DEVELOPMENT OF A SCALE TO MEASURE STUDENTS' LEARNING SATISFACTION AND SELF-REGULATED LEARNING STRATEGIES IN MOOCS

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ABSTRACT

This study validated a scale of students' learning satisfaction (SLS) and self-regulated learning (SRL) strategies in MOOCs to measure the relationship between SRL and SLS based on Zimmerman's SRL theory and Piccoli's web-based Virtual Learning Environment (VLE) effectiveness theory. The process of developing the scale included literatures review, face and content validity, pilot study, data collection, and data analysis. An online self-reporting questionnaire was designed to include constructs such as goal setting (GS), task strategy (TS), self-evaluation (SE), help-seeking (HS), environment structuring (ES), time management (TM) and students' satisfaction (SA). All these constructs were assessed on a 5-point Likert scale. The data was collected from 333 Malaysian students in higher education, and it was analysed by using Partial Least Squares Structural Equation Modelling (PLS-SEM) technique. The resultant constructs have shown empirical result of good reliability and validity where the coefficients of Cronbach's alpha were ranged between 0.784 to 0.877, HTMT values were passed of 0.90 tests and factors loading were more than 0.7. The resulting constructs can be used by the practitioners, academicians, researchers, and policy makers to have a clear understanding on SLS and SRL in MOOC so that, a suitable, effective, positive, and meaningful MOOC learning environment could be established in the universities, higher education learning institutions and/or training organizations.

Keywords: *Massive Open Online Courses (MOOCs), Self-regulated learning (SRL), Students' Learning Satisfaction (SLS), Partial Least Square Structural Equation Modelling (PLS-SEM), Validation*

INTRODUCTION

With an increase of the usage of internet and broadband service, many higher education institutions have increased their number of online courses. Massive Open Online Courses (MOOCs) is one of the examples of online course which getting more popular in the industry of teaching and learning (Patru & Balaji, 2016). Following by the first MOOC in 2008, many of the world-renowned universities have now offered MOOCs in their academic program (Yang, Shao, Liu & Liu, 2017). MOOCs has considered as an online educational model with virtual learning environments (Yang, Shao, Liu & Liu, 2017) that led to a newly emerging paradigm in modern education (Wu & Chen, 2017).

The main goal of MOOCs is to offer more online learning opportunities for people living in the 21st century who is preferring to learn based on their own pace of personal intellectual growth (Kizilcec &

Mar, 2017), as teaching and learning in the 21st century is no longer restricted to a traditional classroom setting but is more location-independent and individualization based (Raspopovic & Jankulovic, 2017). This type of virtual learning environment has become more significant and obvious when the Covid-19 pandemic struck the world in 2020. Most of the higher education institutions have cancelled their face-to-face classes and went virtual due to the implementation of movement control orders or lockdowns set by most countries worldwide and MOOCs is one of the learning approaches during this period. However, a key problem faced by MOOCs is its high enrolment with low completion rate (Baggaley, 2013; Zutshi, O'Hare & Rodafinos, 2013). Many of the MOOCs' students tend to sign up at the beginning of the course but to drop out before completing their course. They have ambitious goals towards the course but hard to commit to achieve at the end of the course (Banerjee & Durflo, 2014). Based on the statistics, less than an average of 10% of the participants eventually completed their course (Anderson, Huttenlocher, Kleinberg & Leskovec, 2014; Bartolome & Steffens, 2015; Evans, Baker & Dee, 2016).

A detailed review of the studies has found out that the primary reasons of low completion in MOOCs are mainly due to low Students' learning satisfaction (SLS) (Gameel, 2017; Shrader, Wu, Owens, & Ana, 2016; Wu & Chen, 2017; Bryant, 2017) and poor self-regulated learning (SRL) (Kituyi & Tusubira, 2013; Zheng, Rosson, Shih, & Carroll, 2015; Alonso-Mencía, Alario-Hoyos, Estévez-Ayres & Delgado Kloos, 2021). According to Piccoli, Ahmad, and Ives (2001), learners' satisfaction of an online learning course is mainly influenced by two antecedents of dimension: human dimension (learners and instructors) and non-human dimension (course content, technology system and interactivity). When these key factors are maximized, learners' satisfaction will be at the maximum level (Sun, Tsai, Finger, Chen & Yeh, 2008; Asoodar, Vaezi & Izanloo, 2016; Hew, Hu, Qiao & Tang, 2020; Zhang & Lin, 2020). In addition, SRL was determined by different type of SRL strategies mainly goal setting, task strategy, self-evaluation, help-seeking, environment structuring, and time management (Zimmerman & Moylan, 2009). Students who lack the ability to perform those SRL strategies are facing difficulties to self-regulate their learning. Thus, hinders their success in online courses (Thomas & Gadbois, 2007; Vilkova & Shcheglova, 2020).

Previous research suggested that low SLS in MOOC was associated with poor SRL as it requires students to learn and participate the activities from course independently (Nawrot & Doucet, 2014; Kizilcec & Halawa, 2015; Albelbisi, Al-Adwan & Habibi, 2021). Many students were struggling to regulate their own learning in MOOCs, causing reduction in their learning satisfaction (Milligan & Littlejohn, 2017; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Albelbisi & Yusop, 2019). Learners who have strong SRL are able to learn faster and perform better compared to those who are weaker in SRL (Hood, Littlejohn & Milligan, 2015; Ejreaw & Drus, 2017). Students who have high SRL skills are able to engage with the course by monitoring their learning progress, hence achieved higher academic performance, intrinsic motivation, and task interest (Kizilcec & Mar, 2017; Martinez-Lopez, Yot, Tuovila & Perera-Rodríguez, 2017; Reparaz, Aznarez-Sanado & Mendoza, 2020).

This fairly acknowledged that SRL is highly needed to ensure high SLS in MOOCs. However, there are no empirical evidence to study on the relationship between SLS and SRL. Hence, the question remains on what is the relationship between SLS and SRL in MOOCs, and what are the significant SRL strategies that should be considered to represent the construct of SRL when assessing SLS in MOOCs?
To the best of our knowledge, there are insufficient published studies to develop a standard scale to measure SLS and SRL strategies in MOOC when the relevant literatures were examined. Thus, there is a need for research in this area. The objective of this study is to contribute significant theoretical contribution of knowledge to academic literature by determining the relationship between SLS and SRL. Therefore, to achieve the objective, we have developed and validated a scale to measure SLS and SRL strategies in MOOCs. This plays an important role for research in the field of e-learning and fill the current literature gap.

METHODOLOGY

The Study Group

The study group involved 333 undergraduate students who are from the top 5 public universities in Malaysia whose students are actively using MOOC in their learnings and have the largest number of student enrolment at the respective universities (UKM: 15%, UUM: 21.9%, UiTM: 12.9%, UNIMAS: 41.1% and UTeM: 9%). Table 1 represents the demographics of the study.

Table 1
Summary of the Participants' demographics

Variable	Category	Frequency (n=333)	Valid percent (%)
Gender	Male	119	35.7
	Female	214	64.3
Prior Experience with MOOC	Yes	148	44.4
	No	185	55.6
Compulsory to Use MOOC	Yes	230	69.1
	No	103	30.9
University	UKM	48	15.0
	UUM	74	21.9
	UiTM	34	12.9
	UNIMAS	139	41.1
	UTeM	38	9.0

There are more female (64.3%) than male (35.7%) participants in this study. 55.6% of them had no prior experience in learning with MOOCs and 44.4% had MOOC learning experience. Totalled 69.1% of the participants expressed that using MOOC to learn a particular course is compulsory for them but only 30.9% of the participants were voluntarily.

Process of Developing a Scale for SLS and SRL Strategies in MOOCs

The development process of a scale for SLS and SRL strategies in MOOCs involved few steps (Straub, 1989):

Comparison between Other Distance Learning approach and MOOCs: Distance learning conceptualize the use of technology systems in teaching and learning process (Anderson & Dron, 2011) in which the main features include physical separation of students and teachers, and the use of various technology during instruction (Aparicio, Bacao & Oliveira, 2016). Online learning, web-based learning, e-learning, virtual learning, blended learning, and even MOOCs are the common terms used to represent distance learning in literatures (Hamzah & Yeop, 2016). The main difference between MOOC and other distance learning models is the scalability, design, and structure of the course that permits a greater number of learners participation (Liyanagunawardena, Adams & Williams, 2013). For instance, MOOC offers free educational course with an unlimited number of participants, but other distance learning methods require payment to learn the course with certain number of participants. MOOC does not require any entry qualification if the internet connection is available whereas other distance learning methods may need to satisfy certain entry requirement to join the course (Geduld, 2016).

Items Adaption from Relevant Distance Learning Literatures: Items in the survey that are represented content of the constructs were adapted from relevant distance learning literatures in the search engines of Scopus and Web of Science. These databases were chosen because they are the two world-leading and competing citation databases (Zhu & Liu, 2020). Table 2 shows the survey items and sources that were adapted from the past literatures.

Table 2
The Survey Items and Sources

Construct	Item	Question	Source
Students' Satisfaction	SA1*	I would gladly do so if I have an opportunity to take another course via MOOCs	Sun et al. (2008); Albelbisi (2019); Albelbisi, Al-Adwan & Habibi (2021)
	SA2	I am pleased with how MOOCs are conducted	
	SA3	I would recommend MOOCs to others	
	SA4	I feel that MOOCs are useful to me in general	
	SA5	I am satisfied with my overall learning experience of MOOCs	
Goal Setting	GS1	I know what I am going to achieve in MOOCs	Kizilcec & Mar (2017); Martinez-Lopez, Yot, Tuovila & Perera-Rodríguez (2017); Albelbisi & Yusop (2019)
	GS2	I set high standards for my works of study in MOOCs	
	GS3	I set targets for all I want to achieve in MOOCs	
	GS4	I set realistic deadlines for learning in MOOCs	
Task Strategies	TS1	I understand the learning outcomes before I start each session of lessons in MOOCs	Onah & Sinclair (2017); Kizilcec & Mar (2017)
	TS2	I work strategically to prioritize tasks to help me achieve my learning goals in MOOCs	
	TS3	I make notes to help me organize my thoughts when I study for MOOCs	
	TS4	I practice the questions in the assessments given in MOOCs until I fully grasp the concepts well	
	TS5	I organize my notes, assessment, work sheets, and assignments in MOOCs	
Self-evaluation	SE1	I am proactive in reviewing my learning progress in MOOCs	Onah & Sinclair (2017); Kizilcec & Mar (2017)
	SE2	I reflect what I have learned after each session of lessons in MOOCs	
	SE3	I examine whether my learning outcomes have been achieved after each session of lessons in MOOCs	
Help Seeking	HS1	I use the interactive communication channels provided to gain support from peers and instructors in MOOCs	Kizilcec & Mar (2017); Martinez-Lopez, Yot, Tuovila & Perera-Rodríguez (2017); Vilkova & Shcheglova (2020)
	HS2	I ask others for help when I do not understand something in MOOCs	
	HS3	I refer to internal resources such as video-lectures, forums, or assessment when I do not understand the lesson in MOOCs	
	HS4	I look for external resources such as digital and physical materials outside the MOOC when I do not understand the lesson in it	

Environment Structuring	ES1	I choose my study location for MOOCs in order to avoid distractions	Albelbisi (2019); Albelbisi & Yusop (2019); Martinez-Lopez, Yot, Tuovila & Perera-Rodríguez (2017)
	ES2	I choose a comfortable place to study for MOOCs	
	ES3	I choose an appropriate place to study for MOOCs	
Time Management	TM1	I set aside time to study for MOOCs	Albelbisi (2019); Albelbisi & Yusop (2019)
	TM2	I choose a good time to study for MOOCs so that I won't be distracted	
	TM3	I organize my study time to accomplish my goals to the best of my abilities in MOOCs	

Note: Items with an asterisk are deleted after data analysis

Based on Table 2, survey items which its Cronbach's alpha, α ≥ 0.7 were adapted from the past literatures according to the rule of thumb for the internal consistency of reliability (Hair, Ringle & Sarstedt, 2017).

Opinion from Experts for Face Validity and Content Validity: After adaptation, items of the survey were sent to a panel of experts for face and content validity. The purpose of this step is to get experts' opinion to confirm whether the items of the survey are representative and suitable to measure SLS and SRL strategies in the MOOCs. For face validity, panel experts have provided comments and suggestions to improve content clarification and to help correct grammar for some items of the survey. The items of the survey were then reviewed and revised according to their comments and suggestions to make the wording of the items more precise.

Meanwhile, Content Validity Ration (CVR) that was developed by Lawshe (1975) was also calculated for content validity. CRV was used to validate the instrument through the quantitative judgment from the experts (Albelbisi, Yusop & Salleh, 2018). Panel experts were requested to respond the importance of each item by judging whether the knowledge measured by the item is essential = 3, useful but not essential = 2, or not necessary = 1 to the performance of the construct. Table 3 shows the summary of the details of the panel of experts.

Table 3
Summary of the Details of the Panel of Experts

Number of experts	Position	Area of expertise	Years of experience
1	Professor	Educational Psychology	20
2	Associate Professor	Educational Technology	10-20
1	Senior Lecturer	Educational Psychology	5
5	Senior Lecturer	Teaching & Learning with MOOCs	6-8
1	Senior Lecturer	Survey Design	6

If more than half the panellists indicate that an item is essential, then the item has at least some content validity. A panel of experts were selected based on specific criteria including academic qualification, years of experience and domain knowledge in the field of practice (Manakandan, Ismai, Jamil, & Ragunath, 2017) and the ideal number of experts involved should be vary from 10-15 (Adler & Ziglio, 1996; Sireci & Faulkner-Bond, 2014).

Pilot study and actual data collection: A modified online survey for pilot study was distributed to 150 undergraduate students from different public universities in Malaysia who have participated in the MOOC of "*Hubungan Etnik*" through OpenLearning platform after the face and content validation from a panel of experts. The pilot study was conducted to minimize the potential problems occurred in the actual data collection and to verify the capability of the survey items. The necessary modification has made based on the results of the pilot study before the actual data collection.

The actual data collection was carried out during the period of April to June 2020 through the chat box in the OpenLearning – MOOC platform. A five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree) was employed to measure SLS and their SRL strategies toward MOOCs. To increase the response rate, some incentives have given out to the participants as a token of appreciation (Leary, 2014). A total of 410 participants have responded to the survey but only 333 are relevant for further analysis after outliers have removed.

Data analysis: Partial Least Square Structural Equation Modeling (PLS-SEM) technique (Ringle, Wende, & Becker, 2015) in Smart PLS version 3 was used to analyse the actual data. The analysis involved in assessing the internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (Average Variance Extracted (AVE) and factor loading), and discriminant validity (Fornell-Larcker criterion, heterotrait-monotrait (HTMT) ratio of correlations criterion) (Fornell & Larcker, 1981; Schumacker & Lomax, 2004; Hair, Ringle, & Sarstedt, 2017).

FINDINGS

Internal Consistency Reliability

Internal consistency reliability was used to measure the reliability of survey items in a construct. Internal consistency reliability is achieved when all items of such measures can reflect the same underlying construct (Myrtveit & Stensrud, 2012). Crobach's alpha (α) and composite reliability are two indicators to measure internal consistency of reliability. To achieve internal consistency reliability, the recommended level of α should be more than 0.70 and composite reliability value should be between 0.70 to 0.95 (Hair, Hult, Ringle & Sarstedt, 2017).

Table 4
The Reliability Results

Construct	No. of Items	Cronbach's alpha (α)	Composite reliability
GS	4	0.883	0.921
TS	5	0.876	0.911
SE	3	0.877	0.924
HS	4	0.784	0.861
ES	3	0.787	0.876
TM	3	0.815	0.890
SA	4	0.867	0.910

Note: GS: goal setting; TS: task strategy; SE: self-evaluation; HS: help seeking; ES: environment structuring; TM: time management; SA: students' satisfaction

Based on Table 4, Cronbach's alpha (α) value for GS, TS, SE, HS, ES, TM, and SA was 0.883, 0.876, 0.877, 0.784, 0.787, 0.815 and 0.867 respectively. This indicated that the α value of all factors was ranged between 0.784 to 0.883 which more than 0.7. In addition, composite reliability value for GS, TS, SE, HS, ES, TM, and SA was 0.921, 0.911, 0.924, 0.861, 0.876, 0.890 and 0.910 respectively which was between 0.861 to 0.924 (> 0.7). This result concluded that all items in this survey study were reliable as they reflected to its own underlying construct.

Convergent Validity

Convergent validity was used to measure the degree of the correlation between items in the same construct (Campbell & Fiske, 1959). Convergent validity is achieved when items in a same construct are strongly correlated to each other (Bagozzi & Yi, 2012). Factor loading and Average Variance Extracted (AVE) are two indicators to measure convergent validity. To achieve convergent validity, each item loads of the construct should be greater than 0.70 and value of Average Variance Extracted (AVE) of each construct should be exceeded 0.50. (Hair, Hult, Ringle, & Sarstedt, 2017).

Table 5
The Convergent Validity Results

Items	Factor loading	AVE
GS1	0.892	0.747
GS2	0.918	
GS3	0.921	
GS4	0.708	
TS1	0.721	0.672
TS2	0.793	
TS3	0.876	
TS4	0.841	
TS5	0.859	
SE1	0.883	0.802
SE2	0.907	
SE3	0.897	
HS1	0.736	0.610
HS2	0.814	
HS3	0.852	
HS4	0.712	
ES1	0.823	0.701
ES2	0.877	
ES3	0.812	
TM1	0.850	0.730
TM2	0.851	
TM3	0.862	
SA2	0.733	0.718
SA3	0.907	
SA4	0.903	
SA5	0.835	

Based on Table 5, factor loading of all items was more than 0.7 (GS: 0.708 to 0.921; TS: 0.721 to 0.876; SE: 0.883 to 0.907; HS: 0.712 to 0.852; ES: 0.812 to 0.877; TM: 0.850 to 0.862; SA: 0.733 to 0.907), and the value of AVE for all of the constructs was above 0.5 (GS: 0.747; TS: 0.672; SE: 0.802; HS: 0.610; ES: 0.701; TM: 0.730; SA: 0.718). This result concluded that all items in a same construct were strongly correlated to each other. Thus, this suggested that the survey items of the study have a good convergent validity.

Discriminant Validity

Discriminant validity was used to measure the degree of the correlation between items in different construct (Campbell & Fiske, 1959). Discriminant validity is achieved when items in a particular construct are not highly correlated with any items in other constructs (Hulland, 1999). Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio of correlations criterion are two indicators to measure discriminant validity. To achieve discriminant validity, square root of the construct's AVE should be the highest correlation with any other constructs and the HTMT value should be lower than 0.90 (Hair, Hult, Ringle & Sarstedt, 2017).

Table 6
The Discriminant Validity Results using Fornell-Larcker Criterion

	ES	GS	HS	SE	SA	TM	TS
ES	**0.837**						
GS	0.471	**0.864**					
HS	0.599	0.567	**0.781**				
SE	0.529	0.651	0.561	**0.896**			
SA	0.581	0.735	0.508	0.599	**0.848**		
TM	0.698	0.478	0.578	0.562	0.561	**0.854**	
TS	0.571	0.717	0.623	0.690	0.666	0.627	**0.820**

Table 7
The Discriminant Validity Results using HTMT Criterion

	ES	GS	HS	SE	SA	TM	TS
ES	1						
GS	0.560	1					
HS	0.757	0.681	1				
SE	0.629	0.735	0.674	1			
SA	0.698	0.826	0.611	0.686	1		
TM	0.869	0.565	0.719	0.663	0.665	1	
TS	0.679	0.815	0.752	0.784	0.763	0.447	1

Based on Table 6, the square root of all the constructs' AVE was larger than the squared correlation with any other constructs. For instance, the value of the square root of AVE for the construct of ES (0.837) is larger than the squared correlation with other constructs of GS (0.471), HS (0.599), SE (0.529), TM (0.698), TS (0.571) and SA (0.581). This means that items in the construct of ES were not highly correlated with any items in other constructs (GS, HS, SE, TM, TS, and SA). In addition, all the values of construct passed HTMT value of 0.90 tests (Table 7). For instance, value of HTMT for the relationship between the construct of ES and GS is 0.560 which was less than 0.90. Therefore, with these results, we concluded that discriminant validity issue was not existed in this study.

DISCUSSION

The aim of the current study was to explore the effectiveness of MOOC by determining the relationship between SRL and SLS in the MOOCs. This provided an insight of higher education on SLS and SRL in MOOCs. We have developed a scale to measure SLS and SRL strategies by establishing the internal consistency reliability and validity (convergent and discriminant) of its items. The validation of these items was verified and confirmed using a formalised procedure (Straub, 1989).

All developed items in the scale showed a good internal consistency of reliability, with goal setting equals to alpha 0.883; task strategy, 0.876; self-evaluation, 0.877; help-seeking, 0.784; environment structuring, 0.787; time management, 0.815 and SLS, 0.867. Besides, the items of GS, TS, SE, HS, ES, TM, and SA showed factor loading between 0.708 to 0.921, and AVE values were above 0.5, suggesting a good convergent validity. The square root of all the constructs' AVE was larger than the squared correlation with any other construct based on Fornell Larcker and all the values passed the HTMT value of 0.90 tests, suggesting a good discriminant validity. Overall, the findings indicated that the items of the scale could effectively be used to assess the effectiveness of MOOCs to measuring SLS and SRL strategies.

However, the present study has some limitations. CVR is used for inter-rater agreement if there are enough experts in the panel. Orts-Cortés, Moreno-Casbas, Squires, Fuentelsaz-Gallego, Maciá-Soler, and González-María (2013), recommended a small number of experts require 100% of agreement to score an item as "essential". Nevertheless, some research determined that at least 10 experts (Sireci & Faulkner-Bond, 2014) or 10-15 (Adler & Ziglio, 1996) or 10-50 (Jones & Twiss, 1978) used for content validity. In addition, Beckstead (2009) has also pointed out that the higher number of the experts in the panel leads to high number of disagreements. Therefore, the excellent rating obtained from the scale of this study could be justified by the 10 experts for content validity.

The scope of this study has been narrowed to the undergraduate students who are from the top 5 public universities in Malaysia whose students are actively using MOOC in their learnings and have the largest number of student enrolment at the respective universities. It does not include students who have dropped out from the course and students who are from any other higher institutions such as Malaysian private universities or universities from other countries. The population and some cultural aspects in the geographical areas of these universities may be distinct from one another. Due to the differences in environment and the purposes of using MOOCs, the findings of this study are context-specific and may not be generalized to all higher institutions that adopts MOOCs (Albelbisi & Yusop, 2020).

The data was collected through online self-administered survey in which students' perceptions are a self-reported measure. This approach of data collection may be lack of objectivity to a certain extent as students may simply select any options to enjoy the incentives (Don, Jolene & Leah, 2009).

CONCLUSION

A scale development that was described in this research offers several implications. The most notable contribution of the present study is the items creation to represent the scale of SLS and SRL strategies in the MOOC context. The scale development process has included distance learning literature review, face and content validity, pilot study, data collection, and data analysis. The items of the scale have been verified and confirmed through reliability and validity testing. This study is of notable important as it provides a valid and reliable scale for current or future research to assess SRL strategies and SLS in the field of e-learning towards developing online course in higher educational institutions such as MOOC. To gain a more robust understanding on the relationship between SLS and SRL strategies in MOOCs, directions for future research studies, could, for example, collecting some qualitative information, such as interviewing the participants. This could also gain more in-depth information to support and to strengthen the validity of the present study. Moreover, longitudinal research could be conducted in the future studies to confirm the obtained results and provide a better insight on the development of MOOC to improve SLS and SRL of using MOOCs. This could also evaluate on how these factors (SLS and SRL) may change over the duration of the study in MOOCs.

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