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ORIGINAL RESEARCH

The Promises and Pitfalls of Self-regulated Learning Interventions in MOOCs

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Abstract

Self-regulated learning (SRL) is a fundamental skill to succeed in Massive Open Online Courses (MOOCs), but many learners do not know how to self-regulate their learning. The need to support SRL in MOOCs led to the idea of social-psychological interventions that promise to improve course performance and decrease dropout rates. However, past research provides mixed evidence of the effectiveness of SRL interventions in MOOCs. In this randomized control trial (RCT), the heterogeneous effects of SRL intervention in three MOOCs were examined. The SRL intervention was embedded in a precourse survey, where learners were randomly assigned to experimental (N = 383) and control (N = 444) conditions. Both groups answered contextual questions, and then the experimental group was guided through a writing activity to boost SRL skills. The study aimed to assess how learner demographics may affect the results of the RCT. The results yielded no significant differences overall between the experimental and control conditions. However, the results of the binary logistic regression demonstrated that the heterogeneous effect is prevalent in SRL interventions in regard to learner demographics: males and older learners received advantages from the intervention. The current study adds to the field of SRL intervention in MOOCs and presents directions for future experiments. Based on the results of the paper, a number of methodological issues of SRL interventions in MOOCs were formulated, including self-selection bias and interventions that were not a part of the learning process, that focused on academic outcomes, and that had no follow-up analysis.

Keywords Self-regulated learning · MOOC · Intervention · Experiment

1 Introduction

Massive Open Online Courses (MOOCs) were considered a disruptive innovation in education. However, MOOCs suffer from low completion rates: up to 90–98% of learners do not reach the finish line (Healy, 2017; Reich, 2014). As research has shown, successful learners differ from their poorer-performing counterparts in behavior: they

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spend more time dedicated to learning (Kizilcec et al., 2016) and choose more flexible approaches toward the learning process (Maldonado-Mahauad et al., 2018).

This variation in behavior can be attributed to differences in self-regulated learning (SRL) skills. Highly SRL learners have the ability to plan, monitor, and manage their learning process (Wang et al., 2013). Initial research into the role SRL plays in MOOCs has identified a range of obstacles. There is growing evidence that many learners lack SRL skills (Littlejohn & Milligan, 2015), which can result in frustration and low performance (Pérez-Sanagustín et al., 2020).

While learners often struggle to self-regulate their learning process, many researchers try to improve their academic achievements through social-psychological interventions. They suggest that learners perform short exercises that target SRL skills. Researchers embed successful strategies (Kizilcec et al., 2016) or questionnaires (Jansen et al., 2020) into SRL interventions. These interventions can be delivered through precourse surveys (Yeomans & Reich, 2017) or video lectures (Wong et al., 2021).

However, despite the variety of SRL interventions in MOOCs, existing studies show mixed results. As researchers have demonstrated, interventions that were primarily created to boost learner performance did not result in any improvement (Davis et al., 2016; Kizilcec et al., 2016). Some SRL interventions have raised educational attainment only in individualist cultures (Kizilcec & Cohen, 2017). At the same time, some experiments with SRL interventions in MOOCs were successful (Jansen et al., 2020; Wong et al., 2021; Yeomans & Reich, 2017).

From studies that show improved SRL skills through interventions in MOOCs, it is hypothesized that these prompts can demonstrate heterogeneous effects when the treatment generates beneficial effects for particular learners. As researchers have demonstrated, MOOC learners have different backgrounds, motivations, intentions, and prior experiences (Kizilcec et al., 2017). In this case, some learners may benefit from SRL interventions in MOOCs more than others.

This paper examines the heterogeneous effects of SRL prompts in MOOCs by replicating successful interventions. In traditional classroom settings, previous studies outline the critical role of students' demographics in the heterogeneous effects of interventions (Clark et al., 2020; Grove & Wasserman, 2006; Jensen, 2010; Schippers et al., 2015; van Lent & Souverjin, 2017). It is assumed that in the case of MOOCs, these effects might be explained by characteristics such as gender (Semenova & Rudakova, 2016; Watson et al., 2017), age (Morris et al., 2015), educational level (Morris et al., 2015; Semenova & Rudakova, 2016), and previous online experience (Semenova & Rudakova, 2016). Thus, the paper seeks to answer the following research question (RQ): Do SRL interventions in MOOCs produce heterogeneous effects based on gender, age, education and prior online experience?

This study provides an important opportunity to advance our knowledge of SRL interventions in MOOCs and contribute to the growing area of research by exploring their heterogeneous effects. Based on the literature review of SRL interventions in MOOCs, the current study is the first to not only assess the effectiveness of SRL interventions but also analyze their pitfalls. This research will serve as a base for future personalized SRL interventions in MOOCs. The study first analyses existing SRL interventions in MOOCs and then explores in detail how learner demographics may affect the results of SRL interventions. Together, these data allow us to formulate the main promises and pitfalls of SRL interventions in MOOCs.

2 Related Work

2.1 Self-regulated Learning in MOOCs

Despite the strict structure of MOOCs set by instructors, the learning process is non-linear and self-paced. Minimal direct interaction between the instructor and learners is challenging. As a result, the open nature of MOOCs gives learners significant autonomy but also requires a high level of SRL skills. In the online environment, learners independently choose the right time and place for learning, and they have to plan, monitor, and manage their own learning process (Wang et al., 2013). Based on the literature review it can be concluded that SRL in MOOCs is an emerging skill (Cerón et al., 2020). As the researchers state, a lack of SRL skills is one of the main reasons why many learners do not complete MOOCs (Pérez-Álvarez et al., 2017).

SRL includes cognitive, behavioral and affective processes (Zimmerman & Schunk, 2012). However, Winne (2001) more specifically outlined the cognitive process, which occurs when a person learns something. It has been suggested that learners with high SRL skills are active and can efficiently manage their own learning through monitoring and strategy use (Greene & Azevedo, 2007). There is convincing evidence that MOOC learners with high SRL skills respond differently to a learning situation than their coursemates with lower SRL skills. Highly self-regulated learners are usually more active in MOOCs (Kizilcec et al., 2016; Maldonado-Mahauad et al., 2018), and as a result, they tend to have higher educational outcomes (Milligan et al., 2013; Vilkova, 2019).

There are numerous theories that examine SRL in the learning process (Panadero et al., 2016). Among the most popular are models suggested by Zimmerman (1990), Winne and Hadwin (2008), and Pintrich (2004). This study will be focused on Zimmerman's model since he is considered one of the first SRL theorists (Panadero et al., 2016). According to Zimmerman (1990), SRL can be described through the actions that students perform during the learning process, which consist of three cyclical phases: planning, performance, and self-reflection. Among the most prominent SRL strategies in MOOCs, researchers identify goal setting, help seeking, time management, self-evaluation, and strategic planning (Cerón et al., 2020). However, it has been revealed that planning is the most effective strategy to succeed in MOOCs (Vilkova, 2019). Although SRL skills are critically important in MOOCs, not all learners know how to self-regulate their learning (Littlejohn & Milligan, 2015). This lack of SRL skills may result in frustration and low performance (Pérez-Sanagustín et al., 2020). Learners who are not able to self-regulate their learning are likely to abandon the MOOCs in which they enroll. This evidence suggests the need to support SRL in the context of MOOCs (Cerón et al., 2020).

2.2 Promoting Self-regulated Learning Through Interventions in MOOCs

Social-psychological interventions (or prompts) are "brief exercises that target students' thoughts, feelings, and beliefs in and about school" (Yeager & Walton, 2011, p. 267). Recent evidence suggests that small interventions can dramatically change students' learning experience by reducing achievement gaps and pushing their behavior in the desired direction (Damgaard & Nielsen, 2018). The mechanism of these interventions is simple: researchers create positive and reinforcing exercises, which reframe the student experience.

In general, SRL interventions can prepare learners for lifelong learning since SRL skills are transferable skills (Cazan, 2020). MOOC learners who learn SRL strategies from interventions can use these skills in future learning situations. Moreover, positive experience with SRL interventions, which led to high educational outcomes, may support learners' motivation to enroll in more courses.

Kizilcec and Brooks (2017) stated that MOOCs provide large amounts of diverse learning data and allow rapid online experiments, even though MOOCs suffer from high dropout rates. Together, this evidence indicates that it is important to enhance learners' experiences with MOOCs. In this case, to successfully study MOOCs, learners should engage their SRL skills. Therefore, a growing body of literature has investigated the effectiveness of SRL interventions on learners' educational outcomes.

The literature provides several important conclusions. First, interventions aimed to target different phases of SRL. Some experiments promoted only one SRL skill, for example, planning (Davis et al., 2016; Kizilcec & Cohen, 2017; Yeomans & Reich, 2017). Some researchers utilize existing theoretical SRL models. Kizilcec et al. (2016) examined the effectiveness of recommended SRL strategies that were built on Pintrich's model of SRL. According to this model, they divided SRL strategies into metacognitive and resource management. Studies by Jansen et al. (2020) and Wong et al. (2021) implemented video SRL interventions that were created in accordance with Zimmerman's model. These interventions utilized a holistic approach, integrating the three SRL phases: planning, performance, and self-reflection.

Second, SRL interventions can be integrated into MOOCs with different connections to course structures. Several experiments were based on SRL interventions included in precourse surveys. In research by Yeomans and Reich (2017), learners in experimental conditions were asked to describe specific plans they had. A similar approach to deliver SRL intervention was utilized by Kizilcec and Cohen (2017). They guided learners through a writing activity about positive outcomes associated with a goal, the obstacles to achieving it, and concrete if–then plans to overcome them. Writing activities can also be embedded into MOOCs. In the experiment conducted by Davis et al. (2016), every week, a retrieval cue was inserted at the end of the final lecture video. Jansen et al. (2020) and Wong et al. (2021) made even stronger connections between interventions and MOOC content by embedding SRL strategies into video lectures.

Finally, researchers often use similar variables to assess the effects of SRL interventions. Most studies rely on self-reported data on course persistence and achievement, but some researchers additionally utilize log data (e.g., Jansen et al., 2020; Wong et al., 2021). Yeomans and Reich (2017) employed data about course completion and payment for certificates. In addition to the data about passed assignments, Kizilcec et al. (2016) also used the number of active days and percentage of viewed lectures as outcome variables. Jansen et al. (2020) suggested employing log data to additionally measure learners' SRL strategies. The proposed intervention was successful both for course completion and learners' metacognitive activities. Using log data, Wong et al. (2021) also demonstrated that the effectiveness of SRL interventions depends on the complexity of the MOOC.

However, studies have reported mixed results. While some SRL interventions showed gains in learners' achievement (Jansen et al., 2020; Wong et al., 2021; Yeomans & Reich, 2017), some raised educational attainment for a particular group of learners (Kizilcec & Cohen, 2017), and others demonstrated no effect (Davis et al., 2016; Kizilcec et al., 2016). It is thus proposed that SRL interventions might affect different experimental subjects in different ways. Such a study would shed light on why some SRL interventions in MOOCs improve learners' achievements while others do not.

3 Objectives

The current research assesses the heterogeneous effects of SRL intervention. A review paper by Yeager and Walton (2011) showed the importance of both theory and context, which is why the study relies on the existing theoretical SRL framework proposed by Zimmerman (1990). A recent study indicated that planning is the most essential SRL phase for succeeding in MOOCs (Vilkova, 2019), and for this research, the existing interventions suggested by Kizilcec et al. (2017) and by Kizilcec et al. (2020) were adapted.

The heterogeneous effects of social-psychological intervention suggest that treatment generates beneficial effects for particular students. Thus, the social-psychological interventions created to address the problem of inequality, in some cases, affect students who are more prepared or successful. In traditional educational settings, researchers report heterogeneous effects for students with different characteristics, such as gender (Clark et al., 2020; Schippers et al., 2015), the level of preparation in the subject (van Lent & Souverjin, 2017), socioeconomic status (Jensen, 2010), and having had a year of study at the university (Grove & Wasserman, 2006).

Collectively, in traditional classroom settings, previous studies outline the critical role of students' demographics in the heterogeneous effects of interventions. It is assumed that the same heterogeneous effects that were shown in traditional classroom settings may appear in MOOCs: some students had more benefits from the intervention. However, no research has yet investigated, and hence little is known about, the heterogeneous effects of SRL interventions in MOOCs. While the mechanism of the heterogeneous effects of such interventions in MOOCs has not been established, it was decided to rely on research about MOOC dropouts to formulate the research question for this study.

In the context of MOOCs, these effects might be explained by learner characteristics since studies of retention in MOOCs confirmed that successful learners tend to differ demographically. Research has indicated that males are more successful in MOOCs than females (Semenova & Rudakova, 2016; Watson et al., 2017). Older learners (Morris et al., 2015), learners with higher educational levels (Morris et al., 2015; Semenova & Rudakova, 2016), and those with previous online experience (Semenova & Rudakova, 2016) finish MOOCs at higher rates. Thus, in this study, the following RQ is investigated: Do SRL interventions in MOOCs produce heterogeneous effects by gender, age, education and prior online experience?

4 Methodology

4.1 Procedure

The research was conducted during the 2018/2019 Fall term on the National Platform "Open Education". The experiment ran in three MOOCs: Modern Art, Introduction to Art History, and Marketing. The intervention activities were implemented at the start of the MOOCs. Learners were invited to participate in an online survey. First, self-reported demographics were collected: age, gender, highest achieved education level, and prior experience with MOOCs. Then, learners were randomly assigned to either an experimental or a control group. Learners from the control condition finished the survey. Learners from the experimental condition were guided through an SRL intervention. The text from an

Table 1 The learning process

	Duration, weeks	Course activities	Link
Introduction to art history	11	10 quizzes	https://openedu.ru/course/hse/ART/
Modern art	15	14 quizzes	https://openedu.ru/course/hse/CONTART/
Marketing	11	10 quizzes + 1 project	https://openedu.ru/course/hse/MARK/

intervention that was successfully tested in prior research (Kizilcec et al., 2017, 2020) was translated into Russian. Before the start of the task, learners were guided through a brief instruction. The task consisted of three open-ended questions, after which learners were offered another instruction on how to use their notes. The questions included information about concrete plans to engage with course content, specific steps which a learner wants to take to complete the course, and the possible obstacles along with plans to overcome them.

4.2 The Learning Process

The experiment was conducted in three MOOCs offered by the Higher School of Economics (HSE) University on the National Platform "Open Education" (NPOE). This platform markets itself as a project for MOOCs, designed in accordance with federal state educational standards, which regulate traditional education in Russia. For this reason, NPOE learners enroll at MOOCs on a fixed schedule, which usually starts either in the fall or spring. Consequently, the three MOOCs used for the research do not have many differences. This fact allowed us to use data from the three MOOCs together without thinking about MOOC content because Wong et al. (2021) demonstrated that the effectiveness of SRL interventions depends on MOOC structure.

The MOOC content was divided into modules that were open every week. The three MOOCs slightly differ in duration and in type and number of course activities (see Table 1). Each module consists of a series of video lectures, weekly quizzes, texts, and discussions. Learners are recommended to spend a certain amount of time in MOOCs and to receive grades by taking weekly quizzes. If a learner obtains 60 plus scores on the weekly quizzes, he or she can make the final test. To receive the verified certificate, learners must pass the final test, mediated by an online paid proctor.

4.3 Sample

A total of 25,941 learners enrolled in the three MOOCs, but not all of them replied to the survey invitation. The average response rate (RR) for the online survey was 3.19% (see Table 2). Approximately 88% were female, the mean age was 32 years ($SD = 10.72$), and 80% of learners had at least a bachelor's degree.

A total of 383 learners were randomly assigned to the experimental condition and 444 learners to the control condition.[1] Eighty-nine percent of learners from the experimental condition and 87% of learners from the control condition were female. The mean age of

[1] The unequal number of learners in the experimental and control conditions is associated with the peculiarities of the organization of the online survey.

Table 2 Descriptive statistics of the sample

	N	RR, %	Women, %	Mean age (*SD*)	Learners with higher education, %	Conditions, number of learners	
						Experimental	Control
Modern art	11,756	2.89	85	33 (11.32)	85	152	188
Introduction to art history	9538	3.92	92	31 (10.29)	80	186	188
Marketing	4647	2.43	86	26 (8.45)	65	45	68
Total	25,941	3.19	88	31 (10.72)	80	383	444

learners in the experimental condition was 32 years ($SD=10.94$), and the mean age of learners in the control condition was 31 years ($SD=10.53$). Eighty-two percent of learners from the experimental condition and 78% of learners from the control condition had at least a bachelor's degree. Balance tests indicated that learners from the two conditions did not significantly differ by gender,[2] age,[3] or higher education.[4]

5 Results

5.1 Descriptive Statistics

After the MOOCs started, only 58% of learners completed the week one quiz. In general, the same patterns of learner dropout were exhibited in the three MOOCs. Every week, fewer learners started to take the weekly quizzes. However, we noticed that some MOOC learners were more active. Looking at the data from the last MOOC quiz, we observed that 40% of learners from the Marketing MOOC completed the course, 24% of learners from Introduction to Art History, and 11% of learners from Modern Art.

Figure 1 shows that week-by-week activity patterns of learners from experimental and control conditions look similar. Learners who were guided through the SRL intervention, on average, took the same number of weekly quizzes as learners who were not. In some weeks, learners from the control condition were even more active.

Note. The data for weeks 11-14 for the MOOC Modern Art. Similar to learner activity, average scores for weekly quizzes were progressively lower every week. For example, in the Introduction to Art History MOOC, the mean score for the first quiz was 43 ($SD=41.98$), but for the last quiz, it was only half that ($M=22$, $SD=39.46$). Large standard deviations reflect a large amount of variation between active and nonactive MOOC learners, indicating that data about learners' activity are spread out over a wide range. This situation can be explained by the fact that many learners obtain a score of 0 on quizzes; as a result, they are considered nonactive. Therefore, there were no differences between the experimental and control conditions (see Fig. 2).

Note. The data for weeks 11-14 for the MOOC Modern Art. The final grade for the weekly quizzes was an average calculated from the completed quizzes. The passing

[2] No significant difference: $\chi 2$ (1, $N=827$) = 1.14, $p=0.29$.

[3] No significant difference: t (827) = -1.07, $p=0.15$.

[4] No significant difference: $\chi 2$ (1, $N=827$) = 1.67, $p=0.20$.

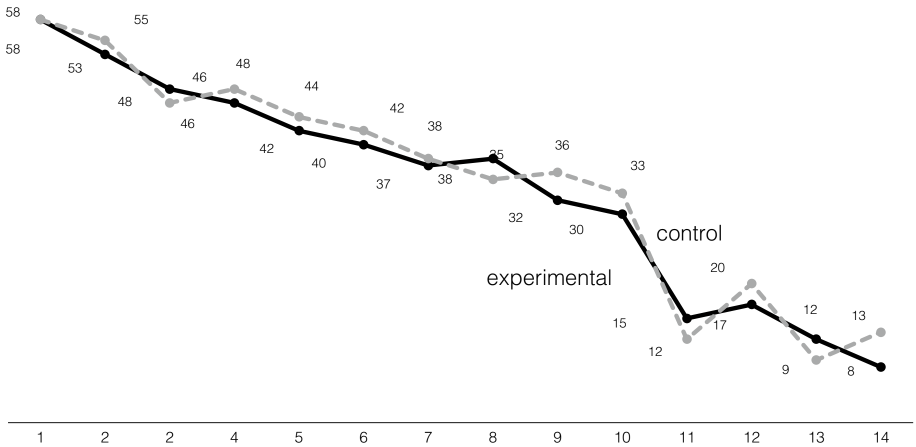

Fig. 1 The share of active learners, %

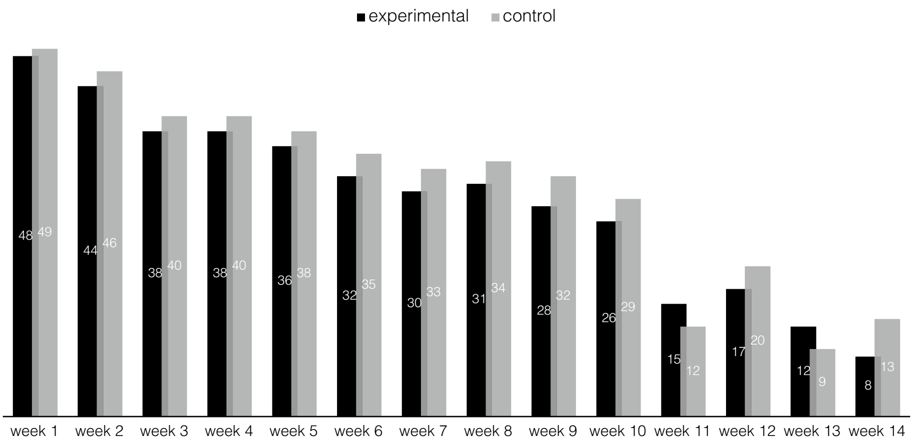

Fig. 2 Average scores for weekly quizzes

threshold for weekly quizzes is a score of 60, which allowed learners to pay for the online proctoring procedure and to take the final test. Overall, only 32% of learners from the three MOOCs passed this threshold. Among the learners from the experimental condition, 30% passed the threshold, as did 34% of learners from the control condition. Similar to learners' activity, during some weeks, learners from the control condition overperformed in the case of average scores for weekly quizzes. These differences can be reasoned by statistical noise. However, a week-by-week comparison of learners from the conditions demonstrated no significant difference in the case of activity and average quiz scores (see Table 3).

It is worth noting that the certification rate was rather low (2.30%). In some MOOCs it was higher (Marketing certification rate = 6.19%), and in others, it was much lower (Introduction to Art History certification rate = 1.60%, Modern Art certification rate = 1.76%). There was no significant difference in the certification rate between learners from the experimental and control conditions (see Table 4). It was assumed that the low certification rate might be explained by the cost of the online proctoring procedure.

Table 3 Differences between experimental and control conditions

Week	% of active learners			Average score (*SD*)		
	Experimental condition	Control condition	Differences	Experimental condition	Control condition	Differences
1	58	58	χ^2 (1, N=827)=0.00, p=0.97	48 (42.32)	49 (43.11)	t (825)=0.50 p=0.69
2	53	55	χ^2 (1, N=827)=0.25, p=0.62	44 (42.31)	46 (42.88)	t (825)=0.72 p=0.76
3	48	46	χ^2 (1, N=827)=0.31, p=0.58	38 (42.32)	40 (43.11)	t (825)=0.73 p=0.35
4	46	48	χ^2 (1, N=827)=0.13, p=0.72	38 (42.45)	40 (43.46)	t (825)=0.62 p=0.73
5	42	44	χ^2 (1, N=827)=0.58, p=0.44	35 (42.72)	38 (43.84)	t (825)=0.90 p=0.82
6	40	42	χ^2 (1, N=827)=0.50, p=0.48	32 (40.72)	35 (41.81)	t (825)=0.86 p=0.80
7	37	38	χ^2 (1, N=827)=0.19, p=0.66	30 (41.30)	33 (42.84)	t (825)=0.88 p=0.81
8	38	35	χ^2 (1, N=827)=0.84, p=0.36	31 (43.20)	34 (44.01)	t (825)=0.90 p=0.82
9	32	36	χ^2 (1, N=827)=1.25, p=0.26	28 (41.21)	32 (43.01)	t (825)=1.27 p=0.89
10	30	33	χ^2 (1, N=827)=0.80, p=0.37	26 (40.99)	29 (42.27)	t (825)=0.89 p=0.81
11	15	12	χ^2 (1, N=254)=0.41, p=0.52	15 (35.41)	12 (32.38)	t (252)= −0.64 p=0.26
12	17	20	χ^2 (1, N=288)=0.49, p=0.49	17 (37.30)	20 (39.94)	t (286)=0.70 p=0.76
13	12	9	χ^2 (1, N=273)=0.52, p=0.47	12 (32.36)	9 (28.84)	t (271)= −0.72 p=0.24
14	8	13	χ^2 (1, N=281)=1.36, p=0.24	8 (27.96)	13 (33.60)	t (279)=1.16 p=0.88

Table 4 Certification rates

Condition	Three MOOCs, %	Introduction to art history, %	Modern art, %	Marketing, %
Experimental	1.57	0	1.97	6.67
Control	2.93[a]	3.19[b]	1.6[c]	5.88[d]

[a]No significant difference: χ^2 (1, N = 827) = 1.70, p = 0.19
[b]Significant difference: χ^2 (1, N = 374) = 6.03, p = 0.01
[c]No significant difference: χ^2 (1, N = 340) = 0.07, p = 0.79
[d]No significant difference: χ^2 (1, N = 113) = 0.03, p = 0.87

Table 5 The outcome variable

	Gender[b]		Higher education[c]	
	Male	Female	No	Yes
% of learners who received 60 plus scores for weekly tests[a]	42	316	32	38

[a]Significant difference in age: χ^2 (54, N = 827) = 73.65, p = 0.04
[b]Significant difference in gender: χ^2 (1, N = 827) = 5.01, p = 0.03
[c]No significant difference in educational level: χ^2 (1, N = 827) = 0.06, p = 0.81

Since there were little data about certification rates, it was decided not to use this as an outcome variable. Instead, the primary outcome measure was the average grade for weekly quizzes, which was dichotomized. Learners who received a score of 60 or higher on the weekly quizzes were considered successful, and learners with a score of 59 or less were unsuccessful. Data from Table 5 show that there were no significant differences in the case of the outcome variable for learners with and without higher education. However, statistical tests revealed significant differences related to learners' gender and age. Males and older learners tended to receive 60 plus scores for weekly tests more often.

5.2 Regression Results

A binary regression was performed to address the RQ regarding whether individual characteristics of MOOC learners can explain the effectiveness of interventions. The outcome variable for the three models was the passing threshold for weekly quizzes. The first model included demographics (gender, age, and educational level) and prior online learning experience. The second model included demographics, prior online learning experience, intervention condition (experimental or control), and a dummy variable reflecting which MOOC the learner intended to complete (Introduction to History of Art was used as a reference group). The third model included demographics, prior online learning experience, an intervention condition, a dummy variable reflecting which MOOC the learner intended to complete, and a number of interaction variables between the intervention condition and demographics and between the intervention condition and the MOOC. These interaction variables allowed to assess the heterogeneous effect of the SRL intervention on learners with different demographic characteristics.

Table 6 VIF statistics

	Model 1 VIF	Model 2 VIF	Model 3 VIF
Gender (1—Male)	1.13	1.13	2.75
Age	6.11	6.46	12.75
Educational level (1—Higher education)	5.61	5.65	13.77
Prior experience with MOOCs (1—No experience)	1.6	1.63	4.12
Intervention condition (1—Experimental)		1.78	13.72
MOOC (1—Introduction to art history)			
Modern art			2.02
Marketing			3.61
Experimental condition * Male			2.81
Experimental condition * Age			17.41
Experimental condition * Higher education			12.82
Experimental condition * No prior experience with MOOCs			3.83
Experimental condition * Modern Art			2.06
Experimental condition * Marketing			3.53

As a preliminary step toward a binary regression, a test for multicollinearity was performed. It was necessary to run a test for multicollinearity because the regression model included a number of predictor variables that overlapped. To avoid false conclusions caused by the inability to distinguish the effects of overlapping variables, the models were checked for the absence of multicollinearity using variance inflation factor (VIF) values. Values of VIF are presented in Table 6. Based on these data, it can be concluded that VIF statistics for most of the variables did not exceed 10, and there was no evidence of multicollinearity (Menard, 2002). The variables with high VIFs are interaction variables, which can be safely ignored (Allison, 2012).

Model 1 demonstrates that demographics such as gender and age significantly predicted learner success (see Table 7). According to the results, males and older learners had a higher probability of obtaining scores above 60 on the weekly quizzes. Educational level and prior experience with MOOCs were not associated with the outcome variable.

Comparing the adjusted R^2 between Model 1 and Model 2, the R^2 predicts that Model 2 was a better model because it had greater explanatory power ($R^2=0.012$ in Model 1 vs. $R^2=0.015$ in Model 2). However, the experimental condition variable was not significant. Other variables stayed the same.

Adding interaction variables to Model 3 also improved the explanatory power ($R^2=0.015$ in Model 2 vs. $R^2=0.03$ in Model 3). Interaction variables between intervention conditions and demographics indicated that some learners received benefits from the intervention, while others did not. Males and older learners from the experimental condition had a higher probability of obtaining scores of 60 and higher on the weekly quizzes. In summary, the intervention was not effective in general, but for particular learners it was.

Table 7 Regression results

	Model 1 OR	Model 2 OR	Model 3 OR
Constant	0.25***	0.27***	0.33**
Gender (1—Male)	1.61*	1.60*	1.93
Age	1.01**	1.02**	1.02
Educational level (1—Higher education)	0.87	0.88	1.33
Prior experience with MOOCs (1—No experience)	1.19	1.19	1.38
Intervention condition (1—Experimental)		0.82	0.27*
MOOC (1—Introduction to art history)			
Modern art			1.03
Marketing			1.93**
Experimental condition * Male			2.09*
Experimental condition * Age			1.02**
Experimental condition*Higher education			1.35
Experimental condition * No experience with MOOCs			1.47
Experimental condition * MOOC (1—Introduction to art history)			
Experimental condition * Modern Art			1.38
Experimental condition * Marketing			1.61
Adjusted R^2	0.012	0.015	0.03

The dependent variable is successful MOOC completion (60 + scores for weekly quizzes)

$N = 799$

OR odds ratio

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$

6 Discussion

Based on successful interventions, this study replicated experiments in MOOC settings. The SRL intervention was inserted into a precourse survey and guided learners from the experimental condition through three writing activities. The research yielded no significant differences overall between experimental and control conditions in the case of weekly quizzes. These results are in line with previous studies about SRL interventions in MOOCs (e.g., Davis et al., 2016; Kizilcec et al., 2016). This study was unable to demonstrate that SRL intervention may lead to gains in learners' achievements, as was shown in some papers (Jansen et al., 2020; Wong et al., 2021; Yeomans & Reich, 2017).

However, some of the prior research was focused on analyzing particular groups of MOOC learners (Jansen et al., 2020; Yeomans & Reich, 2017), focusing on those learners who complied with the SRL intervention. This study paid attention to all learners who participated in the SRL intervention. It was important to investigate such a sample because this study focused on learners with different demographic backgrounds. To answer the RQ, the heterogeneous effects of the SRL intervention for learners with different backgrounds were assessed. Experimental data revealed differences in the benefits from the SRL intervention for particular groups of learners. Males and older learners from the experimental condition received higher scores on weekly quizzes. Females and younger learners showed no benefits from the SRL intervention. However, there were no significant differences in the weekly quiz results based on educational level or prior experience with MOOCs.

In summary, experimental data on learners from three HSE university MOOCs demonstrated that SRL interventions might not work in general, but they provide some learners with greater help. These findings further support the heterogeneous effects but focus on the context of MOOCs, which was not explored in earlier studies. The results of this investigation showed that the heterogeneous effects are prevalent in SRL interventions in regard to learner demographics: males and older learners received advantages from the intervention. Not only do these learners accrue the greatest benefits from the intervention, but previous research has shown that they were already successful in MOOCs. As researchers stated, gender and age served as strong predictors of success in MOOCs (Morris et al., 2015; Semenova & Rudakova, 2016; Watson et al., 2017). These findings are in line with previous studies in traditional classroom settings. As researchers have shown, in some cases, treatment generates beneficial effects for males (Clark et al., 2020; Schippers et al., 2015), more prepared students (van Lent & Souverjin, 2017), and senior students (Grove & Wasserman, 2006).

Despite important conclusions, this study has several limitations. First, the sample of MOOC learners is limited to three courses from one Russian platform. As a result, findings can be generalized to other populations cautiously. Since previous studies demonstrated that self-regulated learning skills can be dependent on the environment (Barnard et al., 2010). Second, this study is partly based on self-report data about self-regulated learning behaviours of MOOC learners. Panadero et al. (2016) noted that such data is retrospective, that is why learners' responses may contain error effects or errors of omission (Sudman & Bradburn, 1973). Finally, the research design was limited to measuring only one construct which is self-regulated learning. However, it is known that other constructs can add more explanations why some learners have a high level of self-regulated learning skills. For example, learners' motivation to pursue MOOCs differs substantially (Semenova, 2021) and may affect their learning process.

Nevertheless, this study provides important contributions to theoretical, practical, and methodological implications of self-regulated learning interventions in MOOCs. The present study provides additional evidence concerning the global achievement gap in MOOCs (Reich & Ruipérez-Valiente, 2019). The results of this investigation show that efforts to establish equal opportunities in MOOCs through self-regulated learning interventions have not been successful. From the theoretical point of view, these findings add more knowledge on how self-regulated learning skills function in the context of MOOCs and how self-regulated learning skills depend on the individual characteristics of MOOC learners. Based on these findings, some practical implications may be suggested. In future investigations, it might be possible to use personalized SRL interventions in MOOCs. The provision of personalized support for learners with particular characteristics (females and younger students) could positively influence their performance. This conclusion match similar finding made in a study by Schumacher and Ifenthaler (2021) in higher education settings.

Additionally, these findings provide several methodological implications such as (1) embedding SRL interventions into the learning process, (2) omitting self-selection bias, (3) learners' engagement with interventions, (4) the evaluation of success in MOOCs, (5) follow-up analysis or longitudinal data on the effectiveness of SRL interventions in MOOCs. Future research should improve the methodology of self-regulated learning interventions in MOOCs.

6.1 Future Research on SRL Interventions in MOOCs

In addition to the heterogeneous effect, there are other possible explanations for the failures of interventions in MOOCs. The underlying reason for the success of some SRL interventions in MOOCs is not always clear. This part of the paper identifies the challenges and limitations of prompts in MOOCs. Conclusions on why SRL interventions have mixed outcomes can be drawn by reviewing the design of existing studies. Based on the experimental replication performed in this paper and the literature review, several methodological issues are proposed.

First, in most studies (including this one), SRL interventions were not a part of the learning process. The intervention was included in a precourse survey, and the invitation to participate in the research was sent to learners' emails. Experiments with interventions in education are usually held in classroom settings, which allow students to make links between prompts and their learning paths. Currently, there are few examples of SRL interventions embedded in MOOCs' structure (see, for example, research by Jansen et al. (2020) and Wong et al. (2021)). It is possible to hypothesize that these conditions are more likely to lead to successful results. Future research should address whether survey-based interventions provide fewer results than platform interventions.

Another disadvantage of interventions included in precourse surveys is self-selection bias, which comes from a voluntary response sample. When learners receive an invitation to complete the survey, they decide whether they volunteer to participate in a study or not. Strong self-selected samples may differ from the population of interest. For example, research by Porter and Whitkomb (2005) indicated that students with higher grade point averages (GPAs) tend to participate in research more often. For interventions in MOOCs, self-selection bias might explain the mixed results. In regard to MOOC survey data, researchers analyze a small proportion of learners. It is possible that survey participants were already more motivated and successful. Further empirical research is needed to assess the quality of survey data in MOOCs.

Third, self-selection bias may affect the effectiveness of SRL interventions. The intervention cannot improve learners' SRL skills when they do not engage with the intervention. As demonstrated previously, even strong integration of the SRL intervention into MOOCs may lead to low intervention engagement (Jansen et al., 2020). To date, there are no data about learners' perceptions of SRL interventions. It is still questionable why some learners engage in such activities more and whether more engaged learners may benefit from interventions more.

The fourth methodological issue of SRL interventions deals with the evaluation of success in MOOCs. Many researchers use data about learners' grades as a proxy of success in MOOCs. Assessing the effectiveness of SRL interventions, most researchers still rely on the same measures. However, such an approach does not account for learners' intentions and behaviors. As Reich (2014) showed, many learners only intend to browse the course. Based on learners' interaction with course items, many of them can be classified as "Auditing": they watch lectures but do not complete tests (Kizilcec et al., 2013). Future research must take a more holistic view of MOOC completion. Based on the platform data about viewing video lectures, participating in forum discussions, and completing weekly quizzes, researchers could evaluate the effectiveness of interventions for learners with different intentions.

Finally, little is known about SRL interventions in MOOCs with follow-up analysis or longitudinal data. Repeated exposure to SRL prompts should increase the chances of success. For example, SRL intervention could be repeated every week, helping learners stay in MOOCs. It is also suggested that longitudinal data might shed light on the effectiveness of interventions in long-term conditions. See, for example, work by Cazan (2020), who investigated the effects of a prolonged SRL intervention in traditional higher education settings.

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Data Availability The datasets generated and/or analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The author declares that there is no conflict of interest regarding the publication of this article.

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