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Self-Regulated Learning in MOOCs: Measurement, Links to Educational Outcomes, and Skills Promotion through Interventions

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List of Publications

1. Vilkova, K. (2019). Self-regulated learning and successful MOOC completion. In *EMOOCs 2019 Work in Progress Papers of Research, Experience and Business Tracks*, Vol. 2356 (pp. 72-78).
2. Vilkova, K. (2020). Measuring self-regulated learning: a review of questionnaires. *Journal of Modern Foreign Psychology, 9*(2), 123–133 (in Russian).
3. Vilkova, K., & Shcheglova, I. (2021). Deconstructing self-regulated learning in MOOCs: In search of help-seeking mechanisms. *Education and Information Technologies, 26*(1), 17-33. https://doi.org/10.1007/s10639-020-10244-x
4. Vilkova, K. (2022). The Promises and Pitfalls of Self-regulated Learning Interventions in MOOCs. *Technology, Knowledge and Learning, 27*(3), 689-705. https://doi.org/10.1007/s10758-021-09580-9.

Conferences, where research results were presented

1. European MOOCs Stakeholders Summit (EMOOCs), 20-22.05.2019, Naples, Italy. Presentation: Self–regulated learning and successful MOOC completion.
2. The 2nd Russia-China Education Research Conference “Digital Transformation of Education and Artificial Intelligence”, 26-27.09.2019, Moscow, Russia. Presentation: Measuring self-regulated learning among Russian students.
3. International diversity in teacher and higher education research in the 21st century Conference: insights from doctoral students, supervisors, and doctoral school leaders, 4-5.12.2020, Budapest, Hungary (online). Presentation: Who benefits from social-psychological interventions in MOOCs?
4. St. Petersburg International Conference on Inequality and Diversity, 11-13.11.2021, Saint-Petersburg, Russia (online). Presentation: The promises and pitfalls of self-regulated learning interventions in MOOCs.

Introduction

Massive Open Online Courses (MOOCs)[1] were created to provide access to high-quality educational resources for everyone (Kay et al., 2013). It was expected that learners would be able to organize their learning process and study the materials at a convenient pace (Lee, Watson, & Watson, 2018). However, numerous studies demonstrate that the vast majority of learners do not finish MOOCs (Reich & Ruipérez-Valiente, 2019) and do not achieve their goals (Semenova, 2021). Researchers state that the lack of self-regulated learning (SRL) skills is one of the main reasons why many learners do not complete MOOCs and do not reach their goals (Pérez-Álvarez, Maldonado-Mahauad, Sapunar-Opazo, & Pérez-Sanagustín, 2017).

SRL is a process during which students set learning goals, and then monitor, regulate and control their knowledge, intentions and behavior, guided not only by their goals, but also by the characteristics of the environment (Pintrich, 2000). Highly SRL learners have the ability to plan, monitor, and manage their learning process (Wang, Shanonn, & Ross, 2013). They 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 is convincing evidence that MOOCs learners with high SRL skills respond differently to a learning situation than their coursemates with lower SRL skills (Pérez-Sanagustín et al., 2020). At the same time, there is growing evidence that many learners lack SRL skills (Littlejohn & Milligan, 2015). The importance of SRL skills for successful MOOCs completion led to the emergence of a large number of research on this topic (e.g. Cerón et al., 2020; Pérez-Álvarez, Maldonado-Mahauad, Sapunar-Opazo, & Pérez-Sanagustín, 2017; Maldonado-Mahauad et al., 2018; Milligan, Littlejohn, & Margaryan, 2013; Littlejohn, Hood, Milligan, & Mustain, 2016; Wong et al., 2021). However, despite this attention to SRL in MOOCs, the conclusions are limited due to the insufficient number of questionnaires for measuring SRL in the MOOCs context. Also it is not completely clear which SRL phase is associated with the educational outcomes of MOOCs learners. Finally, the third problem is considered to be the contradictory results of SRL interventions in MOOCs (e.g. Davis, Chen, Van der Zee, Hauff, & Houben, 2016; Kizilcec & Cohen, 2017; Wong et al., 2021), which can

[1] In this study, we focus on xMOOCs. These MOOCs are similar to traditional offline courses, assume large enrollments, and are asynchronous. We use the abbreviation MOOCs to refer to this type of courses, since xMOOCs are the most common type of MOOCs.

demonstrate heterogeneous effects when the treatment generates beneficial effects for particular learners.

This thesis is aimed at 1) the identification of a reliable and valid tool for measuring SRL in the MOOCs context; 2) the study of the relationship between SRL phases and educational outcomes; 3) the presentation of SRL interventions which can boost these skills and improve educational outcomes of MOOCs learners.

Literature review and the novelty of the research

The research on self-regulation in the educational context originates in the works of A. Bandura (Bandura, 2005), who is the author of the social-cognitive theory. He links SRL with the interaction between cognitive, behavioral, and environmental factors. Later, these ideas were developed by B. Zimmerman and P. Pintrich, who proposed the SRL models (Zimmerman, 1990; Pintrich, 2000). Their main advantage is the operational indicators that are used to measure SRL. In turn, this allows us to create questionnaires based on the proposed theoretical models.

In the Russian tradition, SRL is understood as a special type of educational activity and is embodied in the actions of control and evaluation (Davydov & Markova, 1981). However, this research on SRL (Bozhovich, 2001; Zuckerman, 2010; Morosanova, Fomina, & Tsyganov, 2017) have limitations associated with the lack of operational indicators and questionnaires which measure SRL in the online environment.

The idea of the important role of SRL in the learning process was first developed in research on offline learning (Zimmerman, 1990). When blended and online learning formats emerged, researchers started to pay attention to the relationship between SRL skills and educational outcomes (Barnard et al. 2009). It was demonstrated that SRL serves as the essential skill to succeed in MOOCs (Littlejohn & Milligan, 2015).

In the MOOCs context the research on SRL can be divided into three streams: measurement, links to different variables (including educational outcomes), and skills promotion through interventions. In the first stream researchers create and adapt different questionnaires to measure SRL (e.g. Littlejohn, Hood, Milligan, & Mustain, 2016), use non-reactive data to analyze patterns of SRL behavior (e.g. Maldonado-Mahauad et al., 2018). The second stream is devoted to the links between SRL and dropout (Maldonado-Mahauad et al., 2018), educational outcomes (Guo & Wu, 2015), motivation (Littlejohn & Milligan, 2015), and goal attainment (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). In the third stream researchers suggest SRL interventions which could boost SRL skills and improve educational outcomes of MOOCs learners (Davis et al., 2016; Yeomans & Reich, 2017; Jansen et al., 2020; Wong et al., 2021).

The literature review on SRL in the MOOCs context allows us to make three conclusions. First, there is an insufficient number of validated questionnaires for measuring SRL. Second, there is a lack of data about the relationship between SRL skills and educational outcomes of MOOCs learners. Third, there are contradictory results on the effectiveness of SRL interventions in MOOCs.

The novelty of this thesis is the following: 1) we present the valid questionnaire which allows us to measure SRL in the MOOCs context; 2) we assess the link between SRL and educational outcomes in MOOCs; 3) we explain contradictory results of SRL interventions in MOOCs. The novelty of this research is the exploration of SRL in the MOOCs context. Previous results on SRL in offline and online formats cannot be transferred to the MOOCs context for the following reasons. First, despite the course structure set by MOOCs instructors, learners are independent in choosing the time, place, and pace of learning. Second, there is limited interaction between groupmates and instructors in MOOCs (Baker et al., 2018; Breslow et al., 2013; Qui et al., 2016).

Aim and objectives of the study

This study **aims** to explore: 1) the possibilities for measuring SRL in the MOOCs context; 2) the link between SRL and the test scores of MOOCs learners; 3) the possibilities to promote SRL through an intervention to improve the test scores of MOOCs learners.

The objectives of the study:

1. To find the most suitable questionnaire for measuring SRL in the MOOCs context.

The MOOC format differs from online learning, that is why not all of the existing questionnaires can be used to measure SRL in this format. I analyzed theoretical and empirical research related to SRL measurement and identified two questionnaires. The most suitable questionnaires for measuring SRL in the MOOC format were presented in the following works: "Online Self-Regulated Learning Questionnaire" (OSLQ) by Barnard et al. (2009) and "Self-Regulated Learning in MOOCs Questionnaire (SRLMQ)" by Littlejohn, Hood, Milligan, and Mustain (2016) .

Publication: Vilkova, K. (2020). Measuring self-regulated learning: a review of questionnaires. *Journal of Modern Foreign Psychology, 9*(2), 123–133. https://doi.org10.17759/jmfp.2020090211 (in Russian).

2. To ensure the validity of the Online Self-Regulated Learning Questionnaire in the MOOCs context.

Since the MOOC environment does not allow participants to interact easily with other learners and instructors for better social engagement (Baker et al., 2018; Breslow et al., 2013; Qui et al., 2016), we assumed that SRL might have a different structure from the one proposed by Barnard and colleagues (2009). We hypothesized that 'help-seeking' subscale might not be useful to assess SRL skills of MOOCs learners. Based on the results of binary regression analysis, we conclude that the five-factor hierarchical model is more appropriate for the current MOOCs context than the six-factor hierarchical model for the current MOOCs context.

Publication: Vilkova, K., & Shcheglova, I. (2021). Deconstructing self-regulated learning in MOOCs: In search of help-seeking mechanisms. *Education and Information Technologies, 26*(1), 17-33. https://doi.org/10.1007/s10639-020-10244-x.

Contribution: adaptation of the OSLQ into Russian, literature review, data analysis, writing methodology and results sections.

3. To assess the links between SRL phases of the B. Zimmerman's model and the test scores of MOOCs learners.

The impact of the particular SRL phase on test scores in MOOCs is yet unclear. So we decided to assess the links between the SRL phases (forethought, performance, and self-reflection) and test scores. Based on binary regression results, we can conclude that the only one SRL phase, which is forethought, is statistically significant in the regression model, while performance and self-reflection do not predict learners' test scores. It is widely known that SRL phases work only together (Zimmerman, 1990). However we can pay attention to a particular phase, for example, during interventions.

Publication: Vilkova, K. (2019). Self-regulated learning and successful MOOC completion. In *EMOOCs 2019 Work in Progress Papers of Research, Experience and Business Tracks*, Vol. 2356 (pp. 72-78).

4. To assess the heterogeneous effect of the SRL intervention in MOOCs.

Despite the variety of SRL interventions in MOOCs, the current research demonstrates mixed results (e.g., Davis et al., 2016; Kizilcec & Cohen, 2017; Wong et al., 2021). Based on the analysis of the previous data (Clark et al., 2017; Schippers et al., 2015; van Lent & Souverjin, 2017; Jensen, 2010; Grove & Wasserman, 2006) we assumed that SRL interventions in MOOCs might affect different experimental subjects in different ways. According to binary regression results, experimental data revealed differences in the benefits from the SRL intervention for particular groups of learners. Under experimental conditions, males and older learners received higher scores on weekly tests.

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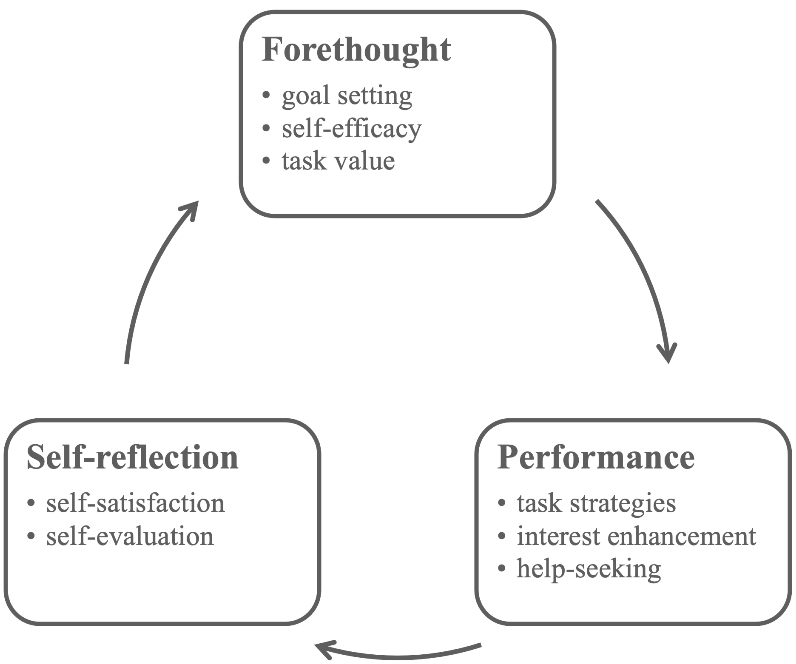
Theoretical framework

This study is based on the social cognitive theory (Bandura, 2005). The concept of SRL appeared within the framework of this theory at the end of the 1980s (Panadero, 2017). According to the social cognitive theory, the process of self-regulated learning is associated not only with the personal characteristics of students, but also with their behavior during the learning process, as well as with environmental stimuli. This study utilizes the conceptual model of SRL proposed by B. Zimmerman (1990). We chose this model for the following reasons. First, this model is not only the most common among researchers, but also the most developed from a theoretical point of view (Panadero, 2017). Secondly, its use in this research will allow us to join the discussion on SRL, while filling the gap in the knowledge about SRL in the MOOCs context.

According to Zimmerman (1990), SRL can be described through the actions that students perform during the learning process, which consists of three cyclical phases: forethought, performance, and self-reflection (see Figure 1).

Figure 1.
SRL model (Zimmerman, 1990)



Each of the phases integrates affective, behavioral or cognitive sub-processes. Forethought phase includes goal setting, self-efficacy, and task value. Performance phase combines task strategies, interest enhancement, and help-seeking. Self-reflection phase consists of such cognitive factors as self-satisfaction and self-evaluation. This model assumes that SRL is a cyclical process: during the learning process, each of the phases appears one after another, combining the results of the previous ones.

Key variables

Educational outcomes in MOOCs can be measured as following indicators: obtaining a certificate of completion (Kizilcec & Cohen, 2017), the fact of enrollment in other courses (Hart et al., 2019), satisfaction with learning (Semenova & Vilkova, 2019), goals achievement (Semenova, 2021), test scores (Ismail, 2021). The latter indicator is the most common in MOOCs (Guo & Wu, 2015). That is due to the fact that test scores are the data that are protected from distortion (they may occur, for example, in a survey about satisfaction). Therefore, we will use test scores as a proxy of educational outcomes in MOOCs urther in the text. At the same time, this indicator has a number of disadvantages, which are primarily related to the various goals of MOOCs learners, and are described in more detail in the limitations section.

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 the following: researchers create positive and reinforcing exercises, which reframe the student experience. In MOOCs 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).

The heterogeneous effect of an intervention suggests that treatment generates benefits for particular students. Thus, the intervention created to address the problem of inequality, in some cases, affects 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 a year of study at the university (Grove & Wasserman, 2006).

Research methodology and design

Three sets of secondary quantitative data were used as an empirical basis for this study.

Online-survey of MOOCs learners enrolled in online-courses on the National Open Education Platform (NOEP) in 2017. The total number of qualified respondents is 913. The sample included 68% of female students, the average age is within the range 19-22 years and the majority of the respondents are pursuing their Bachelor degree.

In this survey we asked learners about their demographics (sex, age, educational level) and assessed learners' level of SRL skills using the Online Self-Regulated Learning Questionnaire – OSLQ (Barnard et al., 2009; Vilkova & Shcheglova, 2021). The OSLQ consisted of 20 items which measure six SRL subscales (goal setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation). The full list of items is presented in Appendix 2. Respondents ranked items on a five-point Likert scale ranging from 1 – strongly disagree to 5 – strongly agree.

The first dataset was used to ensure the validity of the Online Self-Regulated Learning Questionnaire in the MOOCs context (objective no.2). We applied confirmatory factor analysis (CFA) to test the structure of the questionnaire. We tested two CFA models: the original six-factor hierarchical or second-order model suggested for the OSLQ in Barnard et al. (2009) and the alternative five-factor hierarchical model. First, we estimated the fit between the models and the observed data. Three conventional statistics, reflecting the model fit, were reported: the root mean square error of approximation (RMSEA), the Tucker Lewis Index (TLI), and the Comparative Fit Index (CFI). We relied on the following values of statistics which indicated the acceptable fit (Byrne 2010; Schreiber et al. 2006): RMSEA close or below .06 (.08) with confidence interval, TLI and CFI close or above .90 (.95). Second, we calculated the standardized path coefficients from the latent variable constructs to the items, and from the higher order construct to the latent variable constructs. Third, we determined which model better fits the data. We compared them using three standardized fit indexes: RMSEA, TLI and CFI. According to Schreiber et al. (2006), the smaller these indexes are, the better the model fits the data.

Online-survey of MOOCs learners enrolled in 24 online-courses by HSE University on the National Open Education Platform (NOEP) in 2017. A total of 2815 learners participated in the study and completed an online-survey (response rate = 5%). The average age was 31 (*SD* = 10), 73% were females and 81% held a bachelor's or higher degree.

The survey included demographic questions such as sex, age, educational level, and previous online-learning experience. We also assessed learners' level of SRL skills using the Self-Regulated Learning in MOOCs Questionnaire – SRLMQ (Littlejohn, Hood, Milligan, & Mustain, 2016), which we adapted into the Russian language[2]. The questionnaire consists of 29 items which measure three SRL phases suggested by B. Zimmerman (1990). The full list of items presented in Appendix 3. Respondents ranked items on a four-point Likert scale ranging from 1 – strongly disagree to 4 – strongly agree.

Then we merged survey data and learners test scores. This dataset was used to assess the links between the SRL phases of the B. Zimmerman's model and the test scores of MOOCs learners (objective no.3). We performed a binary regression model, the dependent variable was learners' results on test scores; SRL scores were used as independent variables for each phase (forethought, performance, self-reflection). Sex, age, educational level, and previous online-learning experience were included into the model as control variables.

Randomized control trial of three MOOCs by HSE University on the National Open Education Platform (NOEP) conducted during the 2018/2019 Fall term. A total of 25,941 learners enrolled in the three MOOCs (Modern art, Introduction to History of Art, and Marketing), but not all of them replied to the survey invitation. The average response rate (RR) for the online survey was 3%.

Approximately 88% were female, the mean age was 32 years (*SD* = 11), and 80% of learners had at least a bachelor's degree.

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. A total of 383 learners were randomly assigned to the experimental condition and 444 learners to the control condition. Learners from the control condition finished the survey. Learners from the experimental condition were guided through an

[2] This paper (Vilkova, 2019) was not focused on the adaptation procedure of the SRLMQ, so it does not contain any information on it. Please see Appendix 4 for more detailed description of the adaptation process.

SRL intervention (see Appendix 5 for more detailed description of the intervention). A review paper by Yeager and Walton (2011) showed the importance of both theory and context, which is why the research 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 text from an intervention that was successfully tested in prior research (Kizilcec et al., 2017, 2020) was translated into Russian. Learners were guided through a brief instruction before the start of the task. 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.

This dataset was used for the assessment of the heterogeneous effect of the SRL intervention in MOOCs (objective no.4). A binary regression was performed to address whether individual characteristics of MOOCs learners can explain the effectiveness of the intervention. The outcome variable for the three models was the passing threshold for weekly tests. The first model included demographics (sex, 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 us to assess the heterogeneous effect of the SRL intervention on learners with different demographic characteristics.

The learning process on the National Open Education Platform (NOEP)

This platform markets itself as a project for MOOCs, designed in accordance with the federal state educational standards, which regulate traditional education in Russia. For this reason, NOEP learners enroll at MOOCs on a fixed schedule, which usually starts either in the fall or spring. MOOCs on this platform are somewhat longer than, for example, on Coursera or edX. If on the latter the standard length of MOOCs is about 8 weeks, then on NOEP it is more than 10 weeks.

Despite the fact that NOEP is positioned as a MOOC platform for university students, according to our survey data, the average age of learners exceeds 30 years, and most of them already have at least a bachelor's degree. So we can conclude that these MOOCs attract an educated middle-aged audience.

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. The MOOC content was divided into modules that were open every week. MOOCs slightly differ in duration and in type and number of course activities. Each module consists of a series of video lectures, weekly tests, texts, and discussions.

Learners are recommended to spend a certain amount of time in MOOCs and to receive grades by taking weekly tests. If a learner obtains 60 plus scores on the weekly tests (out of 100 scores), 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. The certification rate was rather low (8% in the second dataset and 8% in the third dataset), that is why we decided to use test scores as an outcome variable. Since it was not normally distributed, we recorded it into a dichotomous variable, where 0 refers to 59 and less scores for weekly tests, 1 refers to 60 plus scores for weekly tests.

Limitations

This study has some limitations.

First, this study is based on the self-report data about SRL behaviors of MOOC learners. Such data is retrospective, that is why learners' responses may contain error effects or errors of omission (Panadero, Klug, & Järvelä, 2016).

Second, two different questionnaires which measure SRL were used for two objectives (no.2 and no.3). The Online Self-Regulated Learning Questionnaire is more popular among researchers of online learning. However the MOOCs format differs from online learning, so it was validated for further use in the MOOC context (objective 2). The Self-Regulated Learning in MOOCs Questionnaire is based on B. Zimmerman's SRL model, therefore it was used to find the links between SRL phases and test scores of MOOCs learners (objective 3). We did not have the opportunity to include all the statements of the Self-Regulated Learning in MOOCs Questionnaire in the survey, therefore, during the adaptation process, it was decided to shorten it, see more details about the deleted items in Appendix 3.

Third, as most of previous research (e.g. Kizilcec & Cohen, 2017; Yeomans & Reich, 2017) this study assesses the effectiveness of the SRL intervention based on learners' test scores. However, not every learner is eager to get a certificate, so learners' motivation may differ (Reich, 2014; Semenova, 2021).

Fourth, there is no control over variables related to the characteristics of the platform and the course (for example, the instructional quality of MOOCs and digital accessibility of content). We did not study how MOOCs are presented on the platform, how the materials are arranged, or how accessible they are to learners with different health capabilities. Since these variables were not included in the analysis, we cannot say how they mediate the conclusions.

However, it is worth noting that these limitations are not serious obstacles to obtaining valid conclusions.

Main findings

Questionnaires for measuring SRL in the MOOCs context

Every year the term ‘self-regulated learning’ becomes more common among researchers (Vilkova, 2020). Various assessment tools were created to measure SRL: questionnaires, interview protocols, and think-aloud techniques. In the vast majority of papers, the authors rely on self-report data, which are measured using questionnaires (Roth, Ogrin, & Schmitz, 2016). This is due to both the ease of their use and the quantitative design of the studies (Roth, Ogrin, & Schmitz, 2016).

Among the most popular questionnaires are the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993), the Learning and Study Strategies Inventory (Weinstein, Palmer, & Acee, 2016), the Online Self-Regulated Learning Questionnaire (Barnard et al., 2009), the Academic Self-Regulation Scale (Magno, 2010), the Self-Regulated Learning in MOOCs Questionnaire (Littlejohn, Hood, Milligan, & Mustain, 2016). Appendix 1 presents the comparison of these questionnaires in case of internal structure, number of items, and theoretical framework.

Authors of these questionnaires propose to measure SRL as a multidimensional construct. However, the analysis of these questionnaires shows that at the moment there is no common understanding of the term "self-regulated learning" (Vilkova, 2020). Each of the questionnaires is a reflection of the authors' ideas about the internal structure of this construct. They are based on different conceptual models proposed by Pintrich (Pintrich et al., 1993) or Zimmerman (Zimmerman, 1990), some questionnaires do not provide information about the theoretical foundations. As a result, differences in understanding of what is SRL impose a number of limitations on existing research. Thus, it is difficult to compare the results which were obtained using different questionnaires.

Another open question is the possibility of using the same questionnaires in different educational contexts. Initially, most of them were created to measure university students’ SRL and in the traditional education format. However, the emergence of new formats (blended and online) raised the need to create a new questionnaire. The Online Self-Regulated Learning Questionnaire – OSLQ (Barnard et al., 2009) has become widely used among researchers of online learning. However, currently, there is no reliable information about the possibility of using this questionnaire in the MOOC context, so it requires additional research on its validation.

Barnard and colleagues (2009) conceptualize SRL as acomplex construct consisting of six dimensions: environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation. Since the items of the questionnaire form a hierarchical model, both the total score and individual scores for its subscales can be used to measure SRL. According to Barnard and colleagues (2009), this questionnaire was designed to measure SRL among students who study in blended and online formats.

The OSLQ was used in both cross-sectional (e.g. Kintu & Zhu, 2016; Onah & Sinclair, 2016) and longitudinal (Tabuenca et al., 2015) studies. Also, the OSLQ was adapted into the Turkish (Korkmaz & Kaya, 2012), Romanian (Cazan, 2014), Russian (Martinez-Lopez et al., 2017) and Chinese (Fung et al,. 2018) languages. However, to the best of our knowledge, none of the previous studies managed to provide comprehensive evidence of the validity of OSLQ.

Another disadvantage of the OSLQ is the lack of information about its theoretical background. Barnard and colleagues (2009) do not report which of the SRL models was used for the development of the questionnaire. At the same time, for some research questions in the MOOCs contexts, the theoretical background of the questionnaire can become a key factor. Therefore, some MOOCs researchers prefer to use the Self-Regulated Learning in MOOCs Questionnaire (SRLMQ) created by Littlejohn and colleagues (2016). The SRLMQ is a modified version of the questionnaire for measuring SRL in informal learning settings. Its items form three phases corresponding to Zimmerman's model (forethought, performance, self-reflection). SRLMQ was used to study the relationship between SRL and motivation (Littlejohn, Hood, Milligan, & Mustain, 2016), dropout (Reparaz, Aznárez-Sanado, & Mendoza, 2020), and the learning strategies (Milligan & Littlejohn, 2015).

To sum up, the OSLQ is more popular among researchers of online learning. However MOOCs format differs from online learning, that is why it is necessary to validate this questionnaire for further use (objective no.2). However, we cannot use this questionnaire for assessing the link between the SRL phases of Zimmerman’s model and test scores. That is why we decided to use SRLMQ for the objective no.3.

The validity of the Online Self-Regulated Learning Questionnaire in the MOOCs context

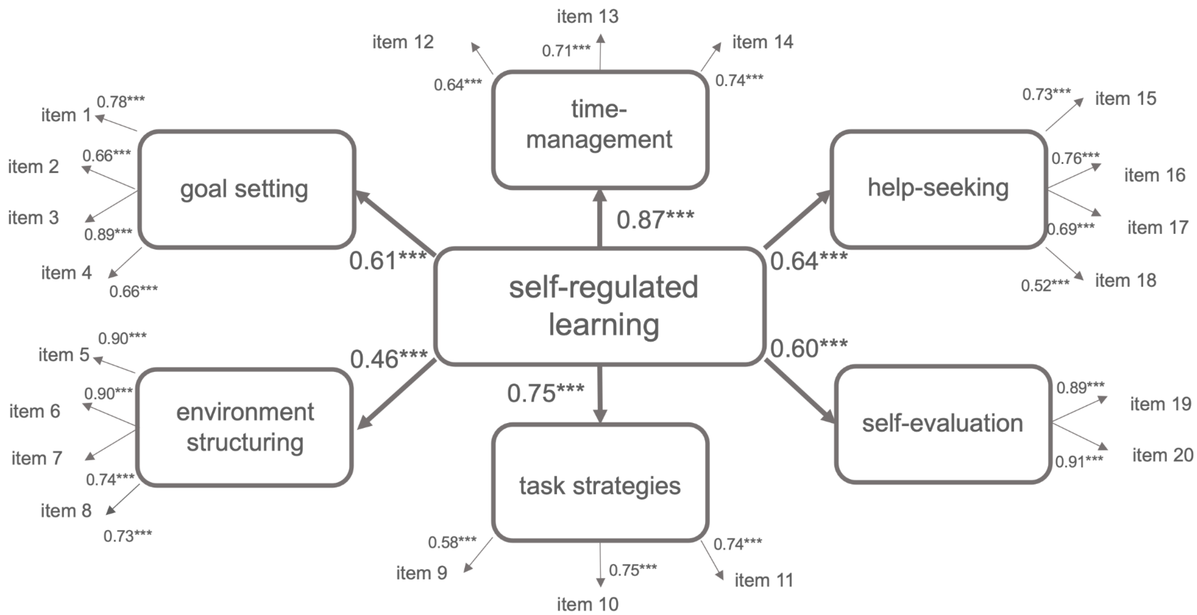
Based on previous research on interaction between MOOCs instructors and learners, we assumed that the OSLQ might have a different structure from the one proposed by Barnard and colleagues (2009). The subscale 'help-seeking' which measures offline or online meetings with groupmates and communication with instructors might be redundant in MOOCs since the MOOCs environment does not allow participants to interact easily with other learners and instructors for better social engagement (Baker et al., 2018; Breslow et al., 2013; Qui et al., 2016). For example, Baker and colleagues (2018) demonstrated that only 7% of learners received feedback from instructors. Moreover, researchers also found that learners rarely use MOOCs forums: 90% of actions on forums refer to viewing information that has already been written (Breslow et al., 2013), 94% of MOOCs learners have never written anything on forums (Qui et al., 2016). Based on the studied literature, we hypothesize that help-seeking subscale might not be useful in assessing SRL skills among MOOC learners, and the five-factor hierarchical model is more appropriate instead of the six-factor hierarchical model for the current MOOCs context.

We tested two models of the OSLQ: the original six-factor model (or second-order model) which was suggested by Barnard and colleagues (2009) and the alternative five-factor model. The following procedures allowed us to analyze the internal structure of the OSLQ in the MOOCs context.

The six-factor model of the OSLQ is presented on Figure 2. The values of fit-statistics indicate an unacceptable fit between the model and the observed data, RMSEA = .08 (.08; .09), CFI = .88, and TLI = .86. Each of the fit indexes exceeds the cutoff criteria suggested by Byrne (2010) and Schreiber and colleagues (2006). The results do not support the original six-factor hierarchical model in the MOOCs context. At the same time, it is worth noting that there is another explanation for the poor quality of this model: two items 17-18 have a fairly high covariance (0.81).

Figure 2.

The six-factor model (N = 913).

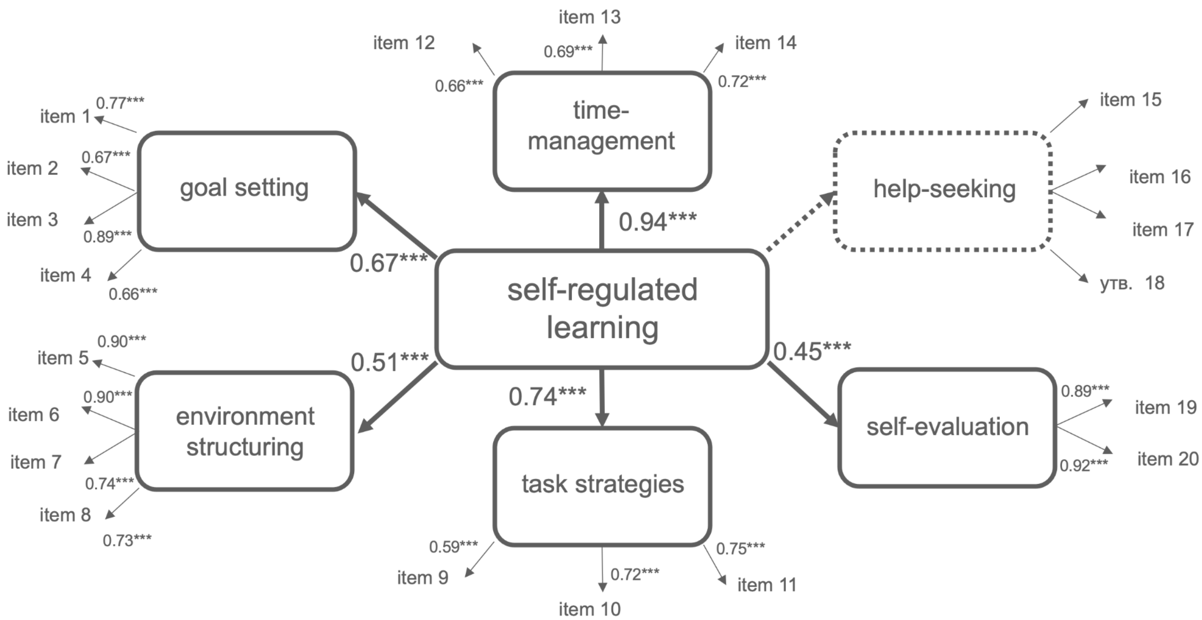


Note. $\chi^2(164) = 1200.68$, $p = .00$; RMSEA = .08 (.08; .09), CFI = .88, and TLI = .86.
*** $p < .001$

Then we tested the five-factor model of the OSLQ. The six-factor hierarchical model was modified by removing the help-seeking subscale from the model. The values of fit-statistics indicate an acceptable fit between the five factor hierarchical model and the observed data, RMSEA = .07 (.06; .07), CFI = .94, and TLI = .93. Figure 3 presents the standardized path coefficients from the latent variable constructs to the items and between the constructs. The paths in the second model are all significant ($p < .001$) with standardized values ranging from .59 to .92 from the first-order factors to the items, and standardized values ranging from .45 to .94 from the second-order factor to the first-order factors.

Figure 3.

The five-factor model (N = 913)



Note. $\chi^2(99) = 513.09$, $p = .00$; RMSEA = .07 (.06; .07), CFI = .94, and TLI = .93.
*** p < .001

Next, we determined which model better fits the data. Table 1 provides the fit indexes for each of the models. According to the standardized fit indexes' values, the second model better fits the data. The five-factor hierarchical model gives a better approximation and interpretation of our data about SRL behavior among MOOC learners. Therefore, we suggest a redefined model of the OSLQ for MOOC learners, because help-seeking skills appear to be irrelevant in this context.

Table 1.

Comparison of model fit indices

	RMSEA (lower bound; upper bound)	CFI	TLI	AIC	BIC
Six-factor hierarchical model	.08 (.08; .09)	.88	.86	53558.51	53876.41
Five-factor hierarchical model	.07 (.06; .07)	.94	.93	42103.73	42359.02

The links between SRL phases of the B. Zimmerman's model and test scores of MOOCs learners

In the MOOCs context, researchers have not treated SRL in much detail: they tend to use a sum variable instead of particular phases, which were originally suggested. In the traditional educational context there are a number of works related to this problem (e.g. Olakanmia & Gumboa, 2017; Peters, 2012). For example, it was demonstrated that during offline classes the forethought phase is the most important SRL phase (Olakanmia & Gumboa, 2017; Peters, 2012).

To assess the links between SRL phases of the B. Zimmerman's model and test scores of MOOCs learners, we used both survey data and learners test scores obtained from the platform. Test scores serve as dependent variable, scores on SRL phases as independent variables, and sex, age, educational level, and prior online-learning experience as control variables. This study examined a binary logistic regression model for learners' test scores in MOOCs, explained by SRL phases and demographics. The following regression equation was suggested:

$$Ln\ (p_i\ (\text{test scores})/1 - p_i) = \beta_0 + \beta_1 \text{ x } \textit{forethought} + \beta_2 \text{ x } \textit{performance} + \beta_3 \text{ x } \textit{self-reflection} + \beta_4 \text{ x } \textit{age} + \beta_5 \text{ x } \textit{sex} + \beta_6 \text{ x } \textit{higher education} + \beta_7 \text{ x } \textit{prior online-learning experience} + \varepsilon_{\mathrm{i}}$$

According to the results, 45% of learners received 60 plus scores on weekly tests. Average scores on SRL phases were rather low: forethought $M = 12$ ($SD = 1$), performance $M =$

11 (*SD* = 1), self-reflection *M* = 11 (*SD* = 2). Regression results are presented in the Table 2 below.

Table 2.
Regression results

	OR	*β*	*S.E.*	*z*
SRL phases				
Forethought	1.12**	.03**	.01	8.54
Performance	.97	–.01	.01	–2.33
Self-reflection	.98	–.01	.02	–1.28
Control variables				
Age	1.01**	.01**	.01	3.21
Sex (1 – male)	1.15	.03	.10	1.59
Higher education (1– yes)	1.18	.04	.13	1.50
Prior online-learning experience (1 – yes)	.74**	–.07**	.06	–3.72
Constant	.04**	–.27**	.01	–8.16

Notes. The dependent variable is test scores, where 0 – 59 scores and less, 1 – 60 plus scores.
OR – Odds Ratio.
$\chi^2 = 127.73$, $df = 7$, $p = 0.00$.
Pseudo $R^2 = 0.03$.
$N = 2815$.
** $p < .01$.

Binary regression results demonstrate that higher test scores are associated with such control variables as age and no prior online-learning experience. We can assume that older learners have higher levels of SRL skills, which, in turn, provide higher test scores. We can also hypothesize that learners who did not have any prior online-learning experience may be more successful due to the fact that they did not experience failure. Since most of MOOCs learners, both with and without prior experience, did not complete these courses. To sum up, older learners and learners without prior online-learning experience have more chances to get 60 plus scores on weekly tests. Such demographics as sex and educational level do not make a significant contribution to obtaining high results on tests.

The results demonstrated that out of three SRL phases the forethought one is statistically significant at $p < .01$. This indicates the forethought phase significantly predicts learners' test scores, taking into control demographics characteristics. To assess the effect of the forethought phase on the outcome variable, other variables remained constant. The results of binary logistic regression showed that the odds to get 60 plus scores on weekly tests were 1.12 times higher for learners with a high level of forethought. Other phases, which are performance and self-reflection, were not statistically significant.

This finding allows us to conclude that the forethought phase is the most valuable SRL skill for obtaining high test scores in MOOCs. This result does not negate the importance of other phases, since phases of B. Zimmerman's model cannot exist separately from each other. However, highlighting the link of the forethought phase with test scores can explain the existing mechanism of dropout in MOOCs. Previous studies have shown that the proportion of active MOOC listeners decreases every week (Wong et al., 2019). It can be assumed that not all learners are able to plan their learning process. The lack of a clear plan does not allow them to move on to the next SRL phases – performance and self-reflection. As a result, the cyclic process of SRL is disrupted.

The heterogeneous effect of the SRL intervention in MOOCs

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), for example, using interventions. Social-psychological interventions (or prompts) are "brief exercises that target students' thoughts, feelings, and beliefs in and about school" (Yeager & Walton, 2011, p. 267).

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.

The heterogeneous effect of an intervention suggests 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 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 effect 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 the research about MOOCs 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), more educated learners (Morris et al., 2015; Semenova & Rudakova, 2016), and those with previous online experience (Semenova & Rudakova, 2016) finish MOOCs at higher rates.

After the MOOCs started, only 58% of learners completed the tests during the first week. In general, the same patterns of learner dropout were exhibited in the three MOOCs. Every week, fewer learners started to take the weekly tests. 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 test was 43 (SD = 42), but for the last test, it was only half that (M = 22, SD = 39). The passing threshold for weekly quizzes is a score of 60, which allows 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. A week-by-week comparison of learners from the conditions demonstrated no significant difference in the case of activity and average weekly tests[3]. Since there was 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 tests.

Model 1 demonstrates that demographics such as gender and age significantly predicted learner success (see Table 3). According to the results, males and older learners had a higher probability of obtaining scores above 60 on the weekly tests. 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 tests. In summary, the intervention was not effective in general, but for particular learners it was.

In summary, experimental data demonstrated that SRL intervention might not work in general, but they provide some learners with greater help. The results of this investigation showed that the heterogeneous effect is 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.

[3] Please see paper Vilkova (2022) for more detailed week-by-week comparison of learners from two conditions.

Table 3.
Regression results

	Model 1	Model 2	Model 3
	OR	*OR*	*OR*
Sex (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
Condition (1 – experimental)		0.82	0.27*
MOOC (1 – History of art)			
Modern art			1.03
Marketing			1.93**
Experimental condition x male			2.09*
Experimental condition x age			1.02**
Experimental condition x higher education			1.35
Experimental condition x higher education			1.47
Experimental condition x MOOC (1 – History of art)			
Experimental condition x Modern art			1.38
Experimental condition x Marketing			1.61
Adjusted R^2	0.012	0.015	0.03
Constant	0.25***	0.27***	0.33**

Notes. The dependent variable is test scores, where 0 – 59 scores and less, 1 – 60 plus scores.
N = 799.
OR – Odds Ratio.
*p < .05. **p < .01. ***p < .001

Thesis statements

1. In the research literature there are two questionnaires, which are suitable for measuring SRL in the online learning settings: the Online Self-Regulated Learning Questionnaire (OSLQ) and the Self-Regulated Learning in MOOCs Questionnaire (SRLMQ). For further use of the OSLQ it is necessary to ensure the validity of this questionnaire in the MOOCs context.
2. Five out of six subscales of the Online Self-Regulated Learning Questionnaire can be used for measuring SRL in the MOOCs context. The subscale 'help-seeking' cannot be applicable for measuring SRL in the MOOCs context within this research.
3. The forethought phase is the most valuable SRL skill for obtaining high test scores in MOOCs.
4. The heterogeneous effect is prevalent in SRL interventions in regard to learner demographics: males and older learners received advantages from the intervention and scored higher at weekly tests. The heterogeneous effect explained mixed results of previous studies on SRL interventions in MOOCs.

Discussion

This study provides important contributions to theoretical, practical, and methodological implications of SRL interventions in MOOCs. Based on the results of the study, a number of methodological issues of SRL interventions in MOOCs were formulated, including interventions that were not a part of the learning process, self-selection bias, that focused on academic outcomes, and that had no follow-up analysis.

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 MOOCs 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 is 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, a work by Cazan (2020), who investigated the effects of a prolonged SRL intervention in traditional higher education settings.

Conclusion

This study contributes to the research of SRL in the MOOCs context. It examines both the issues of measuring SRL, as well as it links to test tasks scores, and the possibility of promoting SRL skills in the MOOCs context. The scientific significance of this study is as follows. Firstly, the study presents a validated questionnaire for measuring SRL in the MOOC context. Secondly, it is shown that the high test scores are primarily explained by such a SRL phase as forethought. Thirdly, through an assessment of the heterogeneous effect in the intervention for the SRL intervention, an explanation of the mixed results of previous work is presented.

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. It might be possible to use personalized SRL interventions in MOOCs in future investigations. The provision of personalized support for learners with particular characteristics (females and younger students) could positively influence their performance.

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Appendix

Appendix 1. Questionnaires which measure SRL

Questionnaire	Scales	Subscales	Number of items	Theoretical background
The Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993)	Motivation	Value (intrinsic and extrinsic goal orientation) Task value expectancy (control beliefs about learning, self-efficacy) Affect (test anxiety)	81	Pintrich's SRL model (Pintrich, 2000)
	Learning strategies	Rehearsal Elaboration Organization Critical thinking Planning, monitoring and regulating strategies Managing time and study environment Effort management Peer learning Help-seeking		
The Learning and Study Strategies Inventory (Weinstein, Palmer, & Acee, 2016)	Skill	Information processing Selecting main ideas Test strategies	60	No data
	Will	Anxiety Attitude Motivation		

	Self-regulation	Concentration Self Testing Time Management Using Academic Resources		
The Online Self-Regulated Learning Questionnaire (Barnard et al., 2009)	Environment structuring	No	24	No data
	Goal setting			
	Time-management			
	Help-seeking			
	Task strategies			
	Self-evaluation			
The Academic Self-Regulation Scale (Magno, 2010)	Memory strategy	No	55	Zimmerman's SRL model (Zimmerman, 1990)
	Goal setting			
	Self-evaluation			
	Seeking assistance			
	Environmental structuring			
	Learning responsibility			
	Organizing			
The Self-Regulated Learning in MOOCs Questionnaire (Littlejohn, Hood, Milligan, & Mustain, 2016)	Forethought	Goal setting Strategic planning Task interest/ value Self-efficacy	42	Zimmerman's SRL model (Zimmerman, 1990)

	Performance	Task strategies Elaboration Critical thinking Help seeking Interest enhancement		
	Self-reflection	Self-evaluation Self-satisfaction		

Appendix 2. Items of the Online Self-Regulated Learning Questionnaire (OSLQ)

The original questionnaire was presented by Barnard et al. (2009)[4].

Instruction for respondents: “Please rank the following items on a scale from 1 to 5, where 1 is strongly disagree and 5 is strongly agree”.

Subscale	Item	
Goal setting	1	I set standards for my assignments in online courses
	2	I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester)
	3	I keep a high standard for my learning in my online courses
	4	I don't compromise the quality of my work because it is online
Environment structuring	5	I choose the location where I study to avoid too much distraction
	6	I find a comfortable place to study
	7	I know where I can study most efficiently for online courses
	8	I choose a time with few distractions for studying for my online courses
Task strategies	9	I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom
	10	I prepare my questions before joining in the chat room and discussion
	11	I work extra problems in my online courses in addition to the assigned ones to master the course content
Time management	12	I allocate extra studying time for my online courses because I know it is time-demanding

[4] The adaptation of the questionnaire into Russian language was carried out by a team of researchers from the Center for Sociology of Higher Education, the procedure is described in more detail in Vilkova and Shcheglova (2021).

	13	I try to schedule the same time everyday or every week to study for my online courses, and I observe the schedule
	14	Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days
Help-seeking	15	I find someone who is knowledgeable in course content so that I can consult with him or her when I need help
	16	I share my problems with my classmates online so we know what we are struggling with and how to solve our problems
	17	If needed, I try to meet my classmates face-to-face
	18	I am persistent in getting help from the instructor through e-mail
Self evaluation	19	I communicate with my classmates to find out how I am doing in my online classes
	20	I communicate with my classmates to find out what I am learning that is different from what they are learning

Appendix 3. Items of the Self-Regulated Learning in MOOCs Questionnaire (SRLMQ)

The original questionnaire was presented by Littlejohn, Hood, Milligan, & Mustain, (2016)[5].

Instruction for respondents: "Please rank the following items on a scale from 1 to 4, where 1 is strongly disagree, 2 is disagree, 3 is agree, 5 is strongly agree, and 99 is do not know".

SRL phase	Item
Forethought	I set personal standards for performance in my learning
	I set short-term (daily or weekly) goals as well as long-term goals (for the whole course)
	I set goals to help me manage studying time for my learning
	I set realistic deadlines for learning
	I ask myself questions about what I am to study before I begin to learn
	I think of alternative ways to solve a problem and choose the best one
	When planning my learning, I use and adapt strategies that have worked in the past
	I organise my study time to accomplish my goals to the best of my ability
	I think I will be able to use what I learn in the future
	I am interested in the topics presented in this course
	The learning that I undertake is very important to me
	I can cope with learning new things because I can rely on my abilities
	My past experiences prepare me well for new learning challenges
	I meet the goals I set for myself in this course
	I feel prepared for the demands of this course
Performance	I try to translate new information into my own words
	I change strategies when I do not make progress while learning
	When I study for this course, I make notes to help me organize my thoughts
	I read beyond the core course materials to improve my understanding

[5] The adaptation of the questionnaire into Russian language was carried out by a team of researchers from the Center for Sociology of Higher Education, the procedure is described in more detail in Appendix 4.

	When I am learning, I combine different sources of information (for example: people, web sites, printed material)
	When I do not understand something, I ask others for help
	I ask others for more information when I need it
	Even if I am having trouble learning, I prefer to do the work on my own
	The most satisfying thing for me in this course is trying to understand the things I learn as thoroughly as possible
	I like opportunities to engage in tasks that I can learn from
	I prefer learning that arouses my interest, even if it is challenging
Self-reflection	I know how well I have learned once I have finished a task
	I think about what I have learned after I finish
	I often think about how my learning fits in to the ‘bigger picture’ of my work/practice

Appendix 4. Adaptation of the Self-Regulated Learning in MOOCs Questionnaire into the Russian language

The original English version of the SRLMQ was adapted to the Russian language according to the ITC Guidelines for Translating and Adapting Tests (International Test Commission, 2017). Back-translation procedures were adopted to ensure conceptual equivalence across languages. Two translators who are fluent in both the source language (English) and the target language (Russian) and had previous experience in translating survey instruments were selected. One translator did the translation of the original version into Russian and a back translation into English was performed by another translator. The content validity was assessed based on experts' opinion as to whether or not the instrument is measuring what it is supposed to measure. The group of experts (8 people) who were part of the research group with the focus on online learning discussed the adapted version in the format of a focus group. Their aim was to obtain evidence of such features of the instrument as sufficiency, clarity, relevance, and the match between the items and the definition of the construct controlling for possible biases. For example, we added information about the forum to the item *"I ask others for more information when I need it"*. In Russian it looks like: «*Если у меня возникает вопрос по курсу и ответа на него нет на форуме, я сам задаю его там*».

Also, during the adaptation, it was decided to delete some of the statements. The original English version of the SRLMQ consists of 42 items, but we used only 29 of them. This study was part of a large project that was conducted by another department, and due to the limitations on the scope of the survey, we did not have the opportunity to insert all 42 items. When removing the items, experts considered some of them unsuitable for a number of reasons:

1. Similar meanings of items. For example, two items when translated into Russian had a similar meaning (*"I often think about how my learning fits in to the 'bigger picture' of my work/practice"* and *"I try to understand how what I have learned impacts my work/practice"*), therefore, it was decided to abandon one of them. A similar decision was made on a number of other items of the SRLMQ.
2. The absence of a similar bubscale in B. Zimmerman's model. Thus, the SRLMQ contained a "critical thinking" subscale, which is not included in the model used in this study. Therefore, the experts decided to delete the following items:

During learning I treat the resources I find as a starting point and try to develop my own ideas from them.

I try to play around with ideas of my own related to what I am learning in this course.

Whenever I read or hear an assertion in this course, I think about possible alternatives.

Appendix 5. SRL intervention

The original questionnaire was presented by R. Kizilcec[6].

Introduction: Please write down a clear, concrete plan to follow through on your goals in the course. Plan-making can be a helpful tool in MOOCs! Successful students in previous courses have made detailed plans for how they will engage throughout the course. In the text boxes below, write out your plans to complete your work for the course.

Please be as specific as you can! Write clearly, in full sentences, so that someone else could understand what you mean.

Q1: When and where do you plan to engage with the course content?

Answer:

Q2: What specific steps will you take to ensure you complete the required course work?

Answer:

Q3: How will you overcome potential obstacles in the course?

Answer:

Follow-up: Thank you for writing down your plans. Sticking to your plans can help you stay on track and achieve your goals in the course! Take a moment now to read over your plans below, to make sure you remember them later. For example: write them down on paper, email them to yourself or a friend, add to a calendar with a reminder, or tell someone about them!

Thank you for your responses, and we hope you enjoy the course.

[6] The adaptation of the questionnaire into Russian language was carried out by a team of researchers from the Center for Sociology of Higher Education.

Appendix 6. List of abbreviations

AIC – Akaike Information Criterion

BIC – Bayes Information Criterion

CFA – Confirmatory Factor Analysis

CFI – Comparative Fit Index

MOOCs – Massive Open Online Courses

NOEP – National Open Education Platform

OSLQ – Online Self-Regulated Learning Questionnaire

RMSEA – Root Mean Square Error of Approximation

SRLMQ – Self-Regulated Learning in MOOCs Questionnaire

SRL – Self-Regulated Learning

TLI – Tucker Lewis Index