged in the course platform and the data was exported using edX and edX Insights from the administrators' access. The learning outcome was computed as summative grades based on a combination of quizzes, assignments, and final exam scores. Demographic data included the learner's age, education level, and gender. Learning behavior data was collected as part of the activity log where the learner's interaction with SRLUI was recorded. To store and retrieve the learner's interaction with SRLUI, an HTTP server was built using Node.js in a MongoDB database. The SRLUI server stored learner responses of self-evaluation, reminder setup, text entry of goals, and tasks planning. A detailed user interface of the treatment group and the control group comparison is illustrated in Table 2. This study was approved by the appropriate Institutional Review Board (IRB) for research. No participants were recruited solely for the study, and the data that was used as part of the study came from the data that was collected as part of the curriculum.

**Table 2.** User Interface Comparison Between the Treatment and Control Group.

| **Page** | **SRL activity** | **Treatment group** | **Control group** |
|---|---|---|---|
| Course Progress | self-reflection | learning behaviors reports (prior week) | learning behaviors reports (prior week) |
| | | prior week's learning goals | NA |
| | self-evaluation | * self-evaluate the completion rate of the study plan | NA |
| | self-reflection | historical report of learning analytics | historical report of learning analytics |
| Study Planning | goal setting | *set learning goals for the next week | show learning topics of the next week |

**Table 2.** *cont.*

| | | | |
|---|---|---|---|
| | task planning | *plan learning tasks | NA |
| | setting reminders | *set email reminders according to learning tasks | NA |
| Study Tips | general SRL tips | provide a general learning tip with an illustration | provide a general learning tip with an illustration |

SRLUI featured an interactive interface and * indicates the opportunity the treatment group can interact with the interface. Note that the control group also offers a base-line intervention but read-only.

*3.5 Measures*

To answer RQ1: "What is the compliance rate of SRLUI?" A series of measures were calculated based on the frequency and amount of interaction with SRLUI (Table 3). RQ2 is to investigate the average effects of SRLUI on learner persistence. The value was explored through the number of days a learner remained active in the course, based on the first date of learning activity to the last day of learning activity during a course period. Any activities before the start date or beyond the course end date were not included in the analysis. In short, the survival analysis was right- and left-censored. For example, the longest survival days were 98 days (14 weeks) and the dropout occurred if a learner left the course before the final exam week started.

**Table 3.** Measure Description Based on Learner Interaction with SRLUI

| **Variables** | **Description** | **Coding or List of Possible Data Entry** |
|---|---|---|
| useSRLUI | If a subject use SRLUI features (goal, tasks, reminders, self-evaluation) at least once, it is considered use SRLUI. | Yes=1, No=0 |
| goals count | The total number of goals learners enter on goal setting | *Possible Responses (2 goal counts):*<br>Watch Week 1 Video, Finish week 1 quiz |
| tasks count | The total number of tasks enter in tasks planning | *Possible Responses (3 task counts):*<br>project wk2, review videos week 3, finish assignment 4 |
| self-evaluation count | The total number of self-evaluation entry | *Possible Responses (2 self-evaluation counts):*<br>Based on your progress this week, how would you rate the completion of your study plan?<br>50%, 90% |
| reminders count | The total number of reminder emails learners schedule to send out based on time planned for the tasks | *Possible Responses (1 reminder count):*<br>[X ]10 mins prior<br>[   ] 1 hr prior<br>[   ] 2 hrs prior |

Table 3. *cont.*

| | | |
|---|---|---|
| ***Other course-related info*** | | |
| Create time | Date and time of each user action | *Example:* 11/6/19 6:41:15 |
| Course ID | Course ID | *Example:* CSMM101 |
| userID | a unique numeric number randomly generated upon account registration | *Example:* 10646139 |

Note: A learner could enroll in more than one course. A valid data was based on a unique user ID and a unique course ID.

*3.6 Data Analysis*

In the performed analysis for RQ2, a nonparametric estimator of the survival function (Kaplan and Meier, 1958) was utilized to compare learner persistence between the treatment versus the control group. Survival analysis, by definition, indicates the probability of when and whether an event occurs during an observed period (Cox, 1972). Willet and Singer (1991) also recommended using survival analysis to investigate educational measures such as teacher attrition and student dropout rate. Rstudio, and the survival and survminer packages were used for analysis (R Core Team, 2020; Therneau, 2020). To proceed with RQ3 analysis on how SRLUI affects learning outcomes, a random intercept two-level hierarchical linear model (HLM) was used to estimate the independent effects of the students' variables and usage of SRLUI. HLM is an appropriate measure because the clustering of students by class violates common assumptions of independence of residuals in linear regression models (Bowers & Urick, 2011). Prior MOOC research (Kizilcec et al., 2020) also utilized the multilevel modeling approach to account for clustering in MOOC data. Thus, HLM was applied to examine the independent effect of SRLUI on learning outcomes from eight MOOCs. The HLM equation can be expressed in Eq. (1).

The HLM equation can be expressed in Equation 1 :

$$\text{Level 1: } Y_{ij} = \pi_{0j} + \pi_{1j}SRLUI_{ij} + \omega X_{ij}\ldots + \varepsilon_{ij} \quad (1)$$

$$\text{Level 2: } \pi_{0j} = \gamma_{00} + u_{0j}$$

$$\text{Level 2: } \pi_{1j} = \gamma_{10} + u_{1j}$$

$Y_{ij}$ = Dependent outcome variable for student i in course j, here learner grade
$\omega$ = Vector of fixed effects of the student level covariates
$X_{ij}$= Vector of student level covariates
$\gamma_{00}$= The value of the intercepts varying across course
$\gamma_{10}$ = The slope of the effect of SRLUI across courses
$\varepsilon_{ij}$ = Level 1 residuals
$u_{0j}$ = Level 2 residuals for the intercept
$u_{1j}$ = Level 2 residuals for the slope

To answer RQ3, the magnitude, direction1, and precision of $\gamma_{10}$ are examined. If the estimate is positive and statistically significant ($p<.05$), then it demonstrates a positive effect of SRLUI on the learning outcome. The student-level variables include learner characteristics such as age, gender, and education level, and the treatment variable. Dummy-coded measures were created to account for indicators: gender (male=1, female=0), educational level indicator, postgraduate (yes=1, no=0). Learners in the treatment group were labeled SRLUI treatment (yes=1, no=0). Given that learners can choose to interact with SRLUI or not, a variable "useSRLUI" (yes=1, no=0) was created to indicate learners in the treatment group who used SRLUI. This allowed subsequent analysis of intent to treat (ITT) and treatment on the treated (TOT) HLM modeling (Murnane and Willett, 2010). The learning outcome is based on a scale from 0–100. No class-level variables were included in the HLM modeling. For all HLM models, the lme4 package in R studio was used for the statistical analysis (Bates et al., 2015).

## 4. Results

### *4.1. RQ1: What is the Compliance Rate of SRLUI?*

To determine the efficacy of SRLUI, the first step was to examine whether learners interact with the tools designed to support their self-regulated learning strategies. 78% of the participants in the treatment group (n=430) engaged in SRLUI at least one time (Table 4). Specifically, goal-setting (n=241) and self-evaluation (n=335) were the most used compared to task planning (n=73) and reminders (n=73). The finding suggested that nearly 80% of the MOOC learners interacted with an SRL intervention, which is higher than the outcomes reported in the previous study (10–30%) (Davis et al., 2018; Jansen et al., 2020).

**Table 4.** Descriptive data of treatment group (n=430) interaction with SRLUI

| **SRLUI Activity** | ***N*** | ***Mean*** | ***SD*** | ***Min*** | ***Max*** |
|---|---|---|---|---|---|
| useSRLUI | 342 | 0.78 | 0.41 | 0 | 1 |
| goals count | 241 | 7.44 | 7.54 | 1 | 41 |
| tasks count | 73 | 6.64 | 7.72 | 1 | 45 |
| self-evaluation count | 335 | 1.35 | 0.85 | 1 | 8 |
| reminders count | 73 | 6.01 | 7.14 | 0 | 42 |
| Number of courses | 8 | | | | |

### *4.2.RQ 2: What is the Impact of SRLUI on Learning Persistence?*

Learner persistence was calculated using the survival functions based on the days a learner remained active during the course period and dropouts, as described in the method section. Learner persistence has been considered a strong indicator of learning outcomes (Hsu, 2020). Thus, the 2nd research question investigated to what extent the offering of SRLUI affects learning persistence. The survival functions compared the control and the treatment group (ITT analysis) as well as the control group and the ones who complied with the intervention (TOT analysis). As for the results, Fig. 8 indicated that learners in the control group had lower dropout rates than the treatment group ($p<0.05$). Specifically, the control group only had 30% of dropout rates while the treatment group had 40% of dropouts. Further evidence in Fig. 8 suggested there were no significant differences between the control and the treatment in the treated (TOT) groups ($p>0.05$).

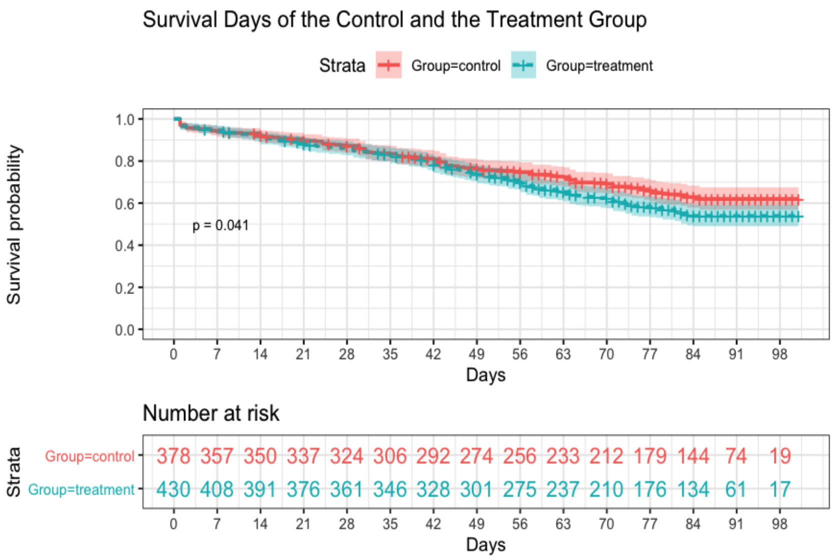


**Fig. 8.** Estimated survival function showed a graduate decline in survival rates. Overall, the control group (n=378) had a statistically significant higher survival rate than the treatment (n=430) (p<0.05). The control group (red) and the treatment group (green) had dropout rates below 50%. The maximum learning persistence was 98 days (14 weeks).

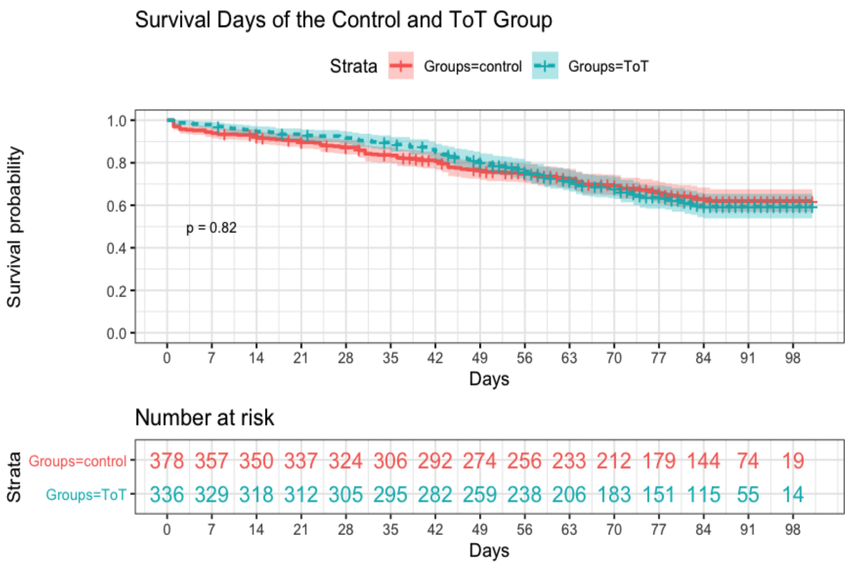


**Fig. 9.** Survival function of the control group versus the treatment on the treated (TOT). There was no statistically significant difference between the treatment and the control groups. The median survival time was greater than the observation window, meaning the dropout rates for both groups were below 50%.

### *4.3.RQ 3: What is the Impact of SRLUI on Learning Outcomes?*

Prior to the analysis, for the initial inspections of the dependent variable, student grades showed a bimodal distribution with zero inflation (n=108). An exploratory linear model to the bimodal outcome showed a violation of assumption testing of normality and linearity of the residuals. The dataset was divided into two subgroups: a passing group (grade >= 60) and a non-passing group (grade < 60) to proceed with the HLM analysis. The results suggested 5% of the variability in the grades were at the class level (ICC=5%) and 95% of the variability in grades was at the student level for the passing group (Table 5). Table 5 showed, on average, students in the treatment group (ITT analysis) performed 2.5 points higher than the control group ($p$<0.01, effect size=0.26) in the learning outcomes. Those with the intervention performed 3.16 points higher ($p$<0.01, effect size=0.25) than the control group (TOT analysis). However, there is no statistically significant difference found between the control and the treatment group in the non-passing group ($p$>0.05, effect size=-0.18) (Table 6).

**Table 5.** Results of Passing Group (>=60) Hierarchical Linear Model

| | ITT | | TOT | | | |
|---|---|---|---|---|---|---|
| **Student (n=247)** | ***Coeff.*** | ***SE*** | ***Coeff.*** | ***SE*** | ***p* value** | **ITT effect size** |
| Intercept | 75.91*** | 2.73 | 75.58*** | 2.70 | | |
| SRLUI treatment | 2.49* | 1.19 | 3.19** | 1.19 | 0.04 | 0.25 |
| Male | 0.02 | 1.31 | 0.48 | 1.32 | 0.99 | 0.001 |
| Age | 0.11 | 0.08 | 0.1 | 0.07 | 0.16 | 0.01 |
| Post_grad | 0.64 | 1.39 | 0.72 | 1.38 | 0.65 | 0.07 |
| Variance at | | | | | | |
| Course Level-2 | 4.45 | | 4 | | | |
| Student Level-1 | 83.88 | | 82.65 | | | |
| ICC | 0.05 | | 0.05 | | | |

*Note.* ***:*p*<0.001, **: *p*<0.01, *:*p*<0.05; ITT=intent to treat; TOT=treatment on the treated

**Table 6.** Results of Passing Group (<60) Hierarchical Linear Model

| | ITT | | TOT | | | |
|---|---|---|---|---|---|---|
| **Student (n=252)** | ***Coeff.*** | ***SE*** | ***Coeff.*** | ***SE*** | ***p* value** | **ITT effect size** |
| Intercept | 2.43*** | 0.27 | 2.32 | 0.26 | <0.001 | |
| SRLUI treatment | -0.18 | 0.12 | 0.11 | 0.12 | 0.13 | -0.18 |
| Male | 0.11 | 0.14 | 0.09 | 0.14 | 0.48 | 0.1 |
| Age | -0.002 | 0.01 | -0.002 | 0.06 | 0.74 | -0.002 |
| Post_grad | -0.15 | 0.14 | -0.18 | 0.14 | 0.28 | -0.15 |
| Variance at | | | | | | |
| Course Level-2 | 0.07 | | 0.06 | | | |
| Student Level-1 | 0.9 | | 0.9 | | | |
| ICC | 0.05 | | 0.05 | | | |

*Note.* ***: $p$<0.001, **: $p$<0.01, *:$p$<0.05 ; Outcome logged transformed to meet assumption of linearity.

## 5. Discussions

In the past decade, a growing number of researchers have attempted to establish the association between SRL and learning by manifesting SRL behaviors in MOOCs but failed to produce conclusive results due to small sample sizes, lack of experimental design, and low compliance rates (Jansen et al., 2020; Alonso-Mencia et al., 2019; R. Pérez-Álvarez et al., 2018). Therefore. the purpose of the study is to provide empirical evidence of an SRL intervention in MOOCs by following the design implications informed by the SRL disciplines and the recommendations from the previous SRL studies.

There are five SRL design principles derived from the literature: (1) The SRL interventions would be more effective if supporting the entire SRL process. (2) An interactive visualization could increase interaction with the artifacts. (3) The interventions should include content-specific information and build the MOOC platforms. (4) Using learning analytics to provide adaptive feedback. (5) SRL support should be longitudinal and recursive.

Following the design principles, a self-regulated learning user interface (SRLUI) was developed to provide a full cyclical SRL process based on Zimmerman's SRL model in eight credential-based MOOCs. SRLUI featured interactive functionality to prompt learners to engage in self-evaluation, goal setting, and task planning. SRLUI also included a personalized dashboard with a learning analytics visualization (numbers of video views, number of problem attempts, number of posts read, and number of posts written) and email notifications as nudging effects. Additionally, participants could access SRLUI easily since it was built in the course as part of the weekly unit.

The results indicated that about 80% of participants made use of SRLUI. SRLUI had a selective impact on the learning outcome for different groups of learners. For a subgroup of learners who passed the course, providing SRLUI helped improve their learning outcomes. Such benefit was not observed in the non-passing groups. A possible explanation is that other factors such as learner prior knowledge and psychological characteristics (i.e. self-efficacy and motivation) could also contribute to the learning outcomes (Gardner and Brooks, 2018). However, there was no evidence showing that SRLUI improved learning persistence measured as a reduction in dropout rates. Since SRLUI was administered on week five and early dropouts (those who dropped out of the course in the first five weeks of the course) were excluded from the study, learners in the study already demonstrated a higher level of persistence. Therefore, SRLUI may have had little impact on their persistence with no differences identified between the treatment and the control groups. To better model learner persistence, future studies could include time-independent (i.e. learner's prior knowledge and experience with MOOCs) and time-dependent factors in the analysis (Bowers, 2010; Chen et al., 2020; Willett and Singer, 1991).

Based on the bimodal grades distribution and the unequal impacts of SRLUI on the passing and non-passing groups, it is inferred that there were various typologies of learners in credential-based MOOCs. In other words, even if a learner paid to register for credential-based MOOCs, not all the learners aim to watch all the lecture videos, complete the graded assignments, or aim to achieve a passing score to earn a certificate. That is, future studies could examine learner typologies in MOOCs and identify which types of learner profiles might need to be supported, and how. For example, learners who have lower prior knowledge or lower self-efficacy could make use of more scaffolding or training in SRL abilities. Students benefit differently from the support offered by the self-regulated learning tools (Wong et al., 2019).

## 6. Conclusions

This research aims to have insights into the affordance of SRL interventions in credential-based MOOCs. In this study, the design principles of SRL support are synthesized to provide empirical findings of a self-regulated learning user interface's effects on learning outcomes. Future studies need to apply the design implications of SRL interventions to support diverse populations rather than using the "one interface fits all" model. More studies should focus on learner interactions with the artifacts and SRL strategies trends (Ceron et al., 2021). Additionally, triangulations with the interactions with SRL interventions and learner engagement in the course (i.e clickstream data) could enrich the understanding of a learning experience.

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