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Using the Presage Variable in the Biggs' 3P Model to Evaluate a Massive Open Online Course in the Philippines

Mari Anjeli Crisanto[1]* • Ma. Gian Rose Cerdeña[2]

[1] Faculty of Information and Communication Studies, UP Open University, Los Baños, Philippines.
[2] Faculty of Information and Communication Studies, UP Open University, Los Baños, Philippines.

***Corresponding author. Email:** marianjeli.crisanto@upou.edu.ph

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Abstract

Massive Open Online Courses (MOOCs) have been recognised as a means of bridging higher education and growing employment needs. A MOOC offered by any institution, therefore, needs to go through continuous evaluation for quality assurance. In 2016, the Commonwealth of Learning released a framework for MOOC Quality Guidelines, incorporating Biggs' 3P Model to list dimensions and instruments which can be used to assure MOOC quality. This was used to assess the 'Artificial Intelligence for Quality Assurance in Education' MOOC for quality assurance in research done under the Diploma in Computer Science program in the University of the Philippines Open University. Evaluation was done using selected metrics from the Biggs' 3P Model: learners; learning process; completion/retention and certification rates; and enjoyment and self-satisfaction. This paper presents the results of the evaluation on learners as a presage variable. The Self-Regulated Learning MOOC Questionnaire was used in measuring the learners presage variable as recommended by the Commonwealth of Learning. The tool included 42 statements arranged into three groups (forethought, performance, and self-reflection) rated using a five-point Likert scale. This study involved voluntary participants from the August 2022 MOOC offering. The scores from 84 learners were analysed by taking the total of the Self-Regulated Learning scores per learner and by computing for the mean and standard deviation of each Self-Regulated Learning sub-process. The Self-Regulated Learning scores were further broken down based on demographics with quartile statistics used to draw further inferences on the distribution of these scores. High Self-Regulated Learning scores affirmed the high learner motivation and good quality of the MOOC. This paper will provide further recommendations for MOOCs based on learner results, thereby contributing to quality in online and distance learning. Results on the process and product variables will be discussed in separate papers.

Keywords: Biggs' 3P model, MOOC evaluation, presage variable, self-regulated learning, quality assurance

1. Introduction

Massive Open Online Courses (MOOCs) are "complete courses consisting of educational content, assessments, peer-to-peer tutoring and/or some limited tutoring by academics" (Jansen et al., 2017, pp. 6-27). These are offered by various institutions, the University of the Philippines Open University (UPOU) being one of them. UPOU has pioneered the offering of MOOCs in the Philippines from 2012 and has continued to offer online courses on various topics as part of the university's mission of providing wider access to quality education and to support the Republic Act 10650 - Open Distance Learning Law (Almodiel et al., 2020). As with other MOOCs, those offered by UPOU face issues like low course completion rates, lack of student support and reliable assessment methods, plagiarism and cheating (Librero, 2020). Because of these issues, MOOCs must be continually evaluated for quality assurance.

Biggs' 3P Model of Student Learning (1993) was used by the Commonwealth of Learning (2016) to list dimensions of MOOC quality, suggesting possible measures to check for quality. The 3P Model divides the learning system into three types of variables which are the presage, process and product variables (Biggs, 1993; Commonwealth of Learning, 2016). The presage variables refer to resources and factors that go into teaching and learning processes which include learners, instructors, institutions, and the platform and platform provider in the case of MOOCs (Commonwealth of Learning, 2016). Presage variables represent the prior experiences and knowledge of teachers and students (Kanashiro et al., 2020).

The focus of this paper will be on this variable of the 3P Model and will center on the learners, specifically their self-regulated learning scores (SRLs) in a MOOC context. Being a presage variable, the SRL gives inference on the "individual learners' motivations for engaging in a MOOC and the nature of their participation" (Commonwealth of Learning, 2016, p. 21). According to the Commonwealth of Learning (2016, p. 10), it is often the learners themselves that drive successful learning in a MOOC rather than the institution. In MOOCs, it is more useful to measure quality by having learners evaluate the quality of their own learning in relation to their goals. Quality in this lens can be shown through the ways that the learners achieve their goals through their MOOC participation which is not just through gaining a course certificate (Commonwealth of Learning, 2016, p. 13). Based on the 3P Model, the quality of learner motivation and goals will also affect the property of the process and product variables and can be explored in future research.

This study involved voluntary participants from the Artificial Intelligence for Quality Assurance in Education MOOC August 2022 class. The methodology detailed in this paper was carried out on the mentioned participants with limitations on time as only three weeks were allotted for data collection.

2. Literature Review

2.1. The 3P Model

John Biggs' 3P Model has had a significant impact on today's teaching and learning assessment methods (Barattucci, 2017). As further explained by Barattucci (2017), the model implies that learning outcomes are affected by numerous elements interacting with one another, necessitating not only effectiveness and high quality, but also component compatibility. According to Kember et al., (2020), the 3P Model was designed with an emphasis on the students' approaches to learning (SAL) paradigm.

Due to its integrative character, the model is used in research as a framework to ensure that all aspects contribute to a student's learning process, allowing for a better understanding of how the factors influence each other (Kanashiro et al., 2020; Song, 2018; Allison, 2021). It has been utilized in various contexts, like MOOCs, K-12 computing instruction, psychological processes studies, and even articles written by healthcare practitioners (Allison, 2021; Crowther et al., 2020; Ganotice & Chan, 2019; Song, 2018).

In fact, studies have utilised the 3P Model as a framework for their MOOCs due to its versatility in adapting to the MOOC context and ability to encompass both surface learning and deep learning, making it an extensive framework for successful learning outcomes in MOOCs (Deng et al., 2019; Pilli & Admiraal, 2017; Yang & Lin, 2023). Due to its conceptualisation of education as a collection of interdependent ecosystems, Littlejohn (2016) utilised the 3P Model in the creation of a set of guidelines for quality assurance in MOOCs. The 3P Model can effectively examine the essential educational and teaching components of MOOCs due to its structured and logical approach detailing the relationships among the teaching and learning factors (Deng et al., 2019).

While studies such as the one Allison in 2021 did acknowledge that the 3P Model can be criticised as outdated, oversimplified and certainly not the only model that can be used to understand educational context, it also seems to be the "most prominent learning model in higher education" as identified by Kanashiro et al. (2020, pp. 671-684).

2.2. On Evaluating Learners: Studies using Self-Regulated Learning Questionnaires

Self-regulated learning (SRL) "involves cognitive, metacognitive, behavioural, motivational and affective processes to face a learning situation and persevere until succeeding" (Alonso-Mencía et al., 2020). SRL is crucial for successful learning in MOOCs due to the greater student autonomy allowed in MOOCs compared to other traditional courses and consists of three steps: forethought, performance, and self-reflection as developed by Zimmerman in 1990 (Jansen et al., 2017; Zalli et al., 2020).

Furthermore, several studies indicate that the ability to self-regulate one's learning is an important skill for learners to be able to complete a MOOCs course (Albelbisi & Yusop, 2019; Rabin et al., 2020; Wong et al., 2019). Research done by Rabin et al. in 2020 has concluded that the higher level of SRL, the higher the level of motivation in learning. Conversely, the lower the goals a learner sets for their learning process, the lower their interest in the MOOC will be.

As Albelbisi and Yusop (2019) have said, a student's success needs effective use of SRL strategies as these would only help develop them become active learners. Prompts, feedback, and integrated support systems were some of the identified SRL techniques; however, one must also take into account the impact of variables like age and gender (Wong et al., 2019).

In order to better understand what leads to better SEL in learning, some researchers such as Jansen et al, (2017) have developed and tested the validity of questionnaires based on the SRL learning process and comprising questions from other questionnaires like Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich et al. (1993), and Online Self-regulated Learning Questionnaire (OSLQ) by Barnard et al. (2009). Other studies choose to refine a specific questionnaire, including Vilkova (2019), who translated the SRL questionnaire validated by Littlejohn et al. (2016) to Russian. In this study, the SRL instrument developed by Littlejohn et al. (2016) was used as it was designed specifically in the MOOCs context, which is named the Self-Regulated Learning MOOCs Questionnaire or SRLMQ/SLMQ.

2.3. Cases of MOOC Evaluation in the Philippines

Currently, though there are various studies covering evaluation of MOOCs, not many have specifically discussed evaluation of MOOCs in the Philippines. One of the first evaluation studies in this context was done for a trial MOOCs course, where Manalo (2014) utilised a subjective survey with a mix of qualitative and quantitative questions through the Kirkpatrick Model of Evaluation. The study found that MOOCs had low completion rates, with the satisfaction levels of the learners bordering between agreeably satisfied and neutral (Manalo, 2014).

The next research more or less focused on the challenges that MOOCs face in the Philippines. To further look into the educational challenges learners have encountered, Gervacio (2015) used an evaluation survey with five categories: course content; working and learning methods; participants; achievement of objectives; and organization of the course. Although one of the limitations the research mentioned was a low number of respondents, the feedback of the learners regarding their satisfaction level was relatively high—a welcome difference from the previous evaluated MOOC in the Philippines. As further discussed by Talusan (2015), the success of the MOOCs in the Philippines can be attributed to the good quality of instructors and curriculum. It is also recommended by Talusan that MOOCs research should focus more on the gender-sensitive aspect, rather than age-conscious as learning is life-long, but results can still be identified based on gender.

Another evaluation which was done by Mabuan (2020) focused on a MOOC Camp done in the Philippines which was conducted using a blended/hybrid approach. The online survey results revealed that most of the learning challenges identified were time constraints and language difficulties due to technical terms used throughout the course. However, Mabuan determined that MOOC camps can be a possible solution to the problem of motivation and engagement among course takers.

In a recent study, Joaquin et al. (2020) ascertained that what MOOCs needed were a clear set of policies and guidelines. For the MOOCs to be successful and remain relevant, a strategy is needed to engage stakeholders and learning innovations must be "grounded on a deeper understanding of distance education".

2.4. MOOCs and its completion rates

With MOOCs being one of the main facilitators for disseminating education, it is important that MOOCs are evaluated to ensure that they meet quality standards (Gamage et al., 2020). These standards can be measured through completion rates which is "an important indicator of learner success" (Pursel et al., 2016). Despite being a free and online platform designed to cater to a large number of learners, however, MOOCs completion rate tend to be low with high dropout rates instead (Khalil & Ebner, 2014; Librero, 2020). In fact, according to Gütl et al. (2014), one of the main reasons for a low completion rate in MOOCs is that students are unable to properly organise their own learning, which is a freedom that the MOOCs give to students.

To start, learners have various reasons as to why they have enrolled in a MOOC but some of the main factors are to enhance professional development or even to simply get a feel for a MOOC course or enrolling without the intention of completing (Gütl et al., 2014; Romero-Rodríguez, 2020). Having noted that most MOOC learners are working people, identified factors that affect completion rate are changes in job responsibilities, the course being too complicated to accomplish while working full time, and the lack of encouragement (Gütl et al., 2014; Khalil & Ebner, 2014; Romero-Rodríguez, 2020). In a survey by Gütl et al. (2014), learners mostly spend their time on MOOCs only after work and typically only for one to two hours per week. This number of hours is insufficient especially for learners that might need at least a background knowledge of the topic to keep up with the lessons, not to mention the need for technical skills as it is fully online, and comprehension skills as most of the lessons are delivered via written language (Khalil & Ebner, 2014).

Pursel et al. (2016) hypothesised that learners with higher completion rates in MOOCs are those with active participation and a higher education level. The study results concluded that student engagement affected by factors such as social presence, sense of distance, and levels of involvement and participation—is a helpful indicator of completion rate. This is further supported by Khalil and Ebner (2014), whose study found that regular communication and interaction with learners helped increase their retention. A few techniques to increase retention are considering students with different schedules, promoting student completion, and strengthening interaction among and between the instructor and students.

Completion rate is the variable often used to evaluate the success of a MOOC, with data readily available. The completion rate for UPOU MOOCs from 2015 to 2018 was 10.18%, out of the 76 courses offered during those years (Almodiel et al., 2020). Internationally, completion rates for platforms MexicoX and edX come in at an average of 13.71% for 12 observed courses, with Udacity sitting at 12.5%, and Coursera at 7.54%, with a wide range of between 0.7% and 36% from a total of 36 observed courses wherein the large range of completion rate is said to come from the discrepancy of low and high numbers of enrolled students from in courses with varying popularity (Khalil & Ebner, 2014; Romero-Rodríguez, 2020).

However, it would be useful to evaluate MOOCs based on other variables as well and see the relationships among these variables and the MOOCs completion rate. It should also be noted though that, according to the Commonwealth of Learning (2016), learners' motivations for enrolling in MOOCs are not limited to getting a course certificate but could include other things like being able to network with other people, gaining new knowledge and skills, sharing experiences and so on. Thus, evaluating the quality of learners and their motivations can be an adequate indicator of MOOC quality.

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The objective of this research paper is to evaluate the quality of the Artificial Intelligence for Quality Assurance in Education MOOC in terms of learner presage variable based on calculated SRL scores.

Specifically, it aims to:

i. Calculate and analyse the means of self-ratings for the eight SRL sub-processes;
ii. Calculate and analyse the SRL scores of the learners; and
iii. Analyse the differences of SRL scores based on demographics.

Since this paper limits itself to the learners as presage variable, evaluation of the quality of content of the MOOC and expected learning outcomes as other presage variables can be recommended as part of future studies.

3. Research Method

For the presage dimension (learners), the Self-regulated Learning MOOC Questionnaire or SRLMQ by Milligan and Littlejohn (2014) was used. The SRLMQ consists of 42 statements arranged into three groups (forethought, performance, and self-reflection). Under forethought, there are two scales: task analysis and self-motivation belief. The performance focuses on the self-control scale, and self-reflection has two scales as well: self-judgment and self-reaction. The survey also consists of eight (8) sub-components: goal setting, task interest/value, self-efficacy, task strategies, help-seeking, interest enhancement, self-evaluation, and self-satisfaction/affect.

3.1. Respondents of the Study

This study involved voluntary participants from the Artificial Intelligence for Quality Assurance in Education MOOC August 2022 class who were 18 years old and above. The MOOC was chosen since the research was done as a Diploma in Computer Science (DCS) study and this was the DCS MOOC in the pipeline for offering at the time the survey instrument was ready to be deployed. A questionnaire incorporating the instruments was given at the end of the class and the learners were able to choose whether they would participate or not. Informed consent was taken from participants when they accessed the survey instrument. Names and other personal information were not collected and all data was treated with confidentiality. Data gathered was stored in Qualtrics and the researchers' Google Drive. These were to be deleted 30 days after the publication of the research.

The target sampling size for the study was 59/155 active MOOC learners. This was calculated with a 95% confidence level and 10% margin of error. The researchers were able to use 84 responses, higher than the target sampling size. The higher sampling size yields a better range for the SRLMQ scores.

A limitation of this study is that it was conducted during the time that UPOU MOOCs received enrollments of less than a thousand per course. Since course enrollment increased to thousands by 2023, it would be worth repeating the study with a larger population and larger sample size.

3.2. Data Gathering Procedure

A questionnaire created using Qualtrics was posted in the MOOC's course site during the fourth week of the course. Initially, the researchers planned to post it during the last week, but since it was also the week that the final assessment was posted, there would be a possibility that the students would feel overloaded, thus the change in scheduling.

In light of ethical standards, the questionnaire included a section on informed consent and allowed the learner to withdraw from participating in the survey anytime without any consequence.

3.3. Data Analysis

Results from the SRLMQ were analysed following the method presented by Littlejohn et al. (2016) for the collected quantitative data. Data generated from the SRLMQ created a Self-Regulated Learning (SRL) score for each participant (min = 42 and max = 210) as well as a score for each SRL sub-process. The mean was computed for each factor structure along with the standard deviation.

The SRL scores were further broken down based on demographics. These demographics were age, sex, civil status, highest education attained, employment status, and previous MOOC experience. Completion was then taken as is from the LMS analytics. The completion was recorded to draw further inferences regarding learners' SRL scores, course completion rate, and MOOC quality.

4. Findings and Discussion

Of 155 active enrolled learners, there were 93 submitted survey responses. One, however, did not have both consent boxes ticked and 8 were incomplete/unfinished for the SRLMQ portion. A total of 84 survey results, 25 more than the targeted 59 responses, were then consolidated for analysis. Total SRL scores were then computed for each of the 84 responses and calculations for the eight sub-processes were made.

4.1. Self-Ratings for SRL Sub-Processes

Table 1 presents the mean and average standard deviation of each sub-component of the SRLMQ instrument. Interest-enhancement had the highest mean (4.62) and help-seeking had the lowest (3.41).

Table 1. Factor Structure and Descriptive Statistics of SRLMQ Instrument, F = forethought, P = performance, SR = self-reflection

Factor	No. of Items	Mean	Ave SD	Example Item	Rank
F1: Goal-setting	8	4.29	.71	I set short-term (daily or weekly) goals as well as long-term goals (for the whole course).	6
F2: Self-efficacy	6	4.48	.58	I feel that whatever I am asked to learn, I can handle it.	3
F3: Task interest/ Value	3	4.57	.54	The learning that I undertake is very important to me.	2
P1: Learning/task strategies	12	4.25	.66	When I am learning, I combine different sources of information (e.g. people, websites, printed material).	7
P2: Interest enhancement	3	4.62	.51	I like opportunities to engage in tasks that I can learn from.	1
P3: Help-seeking	4	3.41	.95	When I do not understand something, I ask others for help.	8
SR1: Self-satisfaction	3	4.45	.67	I try to understand how what I have learned impacts my work practice.	4
SR2: Self-evaluation	3	4.42	.65	I know how well I have learned once I have finished a task.	5

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It could be inferred that learners had stronger agreement with the following statements under "P2: Interest-Enhancement":

- The most satisfying thing for me in this course is trying to understand the things I learn as thoroughly as possible.
- I like opportunities to engage in tasks that I can learn from.
- I prefer learning that arouses my interest, even if it is challenging.

Meanwhile, the learners had lower agreement with the statements under "P3: Help-seeking":

- When I do not understand something, I ask others for help.
- I try to identify others whom I can ask for help if necessary.
- I ask others for more information when I need it.
- Even if I am having trouble learning, I prefer to do the work on my own. (Scores were reversed when calculating for the mean)

Interest-enhancement therefore regulated the learners' learning the most while help-seeking regulated it the least.

Since mean scores were above four for seven out of eight sub-factors, self-regulated learning for the learners who participated were generally high. Computing the SRL scores for the individual respondents provided greater insight on the MOOC quality based on their responses.

4.2. Overall SRL Scores

Figure 1 shows the distribution of the total SRL scores of survey participants. The SRL score is computed by getting the sum of the learners' ratings for each question (Littlejohn, 2016), with a minimum possible score of 42 and a maximum of 210 based on the questionnaire by Milligan and Littlejohn (2014). The lowest score computed from the administered questionnaire was 145 while the highest was 210. The mean score from the 84 respondents who gave consent and completed the SRLMQ portion of the survey was 183.67 with a standard deviation of 17.32. The mode was 210 and the median was 185.

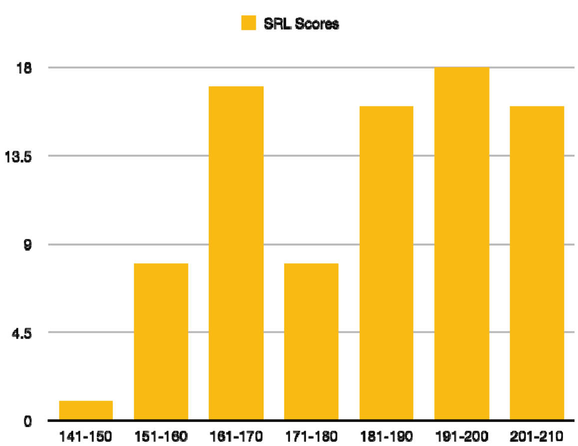

Figure 1. SRL Scores of Survey Participants (min = 42, max = 210)

The scores in Figure 1 affirm that the respondents generally had high SRL scores. It is noted that the recorded minimum, 145, had a 110.16% percentage difference from the possible minimum of 42.

4.3. SRL Scores Based in Demographics

It would be good to note the distribution of SRL scores based on the collected demographic data. To draw better inferences, quartile statistics was used to see the distribution of scores by demographics.

Tables 2 to 7 show the differences in the mean, mode, and median SRL scores of the participants based on their demographics.

Table 2. SRL Scores of Survey Participants based on Age

Groups	18-34 years old	35-50 years old	51-70 years old	All
Sample size (n)	44	38	2	84
Percentage	52.38%	45.24%	2.38%	100%
Minimum	154	145	161	145
Q1	170	168	161	168
Median	187	184.5	171	185
Q3	196.5	198	181	197
Maximum	210	210	181	210
Mean ($\bar{x}$)	184.727273	183.105263	171	183.666667
Skewness	-0.232083	-0.125864	NaN	-0.155181

Most of the participants were from the age ranges of 18-34 years old and 35-50 years old. The medians of the three accounted age ranges differed slightly, but there were no significant differences in the mean SRL scores of the learners based on age. Those aged 18-34 had the highest median and typically had higher SRL scores. Those aged 51-70 years typically had lower ones. Participants aged 35-50 had the highest range and interquartile range and therefore had the least consistent data.

Table 3. SRL Scores of Survey Participants based on Sex

Groups	Male	Female	Prefer not to say	All
Sample size (n)	47	34	3	84
Percentage	55.95%	40.48%	3.57%	100%
Minimum	156	145	154	145
Q1	173.5	167	156	168
Median	189	183.5	158	185
Q3	199	196	162.5	197
Maximum	210	210	167	210
Mean ($\bar{x}$)	186.297872	182.147059	159.666667	183.666667
Skewness	-0.26401	-0.107439	1.055832	-0.155181

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In Table 3, it can be seen that 55.95% of the survey participants were male, 40.48% were female, and 3.57% preferred not to say. The means varied but did not have statistically significant differences. Based on the median, however, male respondents had typically higher SRL scores. It should also be noted that the lowest SRL score came from the female group.

Table 4. SRL Scores of Survey Participants based on Civil Status

Groups	Single	Married	All
Sample size (n)	58	26	84
Percentage	69.05%	30.95%	100%
Minimum	154	145	145
Q1	168	168	168
Median	184.5	187	185
Q3	196	201	197
Maximum	210	210	210
Mean ($\bar{x}$)	183.362069	184.346154	183.666667
Skewness	-0.182963	-0.150263	-0.155181

In terms of marital status, 69.05% of the respondents were single and 30.95% were married. The means of the SRL scores differed but not significantly. The median of the married group was, however, higher but the minimum was also found in the same group.

Table 5. SRL Scores of Survey Participants based on Highest Educational Level Attained

Groups	High school graduate	Bachelors/ undergraduate	Post-baccalaureate/ Diploma	Masters	Doctorate	All
Sample size (n)	2	43	15	22	2	84
Percentage	2.38%	51.19%	17.86%	26.19%	2.38%	100%
Minimum	158	145	161	158	177	145
Q1	158	166.5	169	168	177	168
Median	172.5	183	192	186.5	191	185
Q3	187	195.5	197.5	200	205	197
Maximum	187	210	210	210	205	210
Mean ($\bar{x}$)	172.5	181.534884	186.6	186.181818	191	183.666667
Skewness	NaN	-0.0655022	-0.274245	-0.159794	NaN	-0.155181

As seen in Table 5, there were differences in the means among the different educational levels attained but these again were not statistically significant. The highest median was in the post-baccalaureate/diploma group and the lowest was in the high school graduate group. It should be noted that there were only two participants in the high school group. Since the MOOC was offered under the Diploma in Computer Science programme, this spread in percentage was to be expected since most of the takers would probably come from the programme, currently taking their post-baccalaureate degrees with undergraduate degrees as their previously completed degree.

Table 6. SRL Scores of Survey Participants based on Employment Status

Groups	Employed	Self-employed	Unemployed	All
Sample size (n)	65	9	10	84
Percentage	77.38%	10.71%	11.90%	100%
Minimum	145	154	158	145
Q1	168	157	170	168
Median	186	184	183	185
Q3	197	192	192	197
Maximum	210	210	210	210
Mean ($\bar{x}$)	184.276923	180.111111	182.9	183.666667
Skewness	-0.184342	-0.268763	0.36297	-0.155181

As shown in Table 6, 77.38% of the respondents were employed while 10.71% were self-employed and 11.9% were unemployed. The mean among the three groups differed but there were no significant differences. Those who were employed, however, had the greatest median and typically scored higher, while those who were unemployed had a lower median and typically scored lower.

Table 7. SRL Scores of Survey Participants Based on Prior MOOC Experience

Groups	Have not enrolled in a MOOC before	Have enrolled in a MOOC before	All
Sample size (n)	35	49	84
Percentage:	41.67%	58.33%	100%
Minimum	145	154	145
Q1	168	170	168
Median	182	189	185
Q3	196.5	197	197
Maximum	210	210	210
Mean ($\bar{x}$)	182.342857	184.612245	183.666667
Skewness	0.132326	-0.406595	-0.155181

Table 7 shows that there is a relatively even distribution of those who had previously enrolled in a MOOC and those who had not. Specifically, 41.67% had not enrolled in a MOOC before and 58.33% had. The mean of those who had prior MOOC experience was a little higher, but the difference was not

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statistically significant. Still, the median of those who had prior experience was also higher, showing that their SRL scores were typically higher.

5. Conclusion

Based on the analysis of the means of the self-ratings for the eight SRL sub-process and on the total SRL scores of the respondents, it can be concluded that self-regulated learning in the Artificial Intelligence for Quality Assurance in Education MOOC is generally high. Respondents mostly agreed with statements on learners' goal-setting, self-efficacy, task interest/value, learning/task strategies, interest enhancement, self-satisfaction, and self-evaluation, selecting the responses ranging from 'somewhat true' to 'very true', indicating good quality of the MOOC as rated by the learners, as a presage variable. Interest-enhancement was seen as the respondents' biggest motivation for learning. High SRL scores affirmed the high learner motivation and good quality of the MOOC. It should be noted that when a t-test or a one-way ANOVA was used for the different demographic variables, it was seen that the differences in the scores for each of the demographic variables were not statistically significant. This affirms the open and inclusive nature of the MOOC being evaluated. Demographics do not seem to play a significant role in learners' motivations and self-regulated learning. It is also noteworthy that 84 respondents completed the SRLMQ portion of the questionnaire but only 58 completed the MOOC, based on completion requirements (i.e., submission and peer-evaluation of a final assessment). This shows that 26 out of the 84 respondents did not complete the MOOC in terms of certification. This affirms that MOOC learners do not all necessarily aim to receive certificates of completion and that learner motivation is a worthy indicator of quality. Future research can evaluate other presage variables in the 3P Model to study how quality MOOCs that draw quality learners can be created. Further studies can also be done to investigate the motivations for MOOC enrolment. More studies on the relationship of the learner presage variables to the process and product variables of the 3P model can be conducted to gain a broader understanding of the quality of MOOCs.

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