# **Online Self-Regulated Learning Strategies in MOOCs:**

#### A Measurement Model

https://doi.org/10.3991/ijet.v15i08.12401

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Abstract—Massive Open Online Course (MOOC) is among disruptive innovations in online learning environments that attract a significant interest among students. MOOCs require learners to be actively involved and to utilize an individual process of self-regulated learning. The development of a measurement model for online self-regulated learning (SRL) has been found to be lacking when compared with the traditional, face-to-face context. This research has the objective of developing a model for measuring online selfregulation strategies in Malaysian MOOCs. Data collection was carried out using a sample of 384 learners in three MOOCs operated under the openlearning.com platform. A confirmatory factor analysis was executed to indicate the goodness-of-fit and validate the measurement model. Findings have shown that the measurement model and the data have a good fit after performing model modification procedures. Thus, the model is suitable for measuring online SRL in the setting of MOOC learning. Further, this study recommends several suggestions regarding the applicability of the measurement model with other variables related to teaching and learning in MOOC.

**Keywords**—Self-regulated learning, online learning, measurement model, Massive Open Online Course, MOOC

### 1 Introduction

There is a discernible increase in interest in the issue of teaching and learning in Massive Open Online Courses (MOOCs). MOOCs are free of charge and targeted at students of all types, which means they attract a bigger following in comparison with other platforms of online learning [1]. MOOCs have been growing tremendously and has prompted scholars in this discipline to conduct research into the teaching and learning aspects in MOOCs; from motivations [2], pedagogies [3, 4], participations [5], integrations [6], satisfactions [7, 8] and learning strategies [9, 10].

In the matter of learning strategies, self-regulation becomes a crucial factor for successful learning in MOOC [11]. A self-regulated learner is actively involved in

their learning process. This process comprises three steps, namely forethought (before), performance (during), and self-reflection (after) phases [12]. Students who possess high self-regulated learning (SRL) are more able to participate in learning by setting study objectives individually (forethought phase), determining the practical methods to learn (performance phase), and tracking the achievement of their goals (self-reflection phase) [13]. With the increase in learners' responsibility as well as their autonomy in MOOCs, self-regulation is necessary for MOOCs [11, 14].

In the process of improving learners' self-regulation skills in MOOCs, it is essential that the online self-regulation construct can be measured. Previous studies have developed and validated questionnaires associated with self-regulation in MOOCs [15, 16]. For instance, [15] developed the 'Self-regulated Online Learning Questionnaire' from 4 existing questionnaires for measuring SRL in a conventional and online learning context. This questionnaire has further been revised by [17] in the Netherlands and found to be improved in terms of usability, reliability and validity.

Moreover, [16] adapted the Online Self-Regulated Learning Questionnaires (OSLQ) introduced by [18] in a Russian MOOC. The OSLQ consists of six sub-scales measuring online self-regulation strategies namely: task strategies, help-seeking, environment structuring, goal setting, self-evaluation, and time management. However, findings demonstrated complications in the modification of the measurement model and the convergent validity was not achieved the acceptable value after conducting the confirmatory factor analysis [16]. Since OSRL is applicable to multicultural research [19], the validation of OSLQ could be beneficial if it could be tested to the other diverse context.

Therefore, because of the significance of self-regulation in MOOCs and the dearth of studies on measuring SRL skills in a MOOC environment [15], especially in a developing country like Malaysia, the existing study develops a model for measuring online SRL strategies in Malaysian MOOCs.

## 2 Methodology

#### 2.1 Participants

In this quantitative study, participants were recruited from 3 Malaysian MOOCs operated under the openlearning.com platform. Of 2257 learners who enrolled in these MOOCs, 384 participants responded to the web-based questionnaire, resulting in the response rate of 17.0%. A majority of the participants 206 (53.6%) were from a MOOC named Introduction to Entrepreneurship, while 92 (24.0%) participants from Principles of Economics, and the remaining 86 (22.4%) of participants from International Business MOOC. More than half of the participants 249 (64.8%) have experience learning in MOOCs while 208 (54.2%) participants have successfully completed their MOOC and got the certificate.

#### 2.2 Measure

In order to develop a measurement model of self-regulation among MOOC learners, this study adapted and translated the Online Self-Regulated Learning (OSLQ) questionnaire created by [18]. A total of 24 elements in a 5-point Likert scale were incorporated in the first questionnaire, which ranges from 1 to signify 'Strongly Disagree' to 5 to signify 'Strongly Agree'. For the purposes of this study, some changes were made to the original questionnaire. As suggested by [20], this study incorporated a 7-point Likert scale for increasing the variability of the data. Four items were excluded due to the conceptual lack of clarity. Thus, certain elements had to be rephrased so that the features of the MOOC-related online courses are matched appropriately. As a result, there are 20 items with 6 dimensions to assess the SRL strategies remain for the measurement.

#### 2.3 Data analysis

A Confirmatory Factor Analysis (CFA) through IBM SPSS AMOS was performed to validate the proposed factor loading for each dimension and the construct validity of the measure [21, 22]. Generally, the higher the factor loading, the better; and typically loadings of below 0.3 are not interpreted. The criterion for an adequate factor loading is above 0.5 or ideally 0.7 [23], which indicate that values lower than 0.5 should be deleted to achieve a satisfactory model fit. Further, the goodness-of-fit measures resulting from the CFA were used to indicate the model fit. In performing this work, the fitness of model was assessed by the probability value of chi-square (p-value), normed chi-square (chisq/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), incremental fit index (IFI), Tucker-Lewis index (TLI), and standardized root mean square residual (SRMR). The threshold utilized to evaluate the model fit as suggested by [23] is shown in Table 1.

Table 1. Level of acceptance of fit indices

Fit index	Level of acceptance
Probability value (p-value)	p<0.05
Normed chi-square (chisq/df)	<3
Root Mean Square Error of Approximation (RMSEA)	< 0.08
Comparative Fit Index (CFI)	>0.9
Incremental Fit Index (IFI)	>0.9
Tucker-Lewis Index (TLI)	>0.9
Standardized Root Mean Square Residual (SRMR)	<0.08

### 3 Findings

#### 3.1 Assessment of the measurement model

The goodness-of-fit indices results of the proposed measurement model can be seen in Table 2. All of the absolute fit indices meet the satisfactory threshold values except the normed chi-square (chisq / df) value was 3.336 and a little above the acceptable threshold of a model fit. Consequently, based on the overall goodness-of-fit indices, the measurement model doesn't fit the data adequately. Therefore, model modification is necessary to improve the goodness-of-fit.

Table 2. Goodness-of-fit (GOT) indices

GOT indices	p-value	chisq/df	RMSEA	CFI	IFI	TLI	SRMR
Measurement model	0.000	3.336	0.078	0.941	0.941	0.932	0.070
Acceptable value	< 0.05	<3	< 0.08	>0.9	>0.9	>0.9	< 0.08

Model modification was carried out by checking the standardized factor loadings and modification indices. Examination of the factor loadings shows no values that below 0.5. Hence, no item is suggested for deletion to improve model fit. Further, the modification indices (MI) were inspected in order to identify the redundant items that could cause model misfit. A review of the modification indices reveals one extremely high MI values for the path between e9 (error term for item TS9) and e10 (error term for item TS10) with an MI value of 60.743. In order to improve the model fit, these two error terms need to be covariate as suggested by numerous work of literature [24, 25].

After performing the model modification procedures, the fit indices of the modified model demonstrate a satisfactory fit (Figure 1). In particular, the p-value is significant, chisq/df=2.957 is below than 3, CFI=0.951, IFI=0.951, and TLI=0.943 are above the threshold of 0.9 and RMSEA=0.071 and SRMR=0.059 are below 0.08. Hence, the improved measurement model is considered appropriate to proceed with validity and reliability assessment.

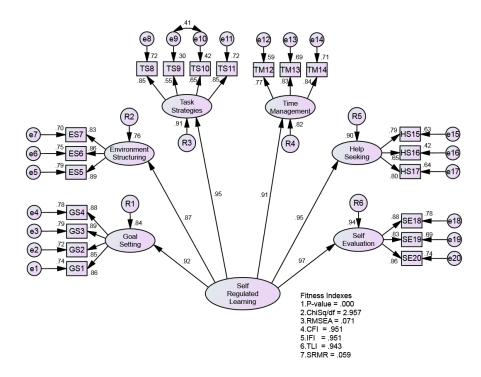


Fig. 1. The improved measurement model of Online Self-Regulated Learning

# 3.2 Assessment of reliability and validity

With the confirmation of the model fit, the constructs were then assessed for reliability and validity. The rule of thumb for good validity and reliability is the values for construct reliability (CR) should be above 0.7 and the average variance extracted (AVE) above 0.5 [23]. As seen in Table 3, the CR ranges from 0.795 to 0.926, while the AVE ranges from 0.543 to 0.758. Further, the factor loadings for all items are significant and more than 0.5. For the second-order construct of self-regulated learning, the factor loading of the first-order constructs ranges from 0.875 to 0.968, the CR value is 0.974 and the AVE is 0.864. As such, the results show that the constructs are reliable and valid.

**Table 3.** Evaluation of validity and reliability of the measurement model

First-order constructs	Second-order construct	Item	Factor Loading	CR	AVE
Goal Setting (GS)		GS1	0.860		
		GS2	0.850	0.926	0.758
		GS3	0.888		
		GS4	0.884		
Environment Structuring (ES)		ES5	0.891		0.746
		ES6	0.865	0.898	
		ES7	0.834		
		TS8	0.850	0.821	0.543
T. 1.C. (T.C.)		TS9	0.551		
Task Strategies (TS)		TS10	0.652		
		TS11	0.848		
Time Management (TM)		TM12	0.768	0.856	
		TM13	0.833		0.665
		TM14	0.843		
Help-Seeking (HS)		HS15	0.793		0.565
		HS16	0.651	0.795	
		HS17	0.802		
Self-Evaluation (SE)		SE18	0.884	0.893	0.735
		SE19	0.828		
		SE20	0.859		
		GS	0.919		
		ES	0.875		
	Self-Regulated Learning	TS	0.953	0.974	0.864
	(SRL)	TM	0.908		
		HS	0.950		
		SE	0.968	1	

### 4 Discussion and Conclusions

The objective of the study is to formulate a measurement model of online SRL strategies in the context of learning in MOOCs. The findings show that the values for goodness-of-fit indices, factor loading, composite reliability and average variance extracted to measure the convergent and construct validity were satisfactory and possess validity and reliability. These results point to the conclusion that all items measured the same construct in agreement. In particular, all of six constructs measuring online self-regulated learning were validated.

The findings of this work further contribute to the applicability of OSLQ in measuring online self-regulation in MOOCs that have been identified in the previous studies [15] – [17]. Moreover, this research demonstrates that the implementation of CFA also supports the reliability and validity of the measurement model, which can add to the knowledge on the area of self-regulated learning.

However, this research is not intended to investigate any hypotheses but a development of a measurement model for online SRL strategies. The results would carry more weight or implications if the model could be tested on other dependent

variables such as in examining the relationship between self-regulation strategies on learners' achievement and satisfaction in MOOCs. Thus, this model of online SRL could be considered as a second-order reflective construct in assessing the success and efficiency of any MOOCs.

### 5 Acknowledgement

The authors of this paper would like to thank the instructors from Universiti Utara Malaysia (UUM MOOC) for their assistance and support especially meant for the first author's doctoral study at UUM.

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Article submitted 2019-11-17. Resubmitted 2020-01-13. Final acceptance 2020-01-13. Final version published as submitted by the authors.