MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach

Abstract

Massive Open Online Courses (MOOCs) provide a great platform to study individual and group differences of learners in perceptions, motivations, and behaviors under self-directed learning context. This study examined the relationships, in particular, influential relationships, among MOOC learners' demographics, their self-regulated learning (SRL) strategy usage, perceived learning, and satisfaction. Participants were 4503 learners from 17 Coursera courses who responded to an online survey in 2018. Structural equation modeling showed that participants' age, gender, highest degree, and the number of online courses previously taken significantly predicted both goal setting and environment structuring usage. Previous experience with the course topics only predicted goal setting, not environment structuring. Gender, goal setting and environment structuring strategy usage predicted participants' perceived affective learning. Highest degree, the number of online courses previously took, goal setting, environment structuring strategy usage and perceived affective learning predicted participants' satisfaction with the course. Participants identified themselves with a *Latin America* culture had better environment structuring strategy usage than any other cultural group and higher perceived affective learning than the other cultural groups except for *Other*. The results provided implications for researchers studying self-directed learning environments, differences in learning of learners with diverse backgrounds, and SRL behaviors, as well as for educators dealing with increasing SRL strategy usage, improving online learners' satisfaction and teaching cross-culturally.

Keywords: MOOC, self-regulated learning, perceived learning, satisfaction,

1. Introduction

Since the rapid expansion of online education, students' behaviors, perceptions, and motivations in online environments have been studied extensively for both theory and practice development. Pintrich & De Groot (1990) urged more researchers to investigate the relationships between students' motivations and behaviors in different learning contexts to understand how these two factors independently or jointly influence students' learning. Practically, designing effective and engaging learning environments requires the knowledge of the factors that influence students' learning and perceptions. For instance, in online learning contexts, course design, interactions with instructors, and interactions with students were three factors having an influence on students' perceived learning and satisfaction with the online course (Swan, 2001). Practitioners can focus on enhancing the three areas when designing online courses.

With the more diversified student body in modern educational contexts, individual and group differences in attitudes, behaviors, and perceptions of online learning environments have also been examined. Gender differences in perceived learning, demographics that associated with online students' dropout, perceived cognitive learning differences among different cultural groups are some examples in this research area (Rovai & Baker, 2005; Lee & Choi, 2011; McCroskey et al., 1996). The overall findings generally support that individual/group differences exist. This information can be used to develop targeted interventions aimed at changing online learners' attitudes, increasing their motivations and preventing them from dropping out for a specific group/individual learners.

Online education and global reach shorten the distance between learners from different cultures. Previous studies have reported the differences in values, beliefs, and behaviors of students from different cultures. An example is the phrase of the "paradox of the Chinese learners" where scholars tried to understand why Chinese learners outperformed learners from the West even though the Chinese educational system focused too much on memorization instead of understanding (Watkins, 2000). Hofstede (1986) described the differences of student/teacher and student/student interactions in terms of a four dimension model: Individualism versus Collectivism, large versus small Power Distance, strong versus weak Uncertainty Avoidance, and Masculinity versus Femininity, which explained the cultural differences among many countries. In addition, studying similarities and differences between different cultures helps educators to develop cultural competency and effectively teach cross-culturally. As early as 2001, Sleeter (2001) proposed to have large-scale curriculum preparing teachers to teach cross-culturally in the U.S. Nowadays, culturally diverse schools are growing in not only the U.S. but many other countries. Thus, the research examines cross-culture differences in teaching and learning is imperative.

As a special type of online education, the Massive Open Online Course (MOOC) has even more diverse learner characteristics. The early batch of MOOC research found there was a diverse student body in terms of locations and demographics, as well as behaviors in courses (Breslow et al., 2013; Kizilcec et al., 2013). The variety of motivations for enrolling in MOOCs is another recognizable difference between MOOCs and traditional credit-bearing online courses. Reasons for enrolling vary from preparation for advanced education to simply examining an online course (Shapiro et al., 2017). Because of the wide range of learner demographics and motivations, their behaviors can differ greatly from completing the course with a good grade to totally disengaged with the course (Kizilcec et al., 2013). Learners' motivations and participation in a MOOC also influence their performances greatly (De Barba et al., 2016). Similarly, their self-regulated learning (SRL) levels and strategy usage can be quite different, such as that professionals reported a higher level of SRL strategy usage than novice learners in MOOCs(Hood et al., 2015). The wide range of learners, their behaviors and motivations have made MOOCs a great platform to study individual and group differences in teaching and learning.

Several recent attempts have been made to reveal the individual or group differences in MOOC learners' attitudes, perceptions, and behaviors (e.g. De Barba et al. (2016); Kizilcec et al. (2017)). However, little attention has been paid to the differences in MOOC learners' perceptions and behaviors among different cultural groups. As mentioned above, MOOC learners can be from any one country in the world, which adds another layer of the diverse background of the learners. In addition, no existing study has examined the relationships between the four variables: MOOC learners' demographics, learning behaviors, particularly SRL behaviors, perceived learning and satisfaction, including mediating effects. This study seeks to explore the relationships among the four variables by applying a structural equation model (SEM). The paper is organized as follows: section 2 reviews relevant literature on demographics, SRL, perceived learning, and satisfaction in online and MOOC environments. Hypotheses are formed from the demonstrated relationships and particularly those contradicted results in previous research. Section 3 describes the research method, data collection, and data analysis. Section 4 presents the study results. Section 5 discusses the results, reveals the study limitations, and provides implications for researchers and practitioners. Section 6 concludes the study.

2. Literature review

2.1. Student demographics and online learning

Students' demographics have long been studied for relationships with many aspects of online learning. Age, gender and prior knowledge are among the frequently investigated demographic variables. Prior experience of online learning has been identified as an important demographic factor that may affect students online learning experiences. Yukselturk & Bulut (2007) reported no relationship between students' general demographic information, such as age and gender, and their success in online courses. Gender was shown as a significant factor in predicting learners' perceived learning — female students had higher perceived learning than their male peers (Rovai & Baker, 2005). While Willging & Johnson (2009) concluded that students' demographics did not influence their dropout decisions from online courses, in a literature review on online course dropout, Lee & Choi (2011) identified three groups of factors that affect students' dropout. Student demographics, including elements like "academic background, relevant experiences, relevant skills, and psychological attributes" (p. 604), was among the three factors.

There are a number of studies focusing on learners' demographics and their learning outcomes in Massive Open Online Courses (MOOCs). MOOCs are special online environments in that the students enrolled in MOOCs can be much more diverse in demographics (Breslow et al., 2013). Thus, demographic variables, which are not reported in traditional learning environments because they are not diversified, such as students' highest degree obtained and current job status have been introduced. Morris et al. (2015) identified that learners' age, prior online learning experience, educational attainment, and job status predicted their learning outcomes. Kennedy et al. (2015) reported that learners' prior knowledge of the topic is the best predictor for success. And DeBoer et al. (2013) found learners' educational attainment a significant predictor for success, but not their prior knowledge of the course topic. The letter H with a numeric number (e.g. H1) denote the hypothesis and its number in this article.

H1: Gender significantly predicts perceived learning.

H2: Experience significantly predicts perceived learning.

2.2. Self-regulated learning

Self-regulated learning (SRL) strategies are defined as "the strategies that students use to regulate their cognition as well as the use of resource management strategies that students use to control their learning" (Pintrich, 1999, p. 459). Self-regulated learners are aware of their strengths, weaknesses and they are able to attribute time, resources, and mental effort toward their goals in learning (Zimmerman, 2002). Paechter et al. (2010) stated that SRL was positively related to learning achievements.

H3: SRL strategy usage significantly predicts perceived learning.

2.2.1. *Student backgrounds and self-regulated learning*

Researchers have investigated the relationship between students' backgrounds, such as demographics, and their learning strategy usage, including SRL strategies. Some researchers reported positive relationships between certain demographics and strategy usage. For example, Colorado & Eberle (2012) found that older and higher level (graduate) students tended to be more self-regulated in learning. Older students used more advanced strategies to monitor their own learning behaviors and used more frequently than younger students (Lan, 2005). Vermunt & Vermetten (2004) reported that older and more experienced learners showed better mastery and usage of effective learning strategies. Demographic variables like gender influenced students' cognitive strategy usage but not regulation/management strategy usage (Wolters & Pintrich, 1998). Artino & Stephens (2009) found that graduate students showed more critical thinking pattern during learning than undergraduate students when their experiences were controlled. Students who had taken online courses before used more SRL strategies (Wang et al., 2013). Law et al. (2008) did not find significant different SRL strategy usage between students of different ages, but they did reveal that female students reported more SRL strategy usage than their male peers. Wang et al. (2013) reported that students who had more successful prior online learning experiences tended to use more SRL strategies.

In MOOCs, researchers also investigate the relationship between student demographics and self-regulated learning because compared to traditional online courses, MOOCs require learners, even more, to be self-regulated in order to learn. As a first step to examine SRL in MOOCs, researchers have studied the differences of self-regulated behaviors in self-reported format between student groups. For example, Hood et al. (2015) found that learners who were pursuing a higher degree in the subject tended to be more self-regulated in the same subject MOOC. It was assumed that the SRL strategy ability was transferable from their own learning contexts. In addition, learners who were already professionals in the field tended to use more SRL strategy. The authors hypothesized that learners who were more familiar with the content and more confident were better able to use SRL strategies. Similarly, Kizilcec et al. (2017) reported that learners with Ph.D. used more SRL strategies than non-PhDs while learners who were current students used fewer strategies than non-students. The authors also found that learners who had different motivations for enrolling in the MOOC reported different numbers of SRL strategy usage. The authors suggested these factors be integrated when designing adaptive learning paths for learners in MOOCs.

H4: Number of MOOCs previously taken significantly predicts SRL strategy usage.

H5: Degree significantly predicts SRL strategy usage.

H6: Experience significantly predicts SRL strategy usage.

H7: Age significantly predicts SRL strategy usage.

H8: Gender significantly predicts SRL strategy usage.

2.2.2. Culture, learning and SRL

Because of the differences in educational systems, cultural values, beliefs, and emphasis on learning, it is possible that students from different cultural backgrounds have different perceptions towards learning. For example, Li (2005) pointed out that education in Confucius cultures emphasized on virtual while Western education focused on the mind. These differences will influence students' beliefs and learning behaviors. Purdie et al. (1996) reported that Japanese and Australian students had different perceptions toward learning. Researchers have examined the relationship between culture and SRL beliefs and strategy usage. Pintrich (2003) emphasized the importance of understanding cultural impacts on individuals' beliefs about self, learning, motivation, and various concepts related to SRL. Wolters et al. (2005) stated that SRL strategy use was very context dependent, meaning, a student might use a completely different set of strategies when studying different subjects or under different learning circumstances. They also stressed the needs to extend the SRL work to a more diverse context with different ethnic groups. Purdie et al. (1996) reported similar SRL strategy usage between Australian and Japanese students despite their different views of education.

Several studies found that students in different countries with different cultural beliefs used different SRL strategies. Purdie & Hattie (1996) discovered slight differences in SRL strategy usage between Japanese and Australian students, specifically using memories-based strategies. They also revealed that the SRL strategies Japanese students who studied in Australia were different from their Japanese peers in Japan and Australian students, showing the SRL strategy usage could be affected by both culture and learning contexts. Unlike the student-centered classroom emphasis in western contexts, a study conducted in Hong Kong revealed that when teachers were involved in students' learning, students tended to use more SRL strategies (Lee et al., 2009). Studies have found different SRL strategy usage among female students in Singapore and America Alexander et al. (1998). While Olaussen & Bråten (1999) reported that Norwegian students reported similar SRL strategy usage as American students, they identified that female Norwegian students used more SRL strategies than their male peers.

H9: Culture significantly predicts SRL strategy usage.

H10: Culture significantly predicts perceived learning.

2.3. Student satisfaction

Students' satisfaction in learning is important because it is often found to be positively correlated with learning outcomes. Course design and structure is one of the factors that significantly predict students' satisfaction and/or perceived learning in online courses (Swan, 2001). Perceived learning has also been found as a significant predictor of students' satisfaction (Eom et al., 2006). Shen et al. (2013) identified that the number of previous online courses taken, gender and grade level (undergraduate or graduate students) significantly predicted students' self-efficacy, which significantly predicted their satisfaction. Ke & Kwak (2013) reported that students with higher educational degrees and minority students both felt less satisfied with online learning. It is also found that minority students tended to be more satisfied with their interactions with teachers while less satisfied with online learning in general (Ke & Kwak, 2013).

H11: Perceived learning significantly predicts satisfaction.

H12: Number of previous online courses taken significantly predicts satisfaction.

H13: Gender significantly predicts satisfaction.

H14: Degree significantly predicts satisfaction.

2.3.1. Student satisfaction and self-regulated learning

Researchers have realized the potential relationship between SRL and student satisfaction and several attempts have been made to address it. Because self-regulated learners constantly monitor their progress and status in order to adjust the strategies that they will use toward their goals, these learners are always satisfied with their learning experiences (Zimmerman, 2002). Research reported that students who had higher metacognition, time and effort management scores — elements of SRL — had higher satisfaction with the online course (Puzziferro, 2008). Students who used more SRL strategies tended to be more satisfied with the course (Wang et al., 2013). On the other hand, some researchers found that students' SRL did not predict their satisfaction (Kuo et al., 2013) nor their achievement significantly (Cho & Heron, 2015) in online learning.

H15: SRL strategy usage significantly predicts satisfaction.

2.3.2. Student satisfaction and culture

The relationship between students' cultural background and their satisfaction with courses has been investigated. Students' cultural backgrounds influenced their satisfaction with computer-supported learning (Zhu, 2013). Zhu (2012) found significant differences of satisfaction with online learning between Chinese students and Flemish students. Although one cannot derive that it is the cultural differences that lead to the different satisfaction, researchers considered culture to influence participants' perceptions of education and learning styles by communication, value, and educational system (Morse, 2003). In addition, research suggests that online course design should consider students' cultural characteristics to make the learning experiences satisfactory (Liu et al., 2010). Morse (2003) studied students' perceptions of online learning and the differences between students from different cultures. He found that students from high context cultures, which did not require a lot of explicit information because the high cues contexts provided, had different satisfactory opinions toward online learning's various of aspects from students from low context cultures. Figure 1 shows all hypotheses (denoted by letter H with a number) in the graphical representation of the SEM.

H16: Culture significantly predicts satisfaction.

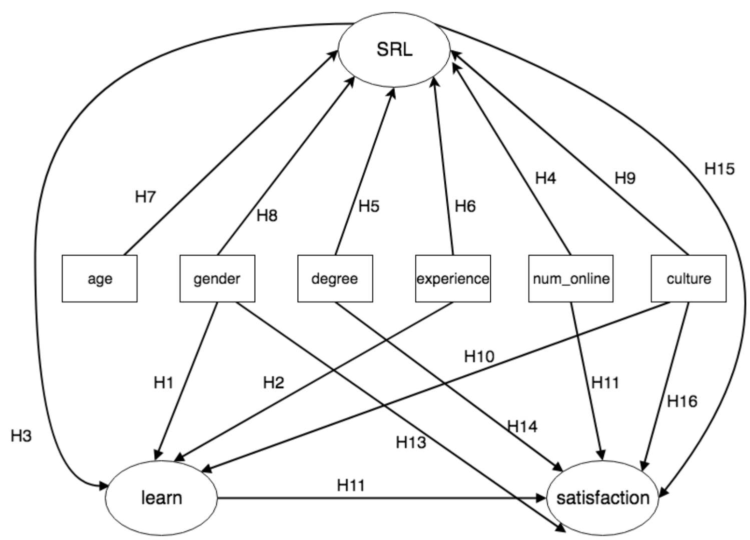

Figure 1. Research model

3. Method

3.1. Participating MOOCs and students

Seventeen MOOCs offered by Duke University on Coursera were used in the study. Courses with more than two instructors were excluded because too many teaching styles could potentially affect students' learning experiences. Courses that are part of a specialization were excluded because students have to pay for specialization courses to access all materials, which would make their experiences quite different than those with free access. If a course has subsequent courses (e.g. part 1 and part 2), only the first course was selected to avoid the possibly large number of overlapping learners. An online survey was distributed to all active students since the launch date in each course via the Coursera email tool. The participating MOOCs, sample sizes and response rates are shown in Table 1.

Table 1

Participating MOOCs and Response Rates

Course Name	Student Number	Sample Size	Response Rate
Advertising and Society	5464	94	1.72%
Art of the MOOC: Activism and Social Movements	5637	135	2.39%
Behavioral Finance	21616	665	3.08%
Bioelectricity: A Quantitative Approach	3549	77	2.17%
Dog Emotion and Cognition	88650	3221	3.63%
Healthcare Innovation and Entrepreneurship	3853	72	1.87%
Image and Video Processing: From Mars to Hollywood with a Stop at the Hospital	17713	498	2.81%
Introduction to Chemistry: Reactions and Ratios	14553	381	2.62%
Introductory Human Physiology	186929	2525	1.35%
Medical Neuroscience	72321	1723	2.38%
Music as Biology: What We Like to Hear and Why	27271	653	2.39%
Sports and Society	7562	260	3.44%
The Brain and Space	17840	372	2.09%
The Challenges of Global Health	17300	416	2.40%
Think Again I: How to Understand Argument	86401	1588	1.84%
Understanding 9/11: Why 9/11 Happened & How Terrorism Affects Our World Today	1361	36	2.65%
Visual Perception and the Brain	11472	250	2.18%

3.2. Instruments

3.2.1. Self-regulated learning strategy usage

Self-regulated learning (SRL) strategies were measured using the Online Self-regulated Learning Questionnaire (OSLQ) designed by Barnard et al. (2009). The OSLQ measures students' SRL usage in blended or online environments — MOOC is a special online learning platform. The total number of the OSLQ items is 24, which makes the instrument suitable to include in a survey containing items measuring other variables of interest. The OSLQ uses a five-point Likert scale response ranging from *Strongly agree* to *Strongly disagree*.

3.2.2. Satisfaction with the course

Three items were designed to measure learners' satisfaction with the course for the reason of both suitable for the research purposes and limiting the total number of questions in the survey. The responses are five-point Likert scales ranging from *Strongly agree* to *Strongly disagree*. The 3 items are: 1. overall I am satisfied with the course. 2. I would recommend this course to other people. and 3. I would take another course taught by the same instructor(s) of this course.

3.2.3. Perceived learning

Perceived learning was measured by the Cognitive, Affective and Psychomotor (CAP) Perceived Learning Scale designed by Rovai et al. (2009). The CAP scale was designed for both face-to-face and online learning. Since many of the participating courses did not include psychomotor skills in their learning goals, for comparable results across courses purposes, only the six cognitive and affective items of the instrument were included in the survey. These items use a seven-point likelihood Likert scale ranging from *Not at all* to *Very much so*.

3.2.4. Demographic information

Table 2 displays the demographic information that was collected in the survey. The participants were asked to self identify their major culture based on a culture map from research on the World Values Survey website. The research classified cultural beliefs into two dimensions: traditional values versus secular-rational values and survival values versus self-expression values. Then the researchers mapped all countries onto a two-dimension coordinate system and clustered similar countries together to form these cultural groups. The map can be viewed using the following link `http://www.worldvaluessurvey.org/WVSContents.jsp?CMSID=Findings`.

Table 2

Demographic Questions and Choices

Question	Choices
How many online courses have you completed before this course?	• None • Less than 5 • 5 - 10 • More than 10
Prior to taking this course, please identify your experience with this course topics.	• I was new to the course content • I was familiar with some topics • I was familiar with most topics • I was an expert on this course content
Please use the culture map to identify the culture that best matches you. (it may not fit you in a perfect sense or you may find multiple cultures apply to you, but please identify one which describes you the most)	• African-Islamic • Baltic • Catholic Europe • Confucian • English Speaking • Latin America • Orthodox • Protestant Europe • South Asia
What is your age?	• Under 18 years old • 18-24 years old • 25-34 years old • 35-44 years old • 45-54 years old • 55-64 years old • 65-74 years old • 75 years or older
What is your gender?	• Male • Female • Other
What is the highest degree or level of school you have completed? If currently enrolled, highest degree received.	• Some high school, no diploma • High school graduate, diploma or the equivalent (for example: GED) • Some college credit, no degree • Trade/technical/vocational training • Associate degree • Bachelor's degree • Master's degree • Doctorate degree • Professional degree (e.g. M.D., J.D.)

3.3. Procedure

The Coursera courses taught by Duke University faculty with one or two instructors were selected. After the IRB approval was obtained, the author asked all instructors teaching these courses for permission to collect data. An Email with the survey link was then sent to all active students in these courses with the instructor(s)' permission in February 2018. All active students since the launch date (vs. active students since last week, last month, etc.) were selected to avoid neglecting students who were inactive for a certain amount of time but still would like to share experiences. The survey was open for two weeks to give participants enough time to complete.

3.4. Data analysis

This study used structural equation modeling (SEM) to test the model. All data cleaning, visualization, and analysis were done using *R 3.4* and relevant packages. Confirmatory data analysis (CFA) and SEM modeling were performed using *R* package *lavaan 0.6.2*, which has been widely used in Psychology, Social Science and other fields. Package *semTools 0.5.1* was used to report several model fit indicator measures. After removing rows with missing values, only 23 (0.51%) respondents indicated *Other* in the gender question. Thus, they were removed from the analysis. The final sample consists 4503 observations ($n =$ 4503), of which 2609 (57.9%) are female and 1894 (42.1%) are male. Participants who were new to content, familiar with some course topic, familiar with the most topic and an expert in course content are 1207 (26.8%), 2300 (51.1%), 900 (20.0%), and 96 (2.13%) respectively. Participants who took zero online courses, less than 5, 5 to 10, and more than 10 are 733 (16.3%), 2151 (47.8%), 1010 (22.4%), and 609 (13.5%) respectively. Figures 2, 3, and 4 respectively show the numbers and percentages of participants' degree, age, and self-identified culture.

A two-step modeling approach was adopted with a CFA followed by an SEM analysis. Because the CFA result was not satisfactory as suggested by model fit indicators and factor loadings, an exploratory factor analysis was

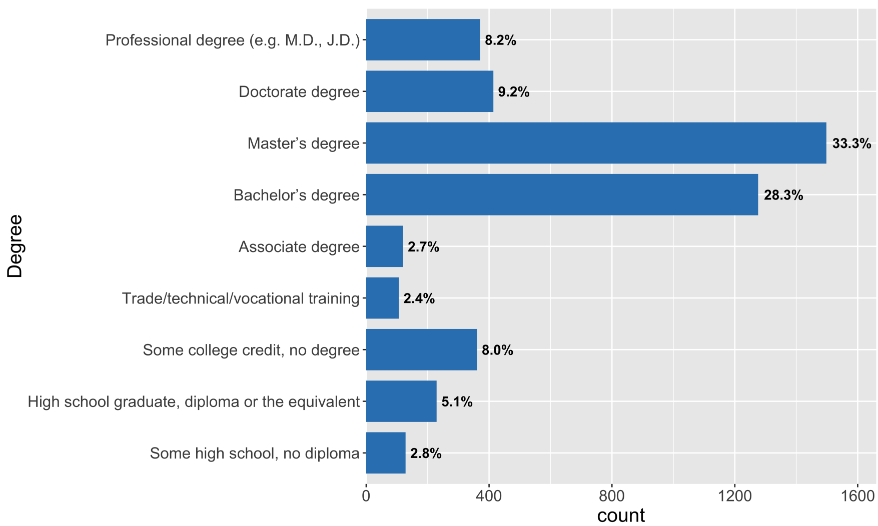

Figure 2. Number and Percentage of Degree

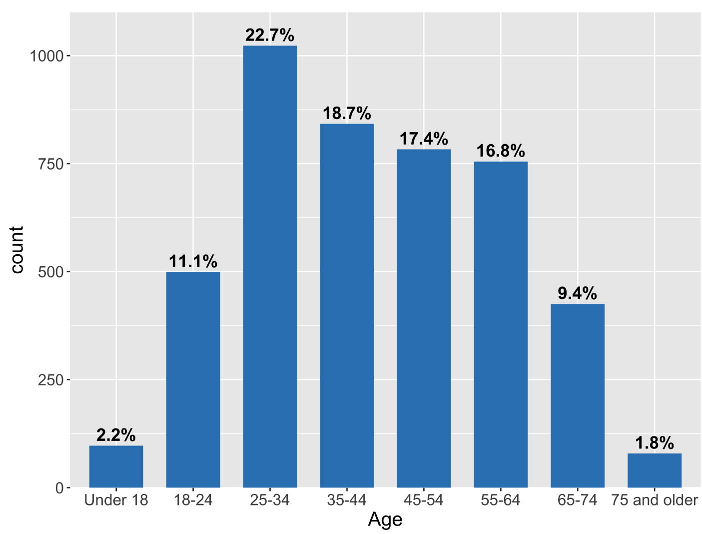

Figure 3. Number and Percentage of Age Group

performed by randomly splitting the sample into two, one of which was used to run the (EFA) and the other one was used to run CFA to cross-validate the EFA results. Only eight items from the OSLQ and two items from the

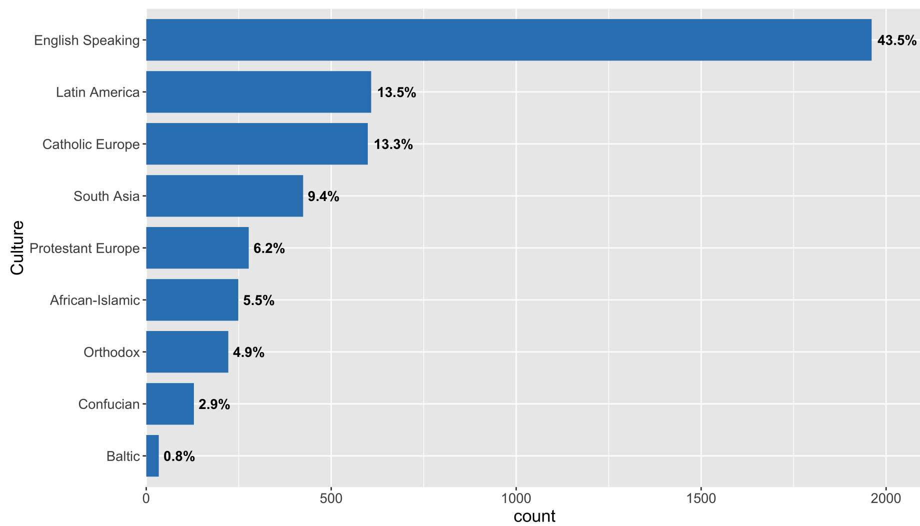

Figure 4. Number and Percentage of Culture

CAP instruments were selected in the final analysis because other sub-scales contradicted with the original instrument. Since instrument validation is beyond the scope of this article, only the ones consistent with the original instrument were included. Because the numbers of respondents with *Baltic*, *Confucian*, and *Orthodox* cultures had the fewest numbers of students and the three were in close positions in the culture map, they were combined into a category named *Other* in the SEM model. Originally, every other cultural group was compared with *English Speaking* because *English Speaking* consisted of the largest proportion of the sample. But later in the analysis, *Latin America* showed strong differences from *English Speaking* in several paths. *Latin America* was then made the base group to which the other groups were compared.

4. Results

4.1. Descriptive statistics

The descriptive statistics of measured variables in the model are reported in Table 3, including skewness and kurtosis which are indicators for univariate normality. Mean scores range from 3.77 to 4.62. Standard deviation scores range from 0.76 to 1.53. All but two items' kurtosis scores (sat 1 and sat 2) do not fall in the acceptable ranges of normality suggested by Kline (2005) (skewness does not exceed |3| and kurtosis does not exceed |10|). But *lavaan* applies the diagonally weighted least squares (DWLS) estimation method for ordinal endogenous variables. DWLS has been proved to be robust with ordinal and non-normal data (Mindrila, 2010). The two items were not considered problematic in the analysis.

Table 3

Descriptive statistics of the items in the measure

Construct and item	Mean	Standard deviation	Skewness	Kurtosis
Goal				
Goal 1	3.89	1.00	-0.79	3.33
Goal 2	3.77	1.07	-0.77	3.03
Goal 3	4.01	1.01	-1.01	3.59
Goal 4	3.79	1.09	-0.77	2.95
Environment				
Env 1	4.22	1.00	-1.33	4.23
Env 2	4.32	0.91	-1.52	5.23
Env 3	4.38	0.88	-1.60	5.60
Env 4	4.23	0.94	-1.34	4.57
Perceived affective learning				
Learn 1	4.33	1.44	-0.97	3.73
Learn 2	4.25	1.53	-0.90	3.41
Satisfaction				
Sat 1	4.62	0.76	-2.65	11.12
Sat 2	4.61	0.78	-2.58	10.44
Sat 3	4.56	0.83	-2.31	8.76

4.2. Measurement model

The CFA results are shown in Table 4. All standardized factor loadings were greater than 0.70, between 0.76 and 0.97. The R squared scores ranged from 0.57 to 0.93, meaning that the survey items were explained by their latent variables at a range from 57% to 93%. All Cronbach's alphas were greater than 0.70 indicating good reliability of items within a construct (Cortina, 1993). The convergent validity of the measurement model was measured by two scores: the composite reliability (CR) and the average variance extracted (AVE) (Fornell & Larcker, 1981). CR measures item internal consistency, which is considered less biased than Cronbach's alpha. In this study, McDonald (1999)'s *omega* was used as a measure for CR. All CR scores in the measurement model are greater than 0.70 indicating good internal consistency (Nunnally & Bernstein, 1994). AVE is the measure of the variance that is explained by the constructs compared to the variance explained by measurement errors. A score greater than 0.70 is considered good while a score greater than 0.50 is considered acceptable. Judging by CR and AVE, the convergent validity of the measurement model can be considered adequate.

Table 4

Results for the measurement model

Construct and item	Standardized factor loading (>0.70)[a]	R^2	Cronbach's alpha (>0.70)[a]	Composite reliability (>0.70)[a]	Average variance extracted (>0.50)[a]
Goal			0.91	0.87	0.71
Goal 1	0.80	0.64			
Goal 2	0.85	0.72			
Goal 3	0.86	0.74			
Goal 4	0.87	0.76			
Environment			0.90	0.88	0.71
Env 1	0.86	0.73			
Env 2	0.87	0.76			
Env 3	0.89	0.79			
Env 4	0.76	0.57			
Perceived affective learning			0.88	0.79	0.78
Learn 1	0.89	0.79			
Learn 2	0.88	0.77			
Satisfaction			0.95	0.92	0.86
Sat 1	0.94	0.88			
Sat 2	0.97	0.93			
Sat 3	0.88	0.77			

[a] Indicates an acceptable level of reliability or validity

Discriminant validity was tested using the heterotrait-monotrait ratio of correlations (HTMT) (Henseler et al., 2015). Table 5 shows the results of the

HTMT ratio of correlations. Values greater than 0.85 indicated lack of the discriminant validity. Results of the measurement model indicate satisfactory discriminant validity.

Table 5

The HTMT ratio of correlation

	Goal	Environment	Perceived affective learning	Satisfaction
Goal	-			
Environment	0.60	-		
Perceived affective learning	0.40	0.30	-	
Satisfaction	0.35	0.35	0.55	-

Multiple model fit indices were reported for both the CFA and the SEM models in the next subsection as suggested by Kline (2005). Since the sample size of this study was quite large ($n = 4503$), Chi-square (χ^2) would be almost inevitably significant. Thus, Chi-square was not reported. *Lavaan* provides robust measures for these fit indices, which accounted for unbiased standard errors. Table 6 shows the robust fit indices of the measurement model and the recommended thresholds. Recommended thresholds were retrieved from Hu & Bentler (1999).

Table 6

Fit indices for the measurement model

	Comparative Fit Index (CFI)	Tucker-Lewis Index (TLI)	RMSEA[a] (90% Confidence Interval)	SRMR[b]
Model indices	0.99	0.99	0.045 (0.04, 0.05)	0.02
Recommended threshold	≥ 0.95	≥ 0.95	< 0.06	< 0.08

[a]: Root Mean Square Error of Approximation
[b]: Standardized Root Mean Square Residual

4.3. Structural model

A test of the structural model showed a good model fit (CFI =0.99, TLI=0.99, RMSEA=0.034, RMSEA's 90% confidence interval is (0.032, 0.036), SRMR=0.03). All measures were reported using *lavaan*'s robust indices, the same as the measurement model. Figure 5 shows the graphical description of the results of path coefficients. The results showed that three hypotheses were not supported by the data. The results failed to reject the null hypothesis of (1) learners' experience with the course content did not predict their perceived learning (H_2). (2) Learners' experience with the course content did not predict their environment structuring strategy usage (H_{6b}). and (3) Learners' gender did not predict their satisfaction with the course (H_{13}).

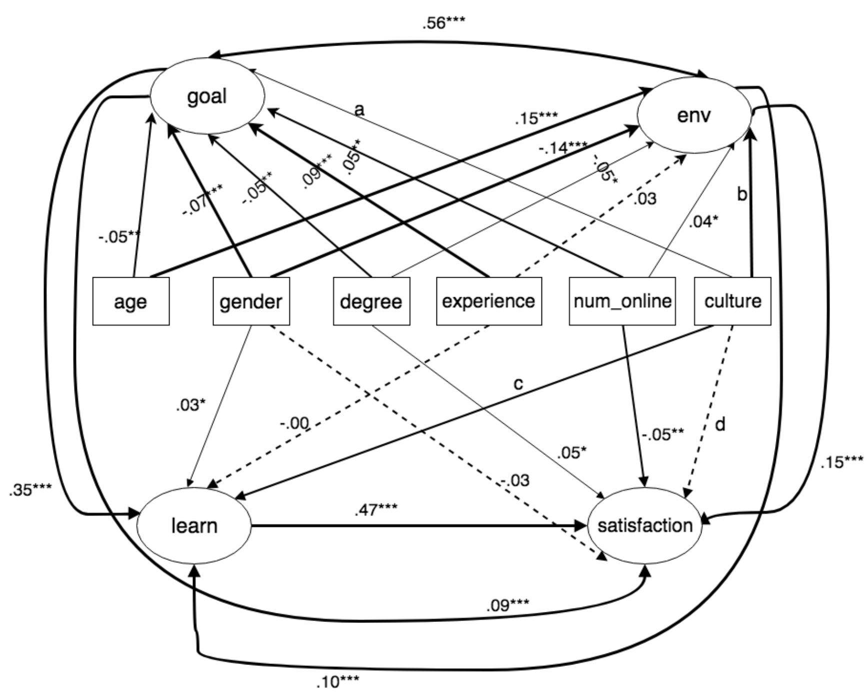

Figure 5. Path coefficients of the research model.

$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. a, b, c, and d see table 7.

For these hypotheses that the results were able to reject, Table 7 presents the findings from this study's data and results except for the relationships of

Table 7

Results

Predictor	Results
Gender	Female students reported more goal setting (GS) and more environment structuring (ES) strategies. Female students perceived lower learning.
Age	Older students reported more GS but fewer ES strategies.
Degree	Students with higher degrees reported fewer GS and fewer ES strategies, but were more satisfied with the course.
Experience	Students having more experiences with the content reported more GS strategies.
Number of course	Students took more online courses previously reported more GS and more ES strategies, but they were less satisfied with the course.
GS strategy	Students who used more GS strategies perceived higher learning and were more satisfied with the course. GS partially mediated the effects of gender to perceived learning, degree to satisfaction, and number of courses to satisfaction. GS was the mediator of the relationship between experience and perceived learning.
ES strategy	Students who used more ES strategies perceived higher learning and were more satisfied with the course. ES partially mediated the effects of gender to perceived learning, degree to satisfaction, and number of courses to satisfaction.
Perceived learning	Students who perceived higher learning were more satisfied with the course. Perceived learning partially mediated the effects of GS and ES on satisfaction. Perceived learning was the mediator of the relationship between gender and satisfaction.

culture (reported in the following paragraph).

Because there were seven cultural groups in the study and the other groups were compared against *Latin America*, the results are presented in Table 8 as a separate section. There are several differences in goal setting strategy usage and satisfaction between some cultural groups and *Latin America*, but the strongest trends lied in the facts that learners identified themselves as *Latin America* culture reported more environment structuring strategy usage than any other cultural groups, as well as higher perceived learning than other cultural groups except for *Other*.

Table 8

Cultural group comparisons with Latin America

a: culture → goal			b: culture → environment	
Culture	β	p	β	p
African-Islamic	.01	.52	-.05	.00**
Catholic Europe	-.04	.08	-.08	.00***
English Speaking	.00	.94	-.10	.00***
Protestant Europe	-.05	.01**	-.08	.00***
South Asia	.05	.01*	-.05	.00**
Other	-.05	.01**	-.08	.00***

c: culture → perceived learning			d: culture → satisfaction	
Culture	β	p	β	p
African-Islamic	-.04	.03*	-.02	.46
Catholic Europe	-.07	.00**	-.01	.74
English Speaking	-.17	.00***	-.02	.36
Protestant Europe	-.09	.00***	.02	.34
South Asia	-.07	.00***	-.06	.00**
Other	-.02	.35	-.02	.37

$*p < .05$, $**p < .01$, $***p < .001$

The proportions of variance in all endogenous variable that are explained by all of its predictors are listed below. Only 2.90% of the variance in goal setting could be explained by all the predictors in the model while 4.50% of the variance in environment structuring could be explained by its predictors. 35.0% of perceived learning's variance was explained by all its predictors and 18.3% variance in satisfaction was explained by its predictors.

4.4. Model comparison

To compare the research model with the model of which the non-significant paths removed, the $\Delta\chi^2$ (chi-square change) and the Δ CFI were reported because of the sensitivity of chi-square to sample size (Cheung & Rensvold, 2002). Table 9 lists the results of the model comparison. Both the $\Delta\chi^2$ ($p > .05$) and the Δ CFI (Δ CFI $< .01$) suggested these two models were not significantly different.

Table 9

Results of model comparisons

Model	χ^2	df	CFI	$\Delta\chi^2$ (p-value)	Δ df	Δ CFI
The research model	544.42	163	0.991	-	-	-
The revised model	575.87	172	0.993	16.448 (.059)	9	0.002

5. Discussions

5.1. Result discussions

The purpose of this study was to examine the relationships among learners' demographics, SRL strategy usage, perceived learning, and satisfaction in MOOC environments at the same time by implementing an SEM model. Guided by a large body of literature on this topic, it is found that many demographic variables predict learners' SRL strategy usage — in particular, goal setting and environment structuring strategies in this study, with the exception of prior experience predicting environment structuring strategy usage. Perceived learning can be predicted by learners' gender, culture, and their SRL strategy usage. Satisfaction can be predicted by learners' highest degree, the number of online courses previously taken, SRL strategy usage and perceived learning.

It is consistent with previous research that female students often reported using more self-regulated learning strategies (Pajares, 2002). Goal setting strategies were assessed specifically by Zimmerman & Martinez-Pons (1990) and female students again reported more usage. Besides the potential fact that females do use more SRL strategies in learning than males, Pajares (2002) proposed four possibilities of why there is a gender difference in SRL strategy usage. They are: (1) achievement is the mediator variable. (2) Males and females respond to self-reported measures differently. (3) Males and females have a different level of confidence in certain areas. (4) Gender stereotype may influence how people position themselves.

Learners who obtained higher degrees tended to report less goal setting and less environment structuring strategies, which contradicts with many previous studies. For example, Kizilcec et al. (2017) found that MOOC learners who have Ph.D.s had stronger SRL skills compared to those non-Ph.D.s. One reason is that this study examined eight degrees while Kizilcec et al. (2017) only compared Ph.D.s with non-Ph.D.s. Another possibility may be related to learners' motivations for enrolling. Learners with higher degrees might take MOOCs just to explore, or to reference specific topics. Thus, there was no need to set specific goals or to control their learning environments versus those who really wanted to learn the entire course.

This study reveals that previous experience with the course topics predicted only goal setting strategies, not environment structuring strategies, which partially supports previous research in that the more online courses learners had taken, the more SRL strategies they used in learning (e.g. Wang et al. (2013)). While previous research generally reports a positive relationship between experience and SRL strategy usage (e.g. Vermunt & Vermetten (2004)), no study has investigated the relationship between particular environment structuring strategies and experience. Further research can examine the reasons for this.

The influences of age on the two SRL strategy usage show opposite results: older students tend to use less goal setting strategies but more environment structuring strategies. This result directly contradicts with what Kizilcec et al. (2017) found, that is, older students reported using more goal setting strategies in MOOCs. One potential explanation for this difference may be in the study samples: this study's participants came from around the world with multiple cultures while the participants in Kizilcec et al. (2017) were mainly Latin American learners taking courses in Spanish.

Male learners perceived higher learning than their female peers. Possible explanations can also be in Pajares (2002)'s article as discussed above. The usage of both SRL strategies — goal setting and environment structuring — significantly predicted learners' perceived learning, which supports the findings in Lee & Lee (2008). The more online courses a learner took, the less satisfied he/she is with the MOOC. Although Shen et al. (2013) found a positive relationship of the number of online courses took and satisfaction, most research has demonstrated that learners' previous experiences of online courses, not merely the number, influence their satisfaction with the current course. The fact that this study measured perceived affective learning instead of cognitive learning may contribute to some of the contradictory results mentioned above. Learners' experience with their previous online courses was not examined in this study. It is possible that their previous online experience was not good, or they continued enrolling but were not able to find a satisfactory course.

Learners with higher degrees were more satisfied with the course, which contradicted the finding by Ke & Kwak (2013). Learners' highest degree earned and their satisfaction are more complicated in MOOCs. For example, Shapiro et al. (2017) showed that MOOC learners with a Bachelor's degree were more positive than students with lower and more advanced degrees through a sentiment analysis of their interview transcripts. Current literature has inconsistent results about the relationship between students' SRL strategy usage and their satisfaction with the course. For example, Cho & Heron (2015) found no relationship. Puzziferro (2008) reported a positive relationship between several SRL strategies, including environment structuring strategies, and their levels of satisfaction. The current study supported that learners who reported using more SRL strategies — both of them — were more satisfied with the course.

One uniqueness of this study was the investigation of culture on MOOC learners' SRL strategy usage, perceived learning, and satisfaction. Learners identified themselves as having *Latin America* culture reported more environment structuring strategies than any other culture. The four items measuring the environment structuring strategies were about choosing quiet, comfortable places and times with few distractions to study. No previous study in English, as far as the author is aware, was found that highlighted the learning habits of *Latin America* students or whether its education emphasizes controlling learning environments. Thus, it can only be assumed that *Latin America* schools or families may be good at teaching students to choose a comfortable environment to study. It is also possible that the *Latin America* participants were associated with some other variables (e.g. current job status or socioeconomic status) that were not measured in the study, and these hidden variables contributed to the better environment structuring strategy usage. *Latin America* participants also showed better perceived learning than the other cultural groups except for *Other*. Research has shown that people in Latin America have a high happiness level despite the fact that many countries in Latin America have high poverty rates and unequal incomes (Rojas, 2016). The author stated that Latin Americans generally have high affective states and high satisfaction. This may be the reason why participants of the *Latin America* cultural group perceived more affective learning than many other groups. Since the group *Other* consisted of *Baltic*, *Confucian*, and *Orthodox*, it is more complicated as why the group of *Other* had similar perceived learning as *Latin America* instead of lower. *South Asia* showed lower satisfaction with the courses than *Latin America* while the other groups' satisfaction did not differ significantly from *Latin America*. Because of the lack of theory and research to support this point, the differences may be attributed to certain unmeasured variables or simply by chance.

5.2. Implications

There are three major implications for researchers and practitioners in the field of self-regulated learning in online learning environments, particularly MOOC environments. The three implications, discussed in detail below with prior research findings, are (1) influences of SRL strategy usage on learners' perceived learning and satisfaction; (2) relationships between learners' demographics and SRL strategy usage; and (3) differences of SRL strategy usage, perceived learning, and satisfaction among different cultural groups.

Firstly, the present study emphasized the importance of SRL strategy usage by revealing its relationships with perceived learning and satisfaction. Zimmerman (2002) explained that by monitoring and reflecting on their goals and progress, learners can feel more motivated and satisfied, and then seek opportunities to improve their learning. Schunk (1990) pointed out that learners' satisfaction is expected to increase after they achieve their goals by allocating effort toward these goals. Learners learn better when they constantly monitor their goals and progress, reflect on their experiences, and adjust effort and learning strategies. Research has shown that SRL strategy usage is teachable even to young students in elementary schools (Dignath et al., 2008). Zimmerman (2002) stated that SRL skills are important for life-long learners. MOOCs are a form of continuing education, life-long learning and self-directed professional development, which requires learners to have SRL skills. In addition, the current study further supports the positive relationship between SRL strategy usage and perceived learning as well as satisfaction. Therefore, researchers and instructional designers should investigate activities that can teach certain SRL strategies in self-directed online learning environments. It is reported that even a small activity to help students to be aware of their learning situations can help learning (Zimmerman, 2002). Researchers can design simple interventions such as weekly emails containing "study tips" to enable this awareness.

Secondly, different levels of SRL strategy usage — goal setting and environment structuring in this study — differed by learners. This is of particular importance for MOOC researchers and practitioners because of the varied backgrounds and demographics of MOOC learners. The demand for SRL strategy training or even small activities to encourage self-regulation in online learning was discussed in the previous section. Understanding the relationships between learners' demographics and their SRL strategy usage helps to teach learners SRL strategies, especially to particular groups of learners. For example, lack of time has been identified as the top reason why learners drop out of MOOCs (Shapiro et al., 2017; Zheng et al., 2015). Designing SRL strategy training interventions for targeted populations who may be diagnosed at risk can prevent learners from discontinuing because of reasons such as lack of resources or lack of time. However, since the total variances of both SRL strategy usage explained by all predictors were small (2.9% and 4.5% respectively), future studies should examine other variables that may contribute to the differences in SRL strategy usage.

Thirdly, the differences in SRL strategy usage, perceived learning and satisfaction among learners from diverse cultures had several implications for researchers, teachers, and instructional designers who need to design instructions cross-culturally. The present study supports that differences among cultural groups in beliefs and behaviors exist in MOOCs. There may be the problem of overgeneralization if the attention has been on cultural differences as a static trait (Gutiérrez & Rogoff, 2003), but like all other literature on group differences, cultural differences bring one more dimension to individual/group differences on teaching and learning. Researchers can examine whether and, if it is, why learners from *Latin America* culture had significantly higher environment structuring strategy than any other cultural group. If there are particular reasons in *Latin America* educational systems or family values that help students adopt more environment structuring strategy, this can potentially be adopted and emulated in other cultures that may lack environment structuring guidance. Similarly, the reasons why learners with *Latin America* culture had higher perceived affective learning can be examined for educational implications. In addition, teaching cross-culturally is an important component in the educational literature. Practitioners and educators should be sensitive about teaching cross-culturally. In an interview with instructional design professionals, Rogers et al. (2007) reported that these professionals were aware of cultural difference to some extent but they also admitted that more awareness needed to be developed. Gay (2002) argued that because culture affects students' attitudes, values, and behaviors, it is crucial to design culturally-relevant curricula, teaching and communication methods, and learning community. Gopal (2011) proposed that faculty in higher education need to work on their attitudes, knowledge, and skills to develop cultural competency in order to better teach cross-culturally.

5.3. Limitations

The present study has four main limitations that, although common in this type of work, should be noted when drawing conclusions from the findings. Survey research that uses convenient samples lacks external validity compared to random samples. MOOCs offered by one university on one platform were not representative of all MOOCs, and respondents to the survey in this study were not a representative sample of all enrolled students. Although the courses selected in this study included multiple topics compared to many research that used students from only one course, conclusions cannot be drawn to the entire MOOC students population. The second limitation is that this study is based on learners' self-reported data. As much as self-reported data can broaden the areas that direct observations or other achievement assessments cannot measure, problems with self-reported data have been discussed intensely in research, including over- and under-reporting and social desirability bias (Gonyea, 2005). Future studies should include more objective measures such as learning management system log data and test scores to offer more holistic insight into learners' behaviors, learning achievement and motivation. Because of the low response rate of surveys, nonresponse bias is the third limitation. Most MOOC research using survey method suffer from this limitation. The last limitation lies in the construct validity. Even though the study used two existing instruments measuring SRL strategy usage and perceived learning, factor analysis did not reveal satisfactory results in terms of their sub-scales. Exploratory factor analysis results were used in this study, which left out some items in the original instrument. Several reliability indicators suggested good reliability of the items that were used in the study; however, future research is still needed to validate the instruments in MOOC environments.

6. Conclusion

Self-initiated and self-directed learning has become increasingly popular and important in education and in professional development. According to one of Pew Research Center's 2016 reports, 74% of American adults had participated in some types of personal voluntary learning activities to enrich their knowledge (source: `http://www.pewinternet.org/2016/03/22/lifelong-learning-and-technology/`). Having SRL skills is essential to students' success in such self-directed learning environments, an example of which is the MOOC. Studies on MOOC learners' SRL skills, such as the current one, emphasize the importance of SRL strategy usage by unraveling its relationships with other crucial factors in learning. These findings suggest positive relationships between SRL strategy usage and perceived learning, and SRL strategy usage and satisfaction. Practically, educators should emphasize the importance of using SRL strategies in self-directed learning and create opportunities to help learners increase SRL awareness and SRL skills in learning.

Today's student body is more and more diverse because of both globalization and online technologies. Studies have already demonstrated that students learn differently, but personalized learning remains a challenge in education. A first step to personalized learning can be to uncover the differences in attitudes, behaviors, and motivations by groups. MOOC learners possibly have the most diversified backgrounds and experiences among all learning contexts, which makes the MOOC an exceptional platform to study group differences. Results of this study show that some differences exist in learning strategy usage, perceptions and satisfaction by groups, such as age groups and highest degrees obtained. Practically, learning activity and assessment's variability is necessary for students with different backgrounds and motivations. Learning analytics algorithms could take these variables as input to predict at-risk students, best learning routes, or pertinent help at an appropriate timing.

Keengwe (2010) stated that "...raising personal awareness about different cultural categories of individual differences, and how these differences enhance or hinder the ways students and teachers generally interact with each other." (p. 203). Theoretically, studying the differences in learning behaviors, attitudes, and perceptions among MOOC learners from multiple cultures can contribute to the cross-cultural education literature, which then adds to the broader area of cultural differences. The study results suggest that learners identified themselves as *Latin American* showed higher environment structuring strategy usage and perceived learning than many other cultural groups. Practically, revealing these cultural differences in self-directed learning explains the differences in thinking, behavior, motivation, and choice during the learning process. Culture can be treated as a variable to predict students' success in order to personalize learning or provide help.

Conflict of Interest

The author declares no conflict of interests.

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