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The Factors Affecting Learning Outcome Intention of MOOCs for an Online Learning Platform

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ABSTRACT

The purpose of this paper was to investigate the factors affecting the learning outcome intention of MOOCs for an online learning platform. The Confirmatory Factor Analysis (CFA) was adopted as the theoretical foundation. A total of 400 valid samples were collected in Thailand and a Structural Equation Model (SEM) was adopted. The results of the four CFA factors (Learning Expectation, (LE), Learning Satisfaction (LS), Learning Attitude (LA), and Learning Behavior (LB)) are significant. The Chi-Square ($\chi 2$) statistic is 220.74 at an independent degree (df) of 168 with a Relative Chi-square ($\chi 2$ / df) of 1.314 indicates that the model is suitable. The Comparative Fit Index (CFI) is 0.994, the Goodness Fit Index (GFI) is 0.971 and the model based on the research hypothesis is consistent with the empirical data. The Root Mean Square Error of Approximation (RMSEA) is 0.025.

Keywords
Learning Outcome; MOOCs; Online Learning; Learning Platform; Factor Affecting

Introduction

The last decade has seen the rapid development of information and communication technology (ICT) and its significant impact on all dimensions of life, including education (Muhua & Yan, 2015). Currently, Massive Open Online Courses (MOOCs) have become very popular in education around the world (Muñoz-Merino, Ruipérez-Valiente, Alario-Hoyos, Pérez-Sanagustín, & Kloos, 2014; Spoelstra, van Rosmalen, Houtmans, & Sloep, 2015).
Massive Open Online Courses (MOOCs) are claimed as the major transformations in the livery of education because of their unique strengths in providing high-quality online learning resources to a massive number of students and eliminating key obstacles to education such as distance education, tuition fees and learning resources (Deng & Benckendorf, 2017).
With the advantage of using MOOCs in the universities with online videos and supplemental materials which were delivered to students (Alraimi, Zo, & Ciganek, 2015; Junjie, 2017). MOOCs technology integrated new communication tools such as forums, discussion, online chat, etc. The MOOC platform supports two-way communication between the learner and the instructor (Junjie, 2017). Online discussion forums create a social aspect of learning and promote in-depth discussion even in different places, leading to constructive learning (Yang, Heinrich, & Kemp, 2011; Junjie, 2017). The advantage of using MOOCs is attractive to scholars who believe that MOOCs can achieve the ultimate democratization in education by being accessed anywhere, anytime and for everyone (Jacobs, 2013; Junjie, 2017).
This leading MOOC is becoming a model for education delivery, with theoretically no limit to enrolment; open, allowing anyone to participate, usually at no cost; online, with learning activities typically taking place over the web; and a course, structured around a set of learning goals in a defined area of study" (Educause, 2013; Wang, 2017).
The learning feature of the MOOC platform is to include learning material, such as text documents, presentations, videos, audio recordings, learning forums, etc. (Espada, et al, 2014; Pernias& Lujan-Mora, 2013).
MOOCs provide varied education services directly to the learners and provide materials for an instructor to practise classroom and blended

teaching meanwhile connecting with traditional education practices (Muhua & Yan, 2015) this leads to change and has a high impact on traditional classroom teaching (Zhang & Han, 2013)

Although MOOCs have many advantages, the average completion rate is lower than 10% (Catropa, 2013; Junjie, 2017). The interesting paradox about MOOCs learning outcomes (Alraimi, Zo, & Ciganek, 2015; Junjie, 2017) is that few learners complete their enrolled courses, making the continuance and learning outcome of MOOCs a problem (Alraimi, Zo, & Ciganek, 2015; Junjie, 2017).

In the current situation of the COVID-19 pandemic around the world, online learning especially MOOCs have gained momentum due to the closure of educational institutions that raises challenges for students' learning outcomes (Khan, et al., 2021; Muzaffar, 2020; Zayabalaradjane, 2020). During the quarantine time, MOOCS are providing a solution for the ongoing learning process through the platform.

To bridge the gap, this study aims to investigate the factors affecting the learning outcome intention of MOOCs for an online learning platform case study in Thailand.

Literature Review

MOOCs

MOOCs were introduced in 2012 (Jacobs, 2013), with the famous MOOCs platform such as Coursera, edX, Udacity, and KHANACADEMY (Jacobs, 2013; Junjie, 2017).

Several research studies investigated the MOOCs' effect on higher education systems, the results found that the majority of university faculties think that MOOCs have a direct impact on improving educational outcomes (Khan, et al., 2021). Although, the results also found that MOOCs have a direct impact on developing students' learning skills. Thus, MOOC is a suitable platform to train and learn because it provides tools to enable students to collaboratively master as well as enhancing an individuals' abilities, key factors which together aid acquisition (Alhazzani, 2020; Cervi, Pérez Tornero & Tejedor, 2020).

The study of learning from MOOCs included four parameters, course delivery, course content, course assessment, and course support (Khan, et al., 2021) and the results of the qualitative assessment highlighted that the participants have gained knowledge from the course and 65% of them preferred the MOOC portals (Khan, et al., 2021). Moreover, MOOCs should focus more on building great course content, ensuring timely and faultless delivery of the lectures along with appropriate course assessment, covering the correct information from the course content (Khan, et al., 2021). Hence, the satisfaction of participants can be achieved, and they can be encouraged to further enrol in other courses along with completing the current course (Khan, et al., 2020; Kumar & Kumar, 2020).

Learner satisfaction in MOOCs

Satisfaction is an essential outcome for learners because it can influence a learners' motivational level, which is an important psychological factor affecting student learning (Astin, 1993; Bolliger & Martindale, 2004). We also considered learner satisfaction an important dependent variable because it is has a strong positive relationship with a learners' perceived quality of instruction, not only in the traditional university learning settings (Denson, Loveday, & Dalton, 2010; Douglas, Douglas, & Barnes, 2006; Ginns, Prosser, & Barrie, 2007; Green, Hood, & Neumann, 2015; Lenton, 2015; Richardson, Slater, & Wilson, 2007; Sutherland, Warwick, Anderson, & Learmonth, 2018), but also in the field of distance education (Elia, Solazzo, Lorenzo, & Passiante, 2019; Wu, Tennyson, & Hsia, 2010).

Learner satisfaction has also been extensively employed in conventional distance education courses (Bolliger & Martindale, 2004; Elia et al., 2019). From the institutional point of view, satisfied learners are likely to attract the enrolment of additional students or "customers" to the particular course; and this will likely increase the financial revenue and reputation of the institution.

In recent years, several researchers have begun to show interest in examining learner satisfaction in the MOOC context.

However, since this is an emerging research topic, only a handful of published studies can be found (e.g., Gameel, 2017; Joo, So, & Ki, 2018; Li, 2019; Rabin et al., 2019). Analysing survey data from 222 university students who took a K-MOOC course in Korea, Joo et al. (2018), for example, reported that perceived ease of use had a positive influence on learner satisfaction with MOOC. Gameel (2017) investigated survey data from 1786 MOOC participants and found that the ability for learners to access the online learning resources after the course ends, as well as learners' taking responsibility for their learning positively, influenced learner satisfaction with MOOC.

Li (2019) examined survey data from 4503 MOOC learners and found that several learners' demographics data (e.g., learners' highest degree, and the number of online courses taken previously) and perceived learning predicted satisfaction with the MOOC. Rabin et al. (2019) found that learners' perceived MOOC benefits and learners' goal-setting ability significantly predicted learner satisfaction in MOOC. Our present study is similarly concerned about the investigation of learner satisfaction in MOOCs, but it takes a different direction than those of previous MOOC research.

Unlike past studies that investigated learner satisfaction mainly from the perspective of learner demographics, learner personal motivation, learner perceived ease of use or perceived benefits of MOOC, and learner disposition (e.g., responsible for own learning, goal-setting ability) (e.g., Gameel, 2017; Joo et al., 2018; Li, 2019; Rabin et al., 2019), we are interested to uncover factors related to the MOOC design perceived by learners that may predict learner satisfaction.

Qi, Zhang & Zhang (2020) study how MOOC learners acquire value from participation, which furthermore shapes their learning satisfaction. 372 learners suggested that learners' participation results in a rise in their perceived knowledge value, hedonic value, and social value. Learners' satisfaction is derived from these value perceptions. Perspectives such as motivation, engagement, and involvement are drivers of learner participation to attract more learners to join and finish MOOCs with effective learning.

Engagement of learner: Motivation, behaviour and attitudes

Factors that influence a learners' motivation to learn such as future benefit, personal development, challenges, and fun. (Davis et al., 2014; Yuan et al., 2013) Belanger, et al., (2013), suggests how a student's motivation typically fell into one of four categories as follows: 1) To support lifelong learning and expectations for completion or achievement. 2) For fun, entertainment, social experience and stimulation. 3) Convenience, often in conjunction with barriers to traditional education options. 4) To experience or explore online education. These expectations are a factor of motivation to each individual learner who studied, based on their knowledge and experience. (Onah & Sinclair, 2015) The importance of expectation and motivation to support better learning and participation. As course developers and instructors consider learners' expectation and motivation before creating and developing a learning management system (LMS).

Rai & Chunrao (2016) argue that success and failures in online learning are mostly dependant on personal factors rather than factors influenced by the surroundings or the external environment. Most of the factors of success or failure are purely individual as most learners are genuinely interested in finishing the course, and most of the learners are fascinated by the reputation of the universities, quality of courses, and deriving fun in solving challenging assignments. In MOOC courses, 80 percent of the statements that were either extremely positive or negative were found to be positive rather than negative, and this is important because an overall positive climate is known to correlate with higher academic achievement in education settings (Shapiro, et al., 2017). The attitude of the interviewee statements was more positive than negative. This result indicates the MOOCs could offer a constructive learning environment with manageable levels of frustration. Learners who had already earned a bachelor's degree as their highest level of education were more positive than learners who had not completed a college degree or those who had an advanced degree, and this was a highly statistically significant result. (Shapiro, et al., 2017).

The study of various variables that could affect learning outcomes were learning expectation, learning satisfaction, learning attitude and learning behaviour.

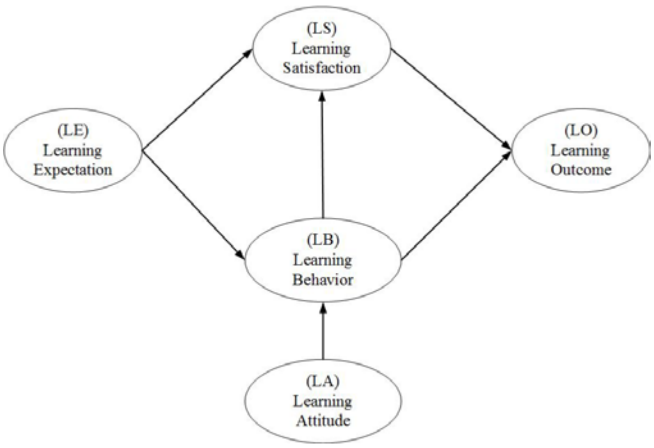

Figure 1. Conceptual Framework

Figure 1 shows the research framework designed for this study to include the five components: Learning Expectation (LE), Learning Satisfaction (LS), Learning Attitude (LA), Learning Behavior (LB) and Learning Outcome (LO) that consisted of 31 variables.

Methodology

This study used a quantitative research approach that collected data from questionnaires and a qualitative approach that collected data from interviewing the learners as follows:

Population and Sampling

The population of this study are students who registered for MOOCs online course SPU003, course title "Career Preparation for Road Freight Transportation" at Sripatum University, Thailand consisting of about 782 people. The sample size was 265 based on Yamane [41] with a confidence level of 95% (α = 0.05), however, to increase the reliability of the study the researcher collected data from a sample size of 400 people. The sampling technique used was simple sampling via MOOCs online course.

Measure and Tools

Based on the research framework and the literature review, 5 closed questions that related to the demographic of the sample were used. The second section of the questionnaire, about the use of MOOCs, was in seven sections (1) learner's expectation before studying MOOCs comprised of 6 questions (2) the behaviour of the learner of MOOCs comprised of 4 questions (3) the learner's attitude towards the learning of MOOCs comprised of 5 questions (4) the design of MOOCs courseware comprised of 4 questions (5) learning outcomes comprised of 6 questions (6) learning satisfaction comprised of 4 questions and (7) the intention to tell others about the MOOC course comprised of 2 questions. The questions used the Likert 5 scale ranging from 5=strongly agree, 4=agree, 3=moderate, 2=disagree, 1=strongly disagree. The reliability of the measures were tested using Conbrach's alpha = 0.979. Data was analyzed using SPSS for descriptive statistics. An Exploratory Factor Analysis (EFA) and Confirmatory Factory Analysis (CFA) were run by using LISREL 9.0.

Data Collecting

The data was collected using a convenient sampling method using an online assessment form. The questionnaire was available online between January and June 2020. A total of 400 completed a response.
The qualitative data was collected from 10 MOOC students by interviewing them about their learning experience online. The qualitative data was analyzed by the content analysis method.

Results

The quantitative results from the questionnaires
1. Demographic profile

The descriptive statistics of the respondents are shown in Table 1, the results found that most of them were female (69.25%), aged between 15-24 (92.75%), with an educational level of an undergraduate (98.50%), the occupation of a student (89.95%) and an income of less than 15,000 Baht a month (86.00%) respectively.

Table 1. Demographic of the respondent

Variable	Frequency	Percent
Gender		

Male	123	30.75
Female	277	69.25
Age		
>15 year	0	0.00
15-24 year	371	92.75
25-34 year	27	6.75
< 34 years	2	0.5
Education level		
Under-graduate	394	98.50
Bachelor's degree	6	1.50
Occupation		
Student	358	89.95
Employee	26	6.53
Business owner	6	1.50
Government officer	8	2.02
Income/month		
> 15,000 Baht	344	86.00
15,001-30,000 Baht	30	7.50
30,001- 45,000 Baht	8	2.00
45,001-60,000 Baht	5	1.25
60,001-75,000 Baht	5	1.25
75,001-90,000 Baht	4	1.00
90,001-115,000 Baht	2	0.50
<115,000 Baht	2	0.50

2. Measurement model assessment

Table 2 show the mean and standard deviation of the 31 variables. The average mean of the highest major component is Learning Satisfaction (LS) ($\bar{x}$ =4.07, S.D. =0.93), second Learning Attitude (LA) $\bar{x}$ =4.06, S.D. =0.95) and third Learning Outcome (LO) ($\bar{x}$ =4.04, S.D. =0.95) respectively. The highest mean variable is MOOC useful content (A5) ($\bar{x}$ =4.15, S.D. =0.95), second is that the learner can apply the knowledge gained from the study of MOOCs ($\bar{x}$ =4.14, S.D. =0.90).

Table 2. Means and Standard deviation

Variable		$\bar{x}$	S.D.
LE	Learning Expectation	3.70	1.00
LB	Learning Behavior	3.64	1.08
LA	Learning Attitude	4.06	0.95
LS	Learning Satisfaction	4.07	0.93
LO	Learning Outcome	4.04	0.95

The KMO test results were 0.97 (greater than 0.5 (Hair, 2010)). That is, the variables were related enough to analyse the survey components and Bartlett's Test of Sphericity Approx. Chi-Square is 13609.54 df. = 465 and the p-value is 0.00, meaning that the variables are related. With statistical significance at the level of 0.05

Table 3. KMO and Bartlett's Test

Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.97
Bartlett's Test of Sphericity Approx. Chi-Square	13609.54
df.	465.00
p-value	0.00

The KMO test results were 0.97 (greater than 0.5 (Hair, 2010)). That is, the variables were related enough to analyse the survey components and Bartlett's Test of Sphericity Approx. Chi-Square is 13609.54 df. = 465 and the p-value is 0.00, meaning that the variables are related. With statistical significance at the level of 0.05
The results of the survey of 31 variables were extracted using the Varimax method. The composition can be classified into 5 components which are outcome (Out), satisfaction (Sat), attitude (Att), behaviour (Beh) and expectation (Exp) with all 5 components able to explain the variation of MOOC by 78.12%

The Chi-Square ($\chi2$) statistic is 220.74 at an independent degree (df) of 168 with a Relative Chi-square ($\chi2$ / df) of 1.314 which indicates that the Relative Chi-square ($\chi2$ / df) is less than 2 and a p-value of 0.072 (greater than 0.05) indicates that the developed model is suitable.

Table 4. Goodness of fit measure

Goodness-of-fit Measure	Value	Acceptable Level
Chi-Square (χ^2)_ms(1065)	220.74	-
df (N-1)	168	-
(χ^2)/df	1.314	< 2.00
Probability (p)	0.072	> 0.05
CFI	0.994	> 0.95

GFI	0.971	> 0.95
AGFI	0.964	> 0.95
RMR	0.023	< 0.05
RMSEA	0.025	< 0.05

The Comparative Fit Index (CFI) is between 0.00 and 1.00. If the value approximates 1.00, the result is 0.994. That is, the model based on the research hypothesis is consistent with the empirical data. In general, if the value is greater than 0.95, then the model corresponds to the empirical data.

The Goodness Fit Index (GFI) is between 0.00 and 1.00. If the value is close to 1.00 and the result is 0.971, that is, the model based on the research hypothesis is consistent with the empirical data. In general, if the value is greater than 0.95, then the model corresponds to the empirical data.

The adjusted goodness of fit index (AGFI) is between 0.00 and 1.00. If the value approximates 1.00, the result is 0.964. That is, the model based on the research hypothesis is consistent with the empirical data.The mean square residual (RMR) index is used to compare the degree of harmony with the empirical data of the two models, for comparison. By using a single set of data, the RMR is between 0.00 and 1.00 and the result is 0.023. If the value is less than 0.05, the model is consistent with the empirical data.

The Root Mean Square Error of Approximation (RMSEA) is between 0.00 and 1.00 and the RMSEA is 0.025. If the value is less than 0.05 then the model is consistent with the empirical data

From the various values used to measure the consistency/harmonization between the models, according to the research hypothesis and the empirical data of this research, it is found that this value used to pass the specified criteria, that is, the model can be used to explain and find relationship values according to the research objectives specified

Table 5 show the correlation matrix which expectation has a combined effect on satisfaction. The total impact size is 1.032. Expectation has a direct positive effect on satisfaction. The effect size is 0.293 and has indirect effects on satisfaction through behaviour. The indirect influence size is 0.739 for expectation There is a direct positive impact on behavior. The effect size is 0.776 and the expectation has an indirect effect on the outcome through behavior and satisfaction. The indirect influence size is 0.721 and 0.021 respectively.

Table 5. Correlation matrix

Var	Behavior			Satisfaction			0utcome		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Exp	0.776	-	0.776		.739	.032	-	.742	.742
Att	0.640	-	0.640	-	.609	.609	-		.595
Beh	-	-	-	.952	-	.952	0.929	.701	.630
Sat	-	-	-	-	-	-	0.736	-	.736

Total Effects :TE, Direct Effects: DE, Indirect Effects: IE

Attitude has a positive direct impact on behaviour with an impact size of 0.640. Attitude has an indirect effect on satisfaction through behaviour with an indirect influence size of 0.609 Attitude has an indirect impact with an outcome via behaviour with an influence size. Detour is 0.595 Behaviour as a direct positive effect on satisfaction and outcome, with impact sizes of 0.952 and 0.929 respectively. Behaviour as indirect effects with outcome through satisfaction, with an indirect influence scale of 0.701 and behaviour has a combined effect of outcome in size. The total impact is 1.630.

Figure 2 show the Learning Outcome Model which found that satisfaction has a direct positive impact on the outcome, with an impact size of 0.736. The composition weight shows the importance of the variable. In the outcome component description, it appears that the variable with the highest weight is that the content of the MOOC is easy to learn and understand, followed by the MOOC system to help students improve their grades and the screen and user interface are beautifully designed respectively and the variables can explain the variation. Outcome were 41.20%, 36.20% and 33.80% respectively.

The composition weight indicates the importance of the variable. In describing the component of satisfaction, it appears that the variable has the highest weight. How much do students expect to get a good experience from studying through

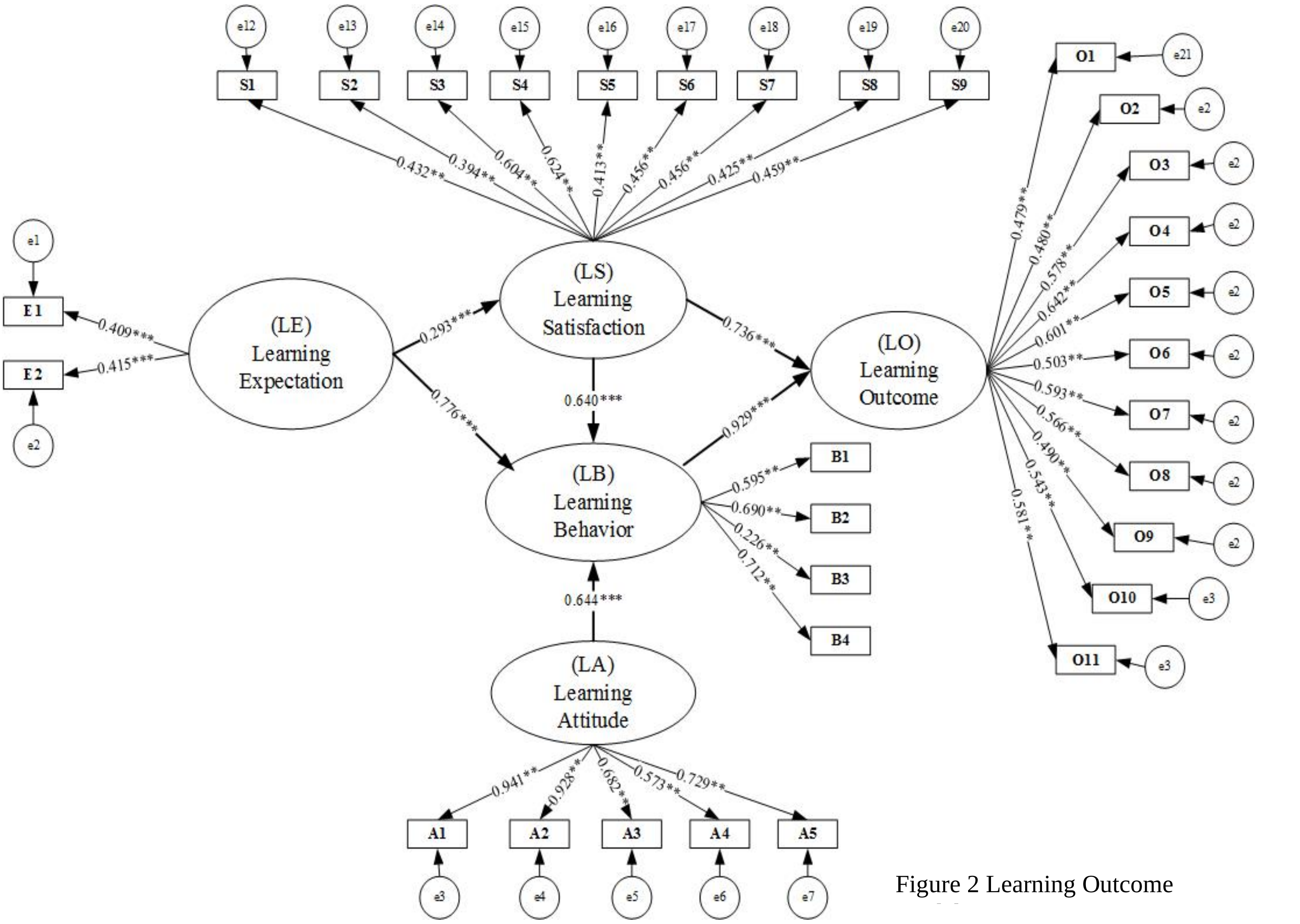

Figure 2 Learning Outcome

MOOC, followed by learners, how much are they expected to gain knowledge from studying MOOCs. The above variables can explain the variation of satisfaction of 38.90%, 36.40% and 22.70% respectively.

The composition weights show the importance of variables. In explaining the components of behaviour, it is found that the variables with the highest weight values are students who regularly communicate with friends in the classroom through the MOOC system, followed by students who study online through the MOOC regularly and students who submitted their work as instructed by the teacher regularly through the MOOC, respectively. The variables could explain the behaviour variation of 50.60%, 47.60% and 35.40% respectively.

When considering the element weight, showing the importance of variables in the explanation of attitude elements, it appears that the variable with the highest weight is content on MOOCs that can be applied in real life, followed by content on MOOCs that is modern and content on MOOCs that is useful knowledge respectively. The variable can explain 88.50% of attitude variations, 86.10% and 53.10% respectively

When considering the component weight, showing the importance of variables in explaining the composition of the expectation, it appears that the variable with the highest weight is students who are more interested in studying through the MOOCs system than going to university, followed by the students who want to study through the MOOC system by themselves. These variables can explain the variation of expectation by 17.20% and 16.70% respectively.

Discussion

Using Moocs, this paper investigates the factors affecting the learning outcome intention of MOOCs for an online learning platform in Thailand. We extended learning expectation integration with learning attitude and learning satisfaction and learning behavior influencing with learning outcome this related to Junjie (2017) the result of the empirical results showed that learning outcome is the first powerful indicator of learning's continuance intention of MOOCs, followed by social influence learner's satisfaction with prior learning experience. The different from other studies such as Lee (2010) found that satisfaction has the most significant effect on user's continuance intention, while other scholar that perceived reputation is the strongest predictor for learner's intention to continue using MOOCs (Alraimi, Zo, & Ciganek, 2015).

Implication for practices of this paper by MOOCs platforms should provide qualitied online course that suitable with learner's expectation such as the course content should provide useful information and learning activity should providing in several dimension especially during Study-From-Home (SFH) while the COVID 19 pandemic that suit with learning behavior such as using micro learning, blended learning, and other learning pedagogy. To bridge in the gap, the learning outcome model from this study should implication with social influence via online that linkage with social media to promote and stimulate the learner to participate with the online course with satisfaction.

Limitations and Future

The contributions of this study to support future research as follows: First, the research model is based on data collected from the MOOC learning platform, which limits the ability to generalize the findings to a University of a region, context or other MOOC platforms. Future studies could overcome this limitation by comparing the data across Universities or platforms.

Secondly, more research is needed in understanding the drivers of learner participation to attract more learners to join and be happy to learn perspectives such as motivation and barriers for further development of effective MOOCs.

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