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Research Article

Education

MALAYSIAN LEARNERS' PREFERENCES-BASED PROFILE MODEL TOWARDS ADAPTIVE MASSIVE OPEN ONLINE COURSES

马来西亚学习者的基于偏好的个人资料模型，面向自适应大规模在线公开课程

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Abstract

Massive open online courses' technology is becoming the most recent innovations in online education and academia. Recently, it has been widely adopted in educational sectors and gained popularity among both students and instructors. Massive open online courses have rapidly become a trend in the field of higher education and received much recognition from scholars and non-profit educational organizations. Therefore, there has been a growing interest in investigating its limitations, challenges, and impact on education. Some issues and problems have been reported in the research and practice, such as problems related to massive open online course learners' motivation and engagement during the courses, and course contents' presentations have a significant impact on learner's motivation. However, there have been few contributions to the literature in discerning the varying motivational drivers for choosing to consume the different presentation styles of massive open online courses. Therefore, the main goal of this work is to propose an innovative framework for adaptive massive open online course based on learners' preferences. As such, the courses' presentations are adapted to the preferred learning style of each learner. In this regard, this paper was conducted based on quantitative research methods.

Keywords: Massive Open Online Course, Higher Education, Preference, Challenge, Malaysia

摘要 大规模开放式在线课程的技术正在成为在线教育和学术界的最新创新。最近，它已在教育领域得到广泛采用，并在学生和讲师中越来越受欢迎。大规模的在线公开课程已迅速成为高等教育领域的

一种趋势，并受到学者和非营利性教育组织的广泛认可。因此，人们越来越有兴趣研究其局限性，挑战和对教育的影响。研究和实践中已经报告了一些问题和问题，例如与大规模开放在线课程学习者的动机和在课程中的参与有关的问题，而课程内容的演示文稿对学习者的动机有重大影响。但是，对于辨别选择使用大型开放式在线课程的不同呈现方式的各种动机驱动因素的文献贡献很少。因此，这项工作的主要目的是根据学习者的偏好提出一个创新的框架，用于适应性大规模开放在线课程。因此，课程的演示适应了每个学习者的偏爱学习风格。在这方面，本文是基于定量研究方法进行的。

关键词: 大规模在线公开课程，高等教育，偏爱，挑战，马来西亚

I. INTRODUCTION

Massive open online courses (MOOCs) are a new innovative approach of open online classes. In this regard, the goal of this research is to examine the Malaysian learners' preferences-based profile model towards adaptive MOOCs over the last decade. Many educational institutions have begun offering online courses in a variety of formats. MOOCs can be recognized as freely available online courses, in which anyone anywhere can participate in these online classes. However, because of being widely accepted among educational institutions, some courses are becoming commercially available. MOOCs are made up of short video lectures combined with computer-graded tests together in a social networked environment, where participants can share knowledge and get support. Today, MOOCs represent a real technological revolution in opening knowledge and ways of teaching and learning. Their main goal is to achieve high-quality online learning contents and enrich online courses with new knowledge and tools through the interactions of various users.

However, despite their effectiveness and being innovative, MOOCs suffer from a number of limitations. One of the main challenging problems is learners' motivation and engagement during the course. Recently, researchers have criticised MOOCs for their low retention and completion rates; each individual learner has unique learning preferences. They learn at varying rates and have different levels of background knowledge, as well as learning goals and styles. Learners have different motivational drivers to choose and consume different categories of MOOCs. Adaptive MOOCs are considered as a promising tool in improving learners' motivations.

However, despite their success, the application of adaptive MOOC is still suffering from a number of challenges, such as what information does the system use for adaptation and how does it gather the information to be adaptive. To address the first challenge, a qualitative analysis should be utilized to identify key factors that influence the learning process of Malaysian learners who are strived to learn the Arabic language. The surveyed individual (a non-native speaker) shall be selected from the Arabic learning institute. The objective of the article is to find the factors of the Malaysian learners' preferences-based profile model towards adaptive MOOCs. Moreover, the research questions are given below:

- What are the available learning factors in the currently existing adaptive learning environment?
- What are the challenges that influence Malaysian MOOC users?
- Are the available learning style models adequate and capable of reflecting the individual's preferred learning environment?
- Are the available learning factors and style models capable of implementing an effective personalized MOOCs?
- What are the main challenges and specific requirements that affect the language learning process?
- How information can be collected from the learner to construct a suitable learning model?
- Does the constructed model effectively reflect the learners' learning preferences?

II. LITERATURE REVIEW

This article describes an approach to measure the Malaysian learners' preferences-based profile model towards adaptive MOOCs. MOOCs are considered as a new extension of the e-learning system, which allows a massive amount of learners to learn on an open and online learning environment. The effectiveness of MOOCs,

however, is an open question because the completion rates and overall use of the system are substantially low. MOOCs are said to be "massive" because there are no prerequisites; thus, the number of subscribers may potentially be very great.

Thus, it is by the "massive" number of those subscribers that MOOC is characterized. However, it is still necessary to distinguish users who sign up from those who actually follow the course. As mentioned previously, MOOCs are "open," which refers to the fact that enrolment is unrestricted and open to all audiences. MOOCs are not conditioned by enrolment at a particular university, attainment of a particular level of study, or professional status. However, the "open" in MOOC does not mean open source or open access; in other words, the software and content are not necessarily open.

Thus, it is not necessarily possible to retrieve the content in order to modify it–or access the data of the participants. Neither does the word "open" signify "free." Regarding MOOC, "online" means that all the courses and exercises are organized for delivery on the Internet. It is not just a question of putting the content of the classes online, otherwise we would speak of "content distribution." In MOOC, there is a true pedagogical agenda and progression. Exercises, homework, and sometimes even exams are online. It is possible to follow the course from absolutely anywhere through the Web–not only on the benches in a university. MOOCs contain many unique characteristics because of their differences from traditional online courses.

The number of registered students in MOOCs is usually very high, and the population is quite diverse [1], [2]. According to Kolowich [3], the median number in the courses that were surveyed in the study was 33,000. Students' varied backgrounds, including location, age, highest degree, participation in class, experience with the subject area, and reasons for selecting the course, are another uniqueness of MOOCs [2]. Universities who offer popular MOOCs reach a much larger population around the world than they ever could before [4]. Students who successfully complete most MOOCs do not receive university credits [4], but usually receive a certificate signed by the course instructor instead (indicating that they have completed MOOCs).

Although MOOCs usually have typical components like videos and quizzes, their formats can vary largely depending on the course's subject areas, technologies, support teams, and instructor's preferences of making the course. Instructional videos normally are picture-in-picture, that is, the instructor's "talking head" inside the slide. There are also other types of videos, including chroma key video (also referred to as a "green screen"), panel discussion, expert interview, lab demonstration, software simulation, and outdoor shooting. The typical length of a MOOC video is between 8 to 12 minutes [5].

Students have full control of playing, pausing, and rewinding during video watching, which gives them more chances to investigate the difficult parts of the content. Practice exercises, quizzes, and exams are often machine-graded, which compares students' responses to pre-defined correct keys and provides a score after submission. Question types often include multiple choices, short answers, and numeric answers. A discussion forum is used as a major method of communication in MOOCs. Students, teaching assistants, technical staff, and instructors interact with each other on a wide range of topics related or unrelated to the course content.

III. Methodology

A research design was utilized to control the methods and approaches in order to congregate and assess the details of the study. To address the defined research questions, an exploratory research method was carried out to identify the available learning factors, which are used in existing adaptive learning systems to investigate the challenges that influence Malaysian MOOC users, as well as to identify existing learning styles that have been utilized in existing adaptive MOOCs. To address the research question, number 4, a quantitative research method was carried out to identify the correlation of the identified factors and learning styles with the effectiveness and efficiency of adaptive MOOC.

Moreover, regarding the research question, number 4, a descriptive research method was carried out to identify the challenges and specific requirements that affect the language learning process. A simulation approach was also selected to propose a new framework to perform adaptive automatic learner model construction and evaluate the proposed framework with a small set of Malaysian learners to identify the proof-of-concept and effectiveness of the proposed framework.

IV. Results and Discussion

A. Gender

Regarding gender, the number of males (*N*: 223, 54.7%) is more than females (*N*: 185, 45.3%) (Table 1). Regarding age, a large percentage of subjects are less than 25 years (*N*: 154, 37.7%), following by between 25 and 35 years (*N*: 142, 34.8%). The category of more than 35 years is less than the previous groups (*N*: 112, 27.5%), i.e., the smallest category. Regarding technology experience, a large number of samples are within the "no answer group" (*N*: 182, 44.6%), following by the "yes, completed full course group" (*N*: 147, 36.0%). The "yes dropout group" is less than the other groups (*N*: 79, 19.4%), i.e., the smallest category. Concerning learning style, a large number of samples are within the "occasionally response group" (*N*: 142, 34.8%), following by the "frequently response group" (*N*: 103, 25.2 %) and the "very frequently response group" (*N*: 71, 17.4 %). The category of "rarely response" is less than the other groups (*N*: 70, 17.2%), following by "never response" (*N*: 22, 5.4%), i.e., the smallest category.

With reference to our goal (learning the Arabic language), a large number of samples are within the "general interest group" (*N*: 231, 56.6%), following by the "school relevance group" (*N*: 106, 26.0%). The "career requirement" is less than the other group (N: 71, 17.4%), i.e., the smallest category.

Regarding the level of expertise, a large number of samples are within the "advanced group" (*N*: 160, 39.2%), following by the "intermediate group" (*N*: 157, 38.5%). The levels of the "expert and basic knowledge groups" are less than the previous groups (*N*: 47, 11.5%) and (*N*: 44, 10.8%; i.e., the smallest category), respectively.

Table 1.
Profile of demographic variables

Variables	Frequency	Percent	Cumulative percent
Gender			
Male	223	54.7	54.7
Female	185	45.3	100.0
Total	408	100.0	
Age categories			
Less than 25 years	154	37.7	37.7
Between 25 and 35 years	142	34.8	72.5
More than 35 years	112	27.5	100.0
Total	408	100.0	
Technology experience			
Yes, completed full course	147	36.0	36.0
Yes, dropout	79	19.4	55.4
No	182	44.6	100.0
Total	408	100.0	
Learning style			
Very frequently	71	17.4	17.4
Frequently	103	25.2	42.6
Occasionally	142	34.8	77.5
Rarely	70	17.2	94.6
Never	22	5.4	100.0
Total	408	100.0	
Learning Arabic language (goal)			
General interest	231	56.6	56.6
School relevance	106	26.0	82.6
Career requirement	71	17.4	100.0
Total	408	100.0	
Level of expertise as an electronic technology user			
Expert	47	11.5	11.5
Advanced	160	39.2	50.7
Intermediate	157	38.5	89.2
Basic knowledge	44	10.8	100.0
Total	408	100.0	
Education level			
Non-graduate	56	13.7	13.7
Diploma	56	13.7	27.5
Bachelor	168	41.2	68.6
Master	72	17.6	86.3
Doctorate	56	13.7	100.0
Total	408	100.0	
Occupation level			
Supervisory & managerial	64	15.7	15.7
Professional	112	27.5	43.1
Operational & technical	48	11.8	54.9
Student	152	37.3	92.2
Unemployed	32	7.8	100.0
Total	408	100.0	
Dominant learning style			
Visual (spatial) learning style	102	25.0	25.0
Aural (auditory-musical-rhythmic) learning style	92	22.5	47.5
Verbal (linguistic) learning style	84	20.6	68.1
Logical (mathematical)	75	18.4	86.5

learning style			
Physical (bodily-kinesthetic) learning style	55	13.5	100.0
Total	408	100.0	
Learner goal			
Learn to become proficient in Arabic language	96	23.5	23.5
Learn to become familiar with Arabic language	136	33.3	56.9
Learn Arabic language to conduct basic conversations	72	17.6	74.5
Learn Arabic language terminologies	56	13.7	88.2
Learn Arabic language for simple greeting word	48	11.8	100.0
Total	408	100.0	

In regard to the education level, a large number of samples are within the "bachelor group" (*N*: 168, 41.2%), following by the "master level" (*N*: 72, 17.0%). The levels of non-graduate, diploma, and doctorate are less than the previous groups (*N*: 56, 13.7%), i.e., equal and smallest categories. Concerning the occupation level, a large number of samples are within the "student category" (*N*: 152, 37.3%), following by the "professional category" (112 – 27.5%) and "supervisory and managerial group" (*N*: 64, 15.7%). The category of operational and technical is less than the previous groups (*N*: 48, 11.8%), following by the "unemployed category" (*N*: 32, 7.8%), i.e., the smallest category.

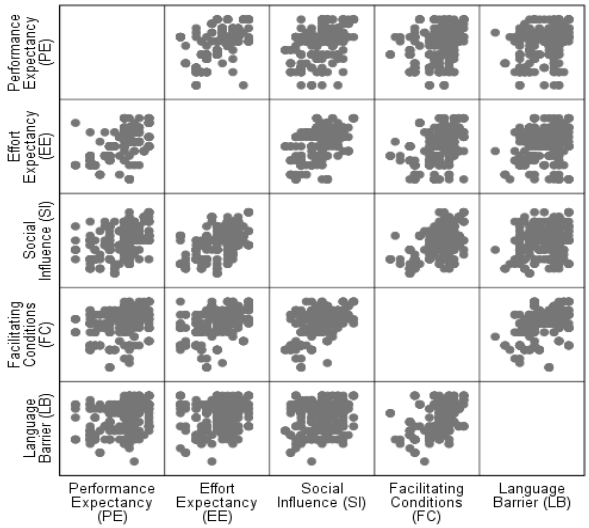
Regarding dominant learning style, a large number of samples are within the visual (spatial) learning style (*N*: 102, 25.0%), following by the aural (auditory-musical-rhythmic) learning style (*N*: 92, 22.5%) and verbal (linguistic) learning style (*N*: 84, 20.6 %). The category of the logical (mathematical) learning style is less than the other groups (*N*: 75, 18.4%), following by the physical (bodily-kinesthetic) learning style (*N*: 55, 13.5%), i.e., the smallest category.

Table 2.
Descriptive statistics, skewness, and kurtosis for all factors of the hypothesized model

Variables	Skewness ≤ 3	Kurtosis ≤ 7
PE	-.914	.372
EE	-.714	-.210
SI	-.365	-.462
FC	-1.226	1.338
LB	-.691	-.437
BI	-1.205	.997
II	-.927	.733
IDT	-.943	.276
CD	-1.195	1.639
SA	-1.035	1.111
LS	-1.803	4.284
MC	-.657	-.630

Regarding the factors' procedures via scatter plots based on Pallant [6], [7], Figure 1 illustrates scatter plots for the individual variable for all constructs used in the hypothesized model, i.e., performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), language barrier (LB), behaviour intention (BI) to use adaptive MOOC, interaction with instructor (II), information delivery technology (IDT), course design (CD), system adaptability (SA), learner satisfaction (LS), and MOOC continuance (MC). Overall, these scatter plots show that there is not any obvious evidence for nonlinearity. Subsequently, the assumption of linearity was not violated and met.

Secondly, the multiple regression analysis was conducted to check the linearity, generating scatter plots, between the set of the exogenous/independent variable and endogenous/dependent variable. That means that they are between BI to use adaptive MOOC as a criterion and its predictors, i.e., PE, EE, SI, FC, and LB. Also, it is between LS as a dependent variable and its predictors, i.e., II, IDT, CD, and SA.



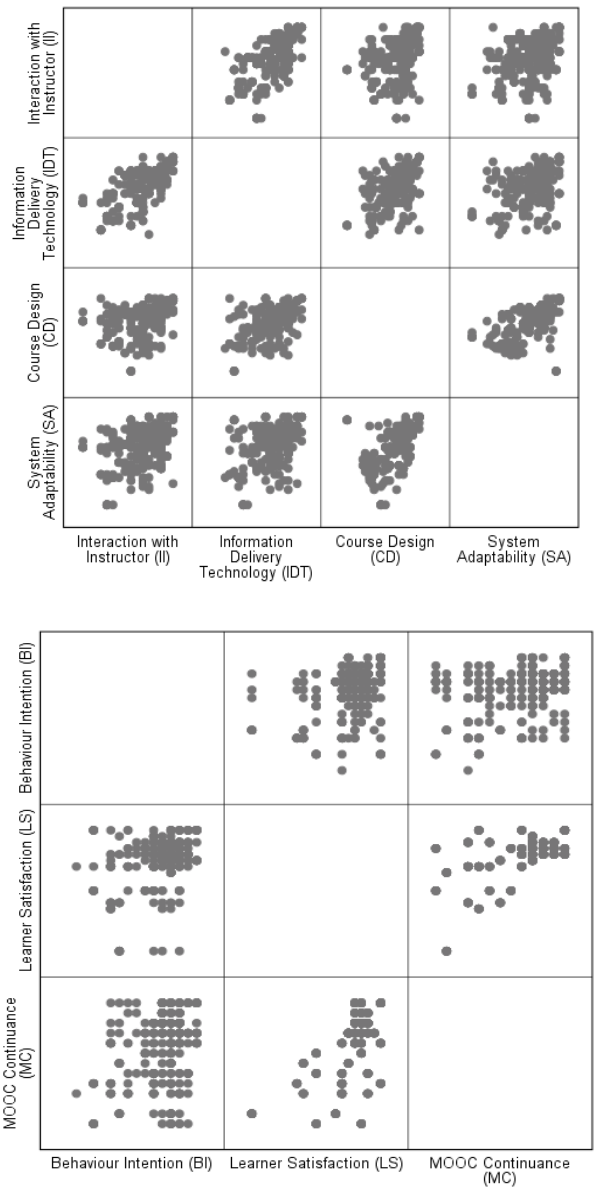


Figure 1. Linearity for each factor in the hypothesized model

Finally, it is between MC as a criterion and its predictors, such as BI to use adaptive MOOC and LS. Figure 2 illustrates the scatter plots for BI to use adaptive MOOC, LB, and MC, concluding that scatter plots validated a non-curvilinear relationship, and the assumption of linearity was supported and met.

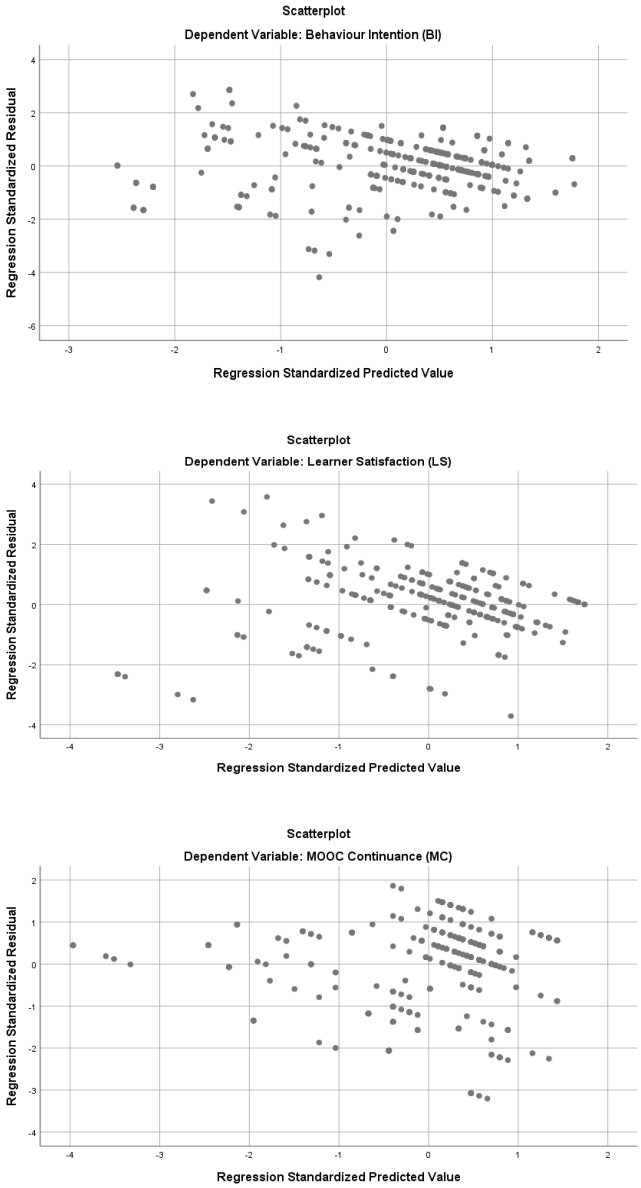


Figure 2. Linearity for each dependent factor in the hypothesized model

Table 3.
Results of the multiple regression for multicollinearity

Independent variables	Tolerance ≥ 0.30	VIF ≥ 5
First multiple regression	-	-
PE	.584	1.714
EE	.534	1.874
SI	.523	1.914
FC	.565	1.770
LB	.723	1.383
Second multiple regression	-	-
II	.569	1.756
IDT	.419	2.387
CD	.510	1.961
SA	.639	1.565

Third multiple regression	-	-
BI	.802	1.247
LS	.802	1.247

Note: Dependent variables: BI to use adaptive MOOC, LS, and MC

The level of significance refers to whether there is a relationship between latent constructs and its indicators/items or not. It also refers to the relationship between two latent constructs and more. To decide whether the relationship is significant, P-value and T-Statistics were used. P-value ≤ 0.05 indicates the significance of the relationship. T-Statistics ≥ 1.964 indicates the significance of the relationship [6], [7], [8], [9], [10], [11], [12]. Table 4 depicts the reflectively developed mode of the present research (PE, EE, SI, FC, LB, II, IDT, CD, SA (as independent/exogenous variables), BI (to use adaptive MOOC), LS (as multiple mediation), and MC (as dependent variable)).

Importantly, all relationships or loading between the latent factors and its parent items are statistically significant in that P-Value = 0.00, and less than 0.05, as well as T-statistics/value is more than the critical value (1.964), demonstrating that all items contribute significantly in shaping and modeling the corresponding exogenous factors.

Table 4.
The reflectively developed mode of the present research

Objective	H	Hypotheses	Decision
Objective 1	H_1	PE → BI	Positively supported
Objective 1	H_2	EE → BI	Positively supported
Objective 1	H_3	SI → BI	Rejected
Objective 1	H_4	FC → BI	Positively supported
Objective 1	H_5	LB → BI	Positively supported
Objective 1	H_6	II → LS	Positively supported
Objective 1	H_7	IDT → LS	Positively supported
Objective 1	H_8	CD → LS	Positively supported
Objective 1	H_9	SA → LS	Positively supported
Objective 1	H_{10}	BI → MC	Positively supported
Objective 1	H_{11}	LS → MC	Positively supported

V. DISCUSSION

The implementation of blended learning became inevitable in the teaching and learning process of universities, where one would redefine higher education institutions as being learning-centered, which facilitates a higher learning experience. However, the e-learning readiness of students must be taken into consideration in the movement towards a blended learning model of instruction. It would be unwise for universities to impose a blended learning environment on students without first identifying their readiness and needs. The contents of a course are mainly delivered through videos and forums and evaluated through online assessment, which can simultaneously encourage peer-to-peer teaching.

Therefore, the idea of using MOOCs in higher education is also to establish necessary online social and academic support, which is usually prevalent in traditional classrooms setting in Malaysia. MOOC is considered as a new initiative by the government to boost the technological level of public and private universities. The Malaysian government is very supportive of the use of MOOCs and sees it as a platform to integrate learning technology and lifelong learning, which concurrently leads the way towards a new direction in teaching methodologies for undergraduate programmes.

The Malaysian MOOC was firstly launched in 2015 through an official MOOC platform for public higher learning institutions called OpenLearning.com. These MOOCs are developed by instructors or lecturers based on the needs set by their institution. In addition, to further extend the development of MOOCs through government policy, the Malaysian Education Blueprint 2015–2025 will be utilized to enable MOOC credit transfer. This makes Malaysia the first country in the world to enable credit transfer by crediting not only Malaysian MOOC, but also by recognising international MOOCs in local undergraduate programmes, which will result in the same time-foster learning.

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