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MOOC Acceptance among high school students in International Schools in Bangkok, Thailand

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Abstract

This study aimed to explore the acceptance and continuation of (Massive Open Online Courses) MOOC among international school students in Bangkok, Thailand. Reviewed here is the potential for Massive Open Online Courses (MOOCs) that has the potential to transform higher education - delivery, accessibility, and costs. Although the MOOC movement which began in 2008 has undergone its own struggle like most innovations but with onset of eLearning and Covid-19 forcing many to resort to distance learning, 5G techno improvements, has created demand for MOOC. The aim of this study is to address the acceptance of Massive Open Online Courses MOOC factors implementation on the continuance intention among students. The study employed a survey technique that was designed from a literature review. The survey adopted a series of questions to gather information about the problem under investigation. Study was conducted using the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, Habit, on MOOC use behaviour and moderated by behavioural intention. Study was conducted among 500 high school students of STEM from international schools in Thailand. A questionnaire was developed cantered on the Unified Theory of Acceptance and Use of Technology (UTAUT). Data collection was done from 500 high school students from various international school students in Thailand. Research used Multistage quantitative approach of probability & non- probability technique. Statistical tool of "Structural Equation Modelling" (SEM) and "Confirmatory Factor Analysis" (CFA) of IBM SPSS, was adopted in exploring the collected data, analysis of the model fit, check reliability and validity of different variables. Results endorsed a strong link among behavioral intention and use behavior of MOOC and also Performance & Efforts Expectancy, Facilitating Conditions, and Habit on the Behavioral Intention.

***Keywords:* MOOC, International Schools, Bangkok, UTAUT**

1.0 Introduction

Higher education institutes, especially in developing countries, should address issues relating to teaching quality, cost of education reduction and disparities in education in order to maintain the system's long-term viability [1]. As in today, Massive Open Online Courses (MOOC), as an emerging paradigm of massive information distribution, has aroused avenues with its capacity to handle pedagogical, strategic, and economic challenges in higher education [2]. Many studies indicated that MOOC would have a negative impact on the higher education at the same time, it is also agreed that MOOC will be incorporated in the higher education system [3]. MOOCs have been utilized as a new kind of online learning with face-to-face traditional university courses [4,5]. When such technologies are integrated into the educational process, it is necessary to assess students' intent to continueusing them.

In this study, the high school students specifically enrolled with international schools in Thailand have been reached out to. After studying many established frameworks, the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et. al. (2003) [6], was used for this research study.

Research Objectives for this study are as below:

1. To identify the relationship between Performance-Expectancy and behavioural-intention
2. To identify the relationship between Effort-Expectancy and behavioral-intention.
3. To identify the relationship between social-influence and behavioral-intention
4. To identify the relationship between facilitating-conditions and behavioral-intention.
5. To identify the relationship between habit and behavioral-intention to use MOOC
6. To identify the relationship between Facilitating-conditions and Use-Behavior
7. To identify the relationship between Habit and actual use and Use-Behavior.
8. To identify the relationship between of behavior-intention and actual usage

The framework identified five independent variables, one mediating variable and one dependent variable withtotal of eight hypotheses to be analyzed. Data for quantitative analysis was collected by distributing 500 questionnaires among high schoolers in international schools in Thailand.

2.0 Literature Review and Hypotheses

2.1 MOOC (Massive Open Online Courses)

MOOC are online courses different from the traditional entry criteria, free participation, full online contents made accessible, project based to assist learners. [7]. There is no conditions of registering with an institutional or with any universities, there are no deadline to register, there are no penalties or fine for discontinuation or refusal [8], and there is effusive and asynchronous knowledge delivery [9]. MOOC was classified as resources that can revamp admission to high-quality higher education [10], "popularize education, and expand access to knowledge" [11].

To summarize the concept behind a MOOC is:

- Reachable & accessible a large number of people **(Massive)**.
- Should be openly accessible to anyone and free of cost **(Open)**.
- An MOOC should also be delivered via the internet **(Online)**.
- Empower learners to uncover new topics **(Course)**.

'MOOCing' is a form of online learning. In fact, it's probably best defined as a form of distance learning.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

A unified theory of acceptance and use of technology (UTAUT) was proposed by Venkatesh et al. (2003).UTAUT has four main constructs that directly influence user acceptance and behavior, namely, performance expectancy, effort expectancy, social influence, and facility conditions.

Performance expectancy is the expectancy of individual technology users who believe that the use of technology will increase the productivity and performance of their work. In other words, it is the expected benefits of using technology.

Effort expectancy explains the possibility of using certain technology without much effort. This illustrates the level of simplicity and ease of use of a particular technology.

Social influence is related to the users' perception reference of the reaction of others to themselves and social groups if certain technology users are used. This is a consideration of technology users who can convince other people in his/her group whether or not users should use the technology.

Facilitating conditions explain that users believe concerning the need for facilities to use new technology in an organization.

Behavioral intention is defined as the likelihood of someone's plan to use technology. It also shows a direct effect on the actual use of behavior.

Use behavior is using behavior in information and communication technology related to how and when people use technology, indicated by the frequency and the objective of use.

2.3 Hypotheses

Using the literature review and various contributions, the research framework was designed and designatesthe below research hypotheses:

H-1: (PE) Performance Expectancy has a positive impact on Behavioral intention (BI)

H-2: (EE) Effort Expectancy has a positive impact on behavioral intention

H-3: (SI) Social influence has a positive impact on (BI) behavioral intention

H-4: Facilitating conditions (FC) has a positive impact on behavioral intentions (BI)

H-5: Habit has a positive impact on significantly (BI) behavioral intentions

H-6: Facilitating conditions (FC) have a positive impact on the Use Behavior (UB)

H-7: (HB) Habit has a positive impact on (UB) Use Behavior

H-8: (BI) behavioral intention has a positive impact on their (UB) use behavior

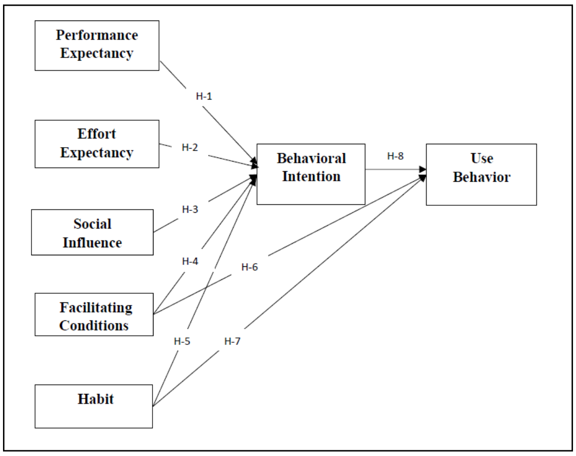

Figure 1: Conceptual Framework

3. Research Approach

3.1 Research Method

This research work implemented the Positivism Quantitative Deductive approach. whence hypotheses and questionnaire are designed meaningfully, administered and tested based on the designed conceptual framework. Quantitative descriptive design process was used for study purpose. The study plans to identify factors impactingthe (BI) behavioral intention and (UB) use behavior of MOOC.

3.2 Target Population and Data Collection

Targeted population were the STEM students from high school from International Schools in Thailand. 500 questionnaires were distributed in various ways to collect the data for analysis. Students were approached directly by going to schools in Thailand.

3.2.2 Sampling Technique

Following sample techniques were engaged for this research study:
Step 1 - Judgmental or Purposive Sampling (Non-Probability)Step 2 - Stratified Random Sampling (Probability Sampling Step 3 - Convenience Sampling (Non-Probability)

3.3 Data Analysis

Inferential Statistics draws out samples from entire data and aims to interpret and conclude for the entire population. Methods commonly engage hypothesis testing, ANOVA- Analysis of variance etc. Inferential Statistics used for this research was with CFA (Confirmatory Factor Analysis) and SEM (Structural Equation Modelling) of SPSS & AMOS.

4. Results and Discussion

4.1 Descriptive Analysis

The mean scores of seven constructs were higher than 1.0 or middle of scale and standard deviation (Tabachnick & Fidell, 2007).[12]. The results of analyses presented in below table 2 indicate that the variable Performance Expectancy, with a mean ±standard deviation (SD) of 3.63±0.708, indicates the largest mean value, and the variable Effort Expectancy, with Mean M± SD of 3.21±0.883 had the least of values. All constructs calculated a SD value that was less than one, implying a fairly consistent measure from respondents

Table: 1 Descriptive Statistics

Variables	# of Indicators	Cronbach's Alpha Coefficient (α)	Mean (M)	Std Dev (SD)
Performance Expectancy -PE	4	0.841	3.63	0.708
Effort Expectancy -EE	5	0.905	3.21	0.883
Social Influence -SI	4	0.806	3.33	0.700
Facilitating Conditions -FC	4	0.806	3.24	0.691
Habit -HB	3	0.864	3.45	0.904
Behavioural Intention -BI	5	0.892	3.50	0.748
Use Behaviour -UB	5	0.910	3.59	0.745

4.3 Confirmatory Factor Analysis (CFA**)**

Present research used the "Confirmatory Factor Analysis" - CFA. All scale items in each construct indicated significance and represented the factor loading to identify/test discriminant validity. The factor loading implies each construct to have fully admissible values indicating the GOF - goodness of fit (Hair, Black, Babin, Anderson, & Tatham, 2006).[13]. Factor loadings values are greater value than 0.30 and p-value of lower than 0.05. The construct reliability (CR) is larger than the cut-off value of 0.7 and the average variance extracted (AVE) was higher than the cut-off point of 0.5 (Fornell and Larcker, 1981) [14] in Table 1. Thus, all the estimates are significant. The square-root of the extracted average variance determined that all the correlations are more than the corresponding correlation values for that variable as of Table 4.

Table: 2 Confirmatory Factor Analysis Result, Composite Reliability (CR) and AverageVariance Extracted (AVE)

Constructs	# of Indicators	Factor Loading	CR	AVE
Performance Expectancy (PE)	4	0.619 ~ 0.871	0.84	0.56
Effort Expectancy (EE)	5	0.711 ~0.893	0.92	0.69
Social Influence (SI)	4	0.665 ~ 0.822	0.81	0.51
Facilitating Conditions (FC)	4	0.628 ~ 0.848	0.82	0.54
Habit (HB)	3	0.801 ~ 0.855	0.87	0.69
Behavioural Intention (BI)	5	0.751 ~ 0.881	0.89	0.63
Use Behaviour (UB)	5	0.772 ~ 0.857	0.92	0.68

Table: 3 Discriminant Validity

	PE	EE	SI	FC	HB	BI	UB
PE	**0.75**						
EE	0.033	**0.83**					
SI	0.064	0.07	**0.72**				
FC	0.054	0.092	0.095	**0.73**			
HB	0.055	0.09	0.139	0.144	**0.83**		
BI	0.375	0.322	0.237	0.288	0.415	**0.79**	
UB	0.215	0.201	0.184	0.334	0.458	0.668	**0.83**

Note: The diagonally listed value is the AVE square roots of the variables

Table 4: Goodness of Fit for Confirmatory Factor Analysis (CFA)

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 Hair et al. (2006)	2.495
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.889
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.865
NFI	≥ 0.80 (Wu & Wang, 2006)	0.897

CFI	≥ 0.80 (Bentler, 1990)	0.935
TLI	≥ 0.80 (Sharma et al., 2005)	0.927
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.055

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

4.4 Structural Equation Model (SEM)

The goodness of fit (GOF) indices for Structural Equation Model (SEM) is measured as indicated in Table 5.

Table 5: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 Hair et al. (2006)	2.502
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.885
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.865
NFI	≥ 0.80 (Wu & Wang, 2006)	0.893
CFI	≥ 0.80 (Bentler, 1990)	0.933
TLI	≥ 0.80 (Sharma et al., 2005)	0.926
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.055

The results of the SEM model are presented in the Figure 2. Both Table 6 and Figure 2 illustrate the relationship between the endogenous variables (performance expectancy, effort expectancy, social influence, facilitating condition, habit, behavioural intention) with the exogenous variables (use behaviour). Behavioural
Intention being the mediating variable. The results indicated students' behavioural intention to engage with MOOC tools is positively and significantly impacted by performance expectancy (β=0.387, $p<0.05$); effort expectancy (β=0.325, $p<0.05$); social influence (β=0.156, $p<0.05$); facilitating condition (β=0.224, $p<0.05$); habit (β=0.393, $p<0.05$. Similarly, behavioural intention by the students to use behaviour towards MOOC indicates a significant positive effect on actual use of MOOC (β=0.619, $p<0.05$).

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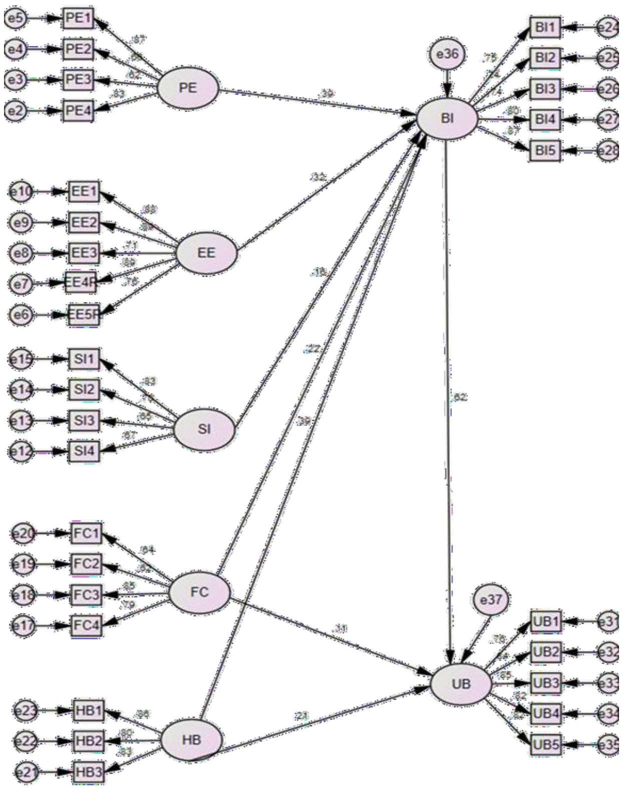
Figure 2: SEM Results



4.5 Research Hypothesis Testing Result

Table 6: Hypothesis testing

Path of Hypothesis	**Standardized path coefficient (β)**	**t-value**	**Testingresult**
H1: Performance Expectancy (PE) -> Behavioural Intention (BI)	0.387	8.735*	Supported
H2: Effort Expectancy (EE) -> Behavioural Intention (BI)	0.325	7.679*	Supported
H3: Social Influence (SI) -> Behavioural Intention (BI)	0.156	3.695*	Supported
H4: Facilitating Conditions (FC) -> Behavioural Intention (BI)	0.224	5.308*	Supported
H5: Habit (HB) -> Behavioural Intention(BI)	0.393	8.875*	Supported

H6: Facilitating Conditions (FC) -> Use Behaviour (UB)	0.106	2.733*	Supported
H7: Habit (HB) -> Use Behaviour (UB)	0.206	4.908*	Supported
H8: Behavioural Intention (BI) -> Use Behaviour (UB)	0.619	11.591*	Supported

Note: *=p-value <0.05

Table 7: Direct, Indirect and Total Effect

Path	Direct Effect	Indirect Effect	Total Effect
PE -> BI	0.387	-	0.387
EE -> BI	0.325	-	0.325
SI -> BI	0.156	-	0.156
FC -> BI	0.224	-	0.224
HB -> BI	0.393	-	0.393
FC -> UB	0.106	-	0.106
HB -> UB	0.206	-	0.206
BI -> UB	0.619	-	0.619

The results of the path analysis, path coefficient, and determinant coefficient (R^2) are presented in the formof an MOOC acceptance model shown in Figure 3 below

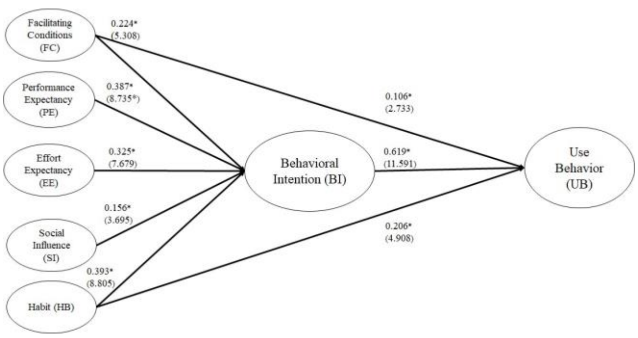


Figure 3: The Results of Structural Model

Note: Solid line reports the Standardized Coefficient with * as p<0.05, and t-value in Parentheses; Dash line reports Not Significant

5.0 Discussion and Conclusion

The results of the study affirmed that all eight hypotheses of the conceptual model (using UTAUT) significantly establish student's behavioural intention to use MOOC and use behaviour. The path coefficients (β), t-statistics, and p-value were sought to measure and compute the significance of all the direct effects or hypotheses in the structural model. The conclusion for each variable is depicted in Table 6 and Figure 3 and propounded that all hypotheses were strengthened with a significance at $p < 0.05$. Habit among the variables has the strongest influence (with $\beta = 0.393$) on Behavioral Intention to use MOOC. Performance Expectancy happened to be the next strong influencer with a $\beta = 0.387$ on BI. Continuity to engage in MOOC and the actual use illustrated by Use Behavior (UB) has the strongest influence on behavioral intention with $\beta = 0.619$ and t values = 11.591.

The acceptance of MOOC use among students in international schools in Thailand was established using constructs and indicators evolved from the UTAUT model. The model utilized core variables in UTAUT: "performance-expectancy, effort-expectancy, social- influence, facilitating -conditions, habit, behavioural-intention and use -behaviour".

The results were affirmed by hypothesis test which emphasised that performance -expectancy, effort-expectancy, facilitating-conditions, and social-influence and habit all had positive, direct and significant impacts on behavioural-intention of MOOC. Facilitating-conditions, habit and behavioural-intention also showed significantly direct and positive impact on MOOC use behaviour. Variables that had the maximum effect towardsMOOC (see Table 7) are Performance-Expectancy and Habit and Behavioural Intention.

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