Research Article

STUDENTS' BEHAVIORAL INTENTION TO ADOPT COGNITIVE LOAD OPTIMIZATION TO TEACH STEM IN GRADUATE STUDIES

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Abstract

The Cognitive Load Optimization (CLO) method provides a quantitative metric for measuring Intrinsic Cognitive Load (ICL), which is a measure of complex knowledge that is hard to teach. CLO provides guidelines to assist in the presentation of information in order to optimize intellectual performance. Using this method, it is possible to produce the simplest learning sequence with the minimum ICL. Business courses, such as IT technology management, require students to study STEM technical subjects such as IT infrastructure. However, business students typically do not have a technical background. The research objective of this study is to investigate students' behavioral intention to adopt CLO to teach STEM disciplines in graduate studies in Bangkok. This research tool is a quantitative approach using a questionnaire method to collect around 210 participants of graduate students who study by using CLO approach in remote learning systems environment in various programs. There were collected from online survey by using stratified random sampling and purposive sampling methods. The survey was distributed electronically via choose yourself and learning management channels which provide by the university. The study is applied the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The conceptual framework focuses to determine the factors that influence the students' intention to adopt CLO-learning via remote learning systems. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) techniques selected to analyze the data to confirm goodness-of-fit of the model and hypothesis testing. The results pointed out that performance expectancy, effort expectancy, lecturers' influence, facilitating condition, perceived usefulness, perceived ease of use, and personal innovativeness have a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in graduate studies; however, the relative advantage illustrated in a non-significant variable only in this study.

Keywords: Cognitive Load Optimization (CLO), Perceived Usefulness, Perceived Ease of Use, Behavioral Intention to Adopt/Use, Structural Equation Model (SEM)

Introduction

There are different learning theories in use today, principally Constructivism, Behaviorism, and Cognitive Psychology. Learning theories attempt to explain how students learn. However, these 20th Century methods are all based on guidelines open to different subjective interpretations with implications for quality learning outcomes. In effect, education is classified as a 'soft' science. This is not a pejorative term as the subject matter (humans) are complex systems not readily tenable to the scientific methods associated with the 'hard' sciences. In order to address this problem a more rigorous scientifically-based learning theory is needed. Our future generation and society are highly subject to the advancements of technology and technical knowledge (Lin et al., 2008; Wall, 2010). Jobs career related to STEM are then expected to be increased and highly demanded in the market. Business environment has been rapidly changed recently from the competitiveness in the industry, economic crisis and pandemic, thus business problems become complex and multidimensional. In order to understand and resolve business problems, entrepreneur require competent workers who employed both soft skills and technical knowledge (Prikshat et al., 2019). Papers have found that business graduates still have insufficient competencies of the workplace (Cumming, 2010). Business students typically do not have a technical background. Therefore, various educational leaders and institutions have greatly value and emphasize on recruiting, building, and retaining students majoring in science, technology, engineering, and math (STEM) (Jørgensen & Valderrama, 2016). The researcher would like to study and identify the students' behavioral intentions that can lead to CLO in STEM disciplines in order to recommend educational leaders, institutes, and professors to develop meaningful remote learning programs that can help foster the student's technical knowledge.

The National Science Foundation (NSF) established the Science of Learning (SoL) program with the goals of developing a fundamental understanding of learning (Science of Learning | NSF - National Science Foundation, n.d.). A number of general research questions were identified by the NSF such as: How does the structure of the learning environment impact rate and efficacy of learning? For example, how do timing, content, learning context, development time and type of engagement impact learning processes and outcomes? (NSF Makes New Awards to Advance Science of Learning | NSF - National Science Foundation, n.d.). The NSF 2013 SoL workshops reported that much remains to be learned but that the goal needs to be to optimize learning for all. In order to translate SoL research into practical implementations the Deans for Impact defined six key questions with the associated cognitive principles and practical implications for the classroom (Donovan, 2012). For example, Research question 1) *How do students understand new ideas?* This is based on three cognitive principles such as: '*students learn new ideas by reference to ideas they already know*.' Practical implications for the classroom include: *A well sequenced curriculum is important to ensure that students have the prior knowledge they need to master new ideas*. The Australian Science of Learning Research Centre (SLRC) defined twelve principles but no practical scientific method (*Science of Learning Research Centre Home - Science of Learning Research Centre*, n.d.). Six cognitive learning strategies (spaced practice, interleaving, retrieval practice, elaboration, concrete examples and dual coding) and their application using biological bases of behaviour from basic psychology have been proposed (Weinstein et al., 2018). However, they only strategies. To achieve the SoL goal of optimised learning for all what is needed is a quantitative, practical scientific method that is easy to use, applicable to all STEM disciplines at all educational levels (school, college, university) resulting in significant improvements in teaching and learning outcomes.

Literature Review and Research Hypotheses

1. Cognitive Load Theory

Cognitive Load Theory (CLT), a cognitive science theory, provides guidelines to assist in the presentation of information in order to optimize intellectual performance (Sweller et al., 1998). CLT is based on the principles of: schemas, short-term memory (STM) e.g. working memory that has limited capacity and duration imposed (Baddeley, 2010; Miller, 1956), long term memory (LTM) that is the repository for schemas and automation that reduces the load on STM (Paas et al., 2003). According to schema theory knowledge is stored as mental constructs called schemas (McVee et al., 2005; Hoz et al., 2001). Meaning and hence understanding is implied by the pattern of relationships in a schema. Learning consists of building these new schemas resident in LTM (de Jong, 2010). Hence learning outcomes may be improved if the material to be taught is highly structured. In CLT the concept of understanding is a function of element interactivity (Marcus et al., 1996). In this context understanding only applies to high element interactivity which is the intrinsic source of cognitive load and simultaneously process in STM (Sweller et al., 2011). Complex knowledge, with a high ICL, is difficult to learn because places a heavy load on STM. By contrast simple knowledge, with fewer elements and low interdependence, has a low ICL, low load on STM but does not show key element of high order learning outcomes (Sweller, 2010). The goal of CLT is to provide guidance on the design of material with a high ICL and how it can be taught. CLT has been extensively used, as the theoretical framework, to enhance and inform: instructional design methods (Chong, 2005); self-regulated learning (de Bruin & van Merrienboer, 2017) and problem-based learning (Wahyudi & Aqidawati, 2019; Leppink, 2017; Reedy, 2015). However, all these implementations are subjective and hence open to different interpretations.

CLO (CLO) is a simple method for quantitatively measuring ICL. Using CLO, it is possible to convert complex knowledge with a high ICL to the lowest ICL that does not overload STM. In doing so CLO creates the simplest, optimum learning sequence that can be used as the basis of instructional materials and methods (Maj, 2018). Published work to date has shown that using CLO, in the college and university sectors, results in significant improvements in learning outcomes for a wide range of disciplines (engineering mathematics, object oriented programming, project management, cybersecurity, network technology, computer systems, biomedical engineering, engineering drawing, science (chemical, biological, environmental) etc.) allied with high pass and retention rates without compromising academic quality in all delivery modes. Also, the CLO method was the preferred teaching method for business students who need to study complex technical topics such as IT infrastructure, Cyber security etc. Significantly 99% of students considered the CLO based method of instruction best prepared them for working in commerce and industry (Maj, 2018; Maj & Nuangjamnong, 2020; Maj, 2020).

2. The Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM)

The Unified Theory of Acceptance and Use of Technology (UTAUT) model has been broadly utilized since it was being proposed by Venkatesh et al. (2003). The UTAUT model defines user intentions to use an information system and subsequent usage behavior. In addition, the theory model emphasizes four key constructs which are 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (Venkatesh et al., 2003). Four key constructs of the UTAUT consist of:

2.1 Perceived usefulness (PU) and Perceived ease-of-use (PEOU)

Perceived usefulness (PU) – this was defined by Davis (1989) as "the degree to which a person believes that using a particular system would enhance his or her job performance". By the PU's definition means whether or not someone perceives that technology to be beneficial and useful for what they want to do (Davis et al., 1989). The Perceived Usefulness (PU) of cognitive load optimization for teaching STEM disciplines via remote learning systems (in this case, tools applied for university remote learning systems such as Zoom Meeting, Microsoft Team; Neolms, etc.) is one of the most important elements in the Technology Acceptance Model (TAM). In this study, PU referred as the degree to which graduate students of a particular system believe that it would improve graduate students' work or study performance as compared to alternative methods of carrying out this student's tasks (Liu et al., 2009; Abdullah et al., 2016) . Perceived Usefulness convinced the decision of students on whether to accept or reject the particular approach of learning methods based on current technology. Perceived ease-of-use (PEOU) - as stated by Davis (1989), this defined as "the degree to which a person believes that using a particular system would be free from effort". Through PEOU, it implies if the technology is easy to use, then the obstacles conquered. If it is not easy to use and their interface are complicated, no one has a positive attitude towards them (Davis et al., 1989). In accordance with the original TAM (Davis, 1986), PU and PEOU of users influences their Attitude Towards Using and Intention to Use technology. Hence, the hypotheses proposition are derived as follows:

H1: Perceived ease of use has a significant effect on perceived usefulness to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

H2: Perceived usefulness has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.2 Effort expectancy

Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Effort expectancy indicates graduate students' perception that adoption of cognitive load optimization for teaching STEM disciplines via remote learning systems will be easy and free of effort. They can absorb the difficult contents of their STEM course like the management information system (MIS) unit. Since many students in developing countries are not exposed to many information systems, therefore, most of their study is emphasized with memorizing the contents rather than gain understanding from the contents. This construct is an important determinant of the adoption of cognitive load optimization for teaching STEM disciplines via remote learning systems. It is expected that acceptance to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems will depend on whether students believe to apply cognitive load optimization for teaching STEM disciplines via remote learning systems will be ease of use. Therefore, this hypothesis proposition is derived as follows:

H3: Effort expectancy has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.3 Social influence as lecturers' influence

Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). Social influence in this study, its correlates to lecturers' influence which illustrates the degree to which students perceive other students or important people believe they should adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems. Prior studies have demonstrated that a student's decision is normally influenced by peer students or by other people such as instructors/lecturers and parents (Miller et al., 2003; Rodprayoon et al., 2017). Hence, there are important to include lecturers' influence as the social influence of the constructs in the modified research model. This hypothesis proposition is derived as follows:

H4: Lecturers' influence has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.4 Facilitating condition

Facilitating condition is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). Facilitating conditions refers to availability of resources to support adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems at a given by institutions. In the context of cognitive load optimization for teaching STEM disciplines via remote learning systems, the resources include availability of computer-based information systems, mobile devices, reliable broadband connection, and other related resources. Therefore, graduate students' decision to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems will be influenced by their perception of the availability of support services and resources to deliver remote learning. The hypothesis proposition is come from as follows:

H5: Facilitating condition has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

The technology acceptance model (TAM) by Davis (1989) describes an information systems theory that replicas how users come to accept and use technologies which the actual system use is the end-point where people use technology (Davis et al., 1989; Davis, 1989). In the theory of TAM, behavioral intention is a major factor that introduces people to use the technology. The behavioral intention is influenced by the attitude, which is the general impression of the technology. This model proposes that when people are presented with new technology, a number of factors influence their decision about how and when they will use it, particularly.

2.5 Performance expectancy

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". Performance expectancy is the strongest predictor of behavioral intention to use several technologies in both voluntary and involuntary settings (Venkatesh et al., 2003). In this study context, it represents the degree to which students believe that adoption of cognitive load optimization for teaching STEM disciplines via remote learning systems will help to enhance graduate students' learning performance and gain better grades (Wang et al., 2009). Strengthening this belief will increase students' behavioral intention to adopt and use cognitive load optimization to teach STEM disciplines via remote learning systems. This construct has been driven from perceived usefulness described in TAM. A similar study conducted to identify and examine Cognitive Load Optimization – a statistical evaluation for three STEM disciplines by Maj (2018) in the qualitative research method. The hypothesis can be explained as follows:

H6: Performance expectancy has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.6 Personal innovativeness

Personal innovativeness is the construct that appears in the Theory of Reasoned Action, Theory of Planned Behavior, Technology Acceptance Model, Combined TAM-TPB, and the Motivation Model. Personal innovativeness is referred to as the willingness of an individual to try out any new information technology (Agarwal & Prasad, 1998). Also, the study by Agarwal and Karahanna (2000) established a multidimensional construct labeled cognitive absorption and suggested this construct to be a predecessor of the two regularly recognized behavioral beliefs about technology use namely perceived usefulness and perceived ease of use. As well, they proposed that the individual traits of liveliness and personal innovativeness are important determinants of cognitive absorption. For adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems such as computer network security, wireless mobile technology, most graduate students do not have any or much knowledge and experience to help them form clear perception understanding. Personal innovativeness is support to present sheer boldness and curiosity in students' characters may not only strongly amplify their perception of potential benefits but also heighten their confidence in their capabilities to handle learning and understanding technology under adoption. Meanwhile, for the reason that individuals with higher personal innovativeness tend to be more risk-taking, they also reasonable to expect them to develop more positive intentions toward the adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems. Thus, the innovative character may very well serve as the main and direct determinant for adoption decision. Therefore, we propose:

H7: Personal innovativeness has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.7 Relative advantage

According to Chen and Hung (2010) added that "relative advantage is a measure of the degree to which an action provides more benefit than its precursor". With particular respect to adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems, the individual perception of potential benefits associated with learning outcomes is one of the key components that could drive adoption that is more positive and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems behaviors. In this study, relative advantage referred to positively adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems has more advantages than in-class on campus because teaching and learning methods are not limited by location. In addition, the adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems is more convenient efficient, and effective than in-class on campus at the university. Therefore, we propose:

H8: Relative advantage has a significant effect on students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in Graduate Studies School.

2.8 Behavioral Intention to use Cognitive Load Optimization

According to Venkatesh et al. (2003) convinced, that behavioral intention to adopt and use a given technology has significant influence on usage behavior. Currently, there is no tangible related with adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems at a given by institutions. The study measures students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines in Bangkok focuses on graduate studies in private university.

Methodology

1. Measurement Instrument

Figure 1 illustrates the research model and the hypotheses formulated in the study. From the literature discussed above, this research model is to investigate students' behavioral intention to adopt/use cognitive load optimization to teach STEM disciplines in graduate studies school in Bangkok. This study is emphasized on specific factors: performance expectancy, effort expectancy, lecturers 'influence, facilitating condition, perceived usefulness, perceived ease of use, personal innovativeness, relative advantage, and behavioral intention to adopt/use cognitive load optimization (CLO).

To guide the present research, we developed a system-specific model integrating important elements from UTAUT and TAM (Figure. 1). This model proposes that the intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems at a given by institutions is a combined effect of performance expectancy, effort expectancy, lecturers 'influence, facilitating condition, perceived usefulness, perceived ease of use, personal innovativeness, and relative advantage toward students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems. The highlighting of this framework is on explaining the antecedent beliefs of the perceptions and behavioral intentions. Our assumption is that personal attributes in perception psychology and social relationships are both important determinants of innovation adoption perceptions.

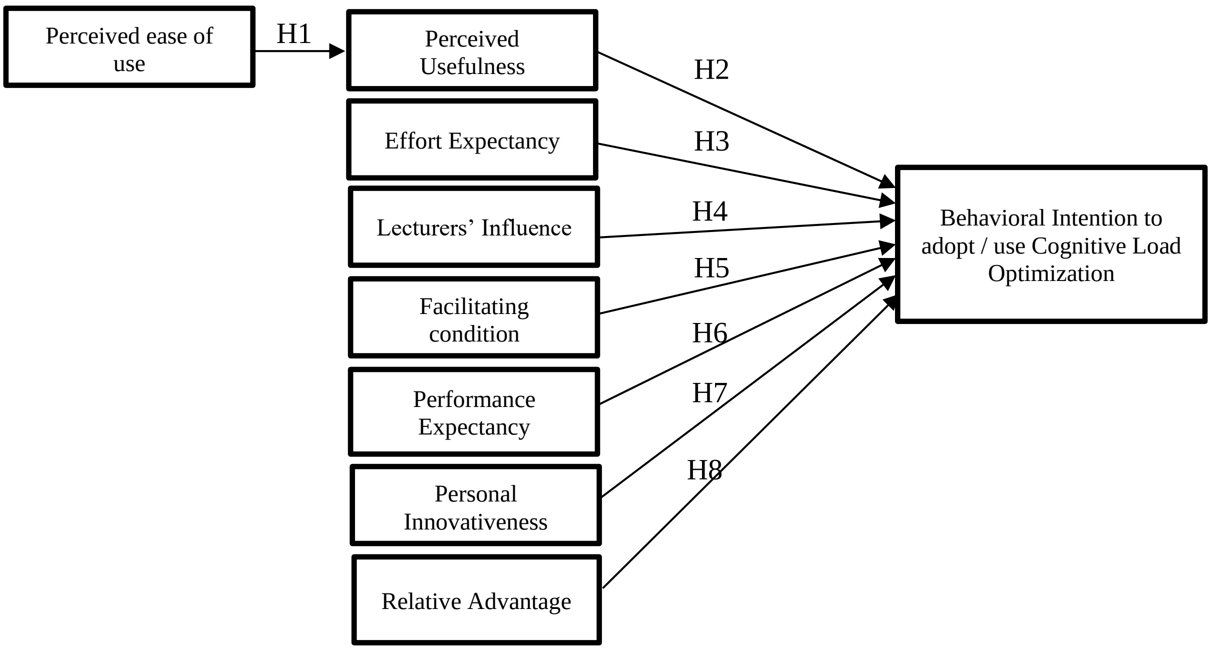

Figure 1. The research conceptual framework

2. Research method

This research tool is a quantitative approach using a questionnaire method to collect responses from graduate students. The survey was developed and distributed electronically via choose yourself and learning management channels which provide by the university. The data collected will be analyzed to determined students' behavioral intention to adopt CLO to teach STEM disciplines via remote learning systems in graduate studies in Bangkok.

3. Population and sample size

The population of this study is the graduate students who enrolled in the private university in Bangkok in the academic year of 2019–2020. According to Soper (2021), the recommended minimum sample size was 200. Appropriate sample size was also relied on model size, several parameters, several indicators and factors, which supported by Soper (2021), who developed the calculator for SEM to determine a minimum required sample size for the study when SEM was applied. The results of anticipated effect size was 0.3, desired statistical power level was 0.8, a number of latent and observed variables was nine and twenty-seven respectively, probability level was 0.05, a minimum sample size to detect effect was equal to 184, a minimum sample size for model structure was equal to 200, and the number of recommended minimum sample size was equal to 200 samples.

4. Sampling techniques

The researcher has collected survey by using stratified random sampling and purposive sampling methods. The survey was distributed electronically via choose yourself and learning management channels during the final week of each semester which expected 250 respondents. Those graduate students were exactly informed that if they were interested primarily in their perceptions about the adoption and usage of cognitive load optimization to teach STEM disciplines via remote learning systems and then invited to respond as honestly as possible to the survey.

The questionnaires were completed by 210 respondents with a response rate of 84%. Responses were then tested by the conceptual model to determine whether the number accepted as a sample size. The margin of error is 5.0%, with a confidence level of 95%. The analysis was performed using structural equation modeling. Thus, 210 as the sample size is considered high compared to the unimportant requirements used to analyze the hypotheses (Chuan & Penyelidikan, 2006). As a result, 210 replies are received. According to Hair et al. (2010) and Wolf et al. (2013) defined reliability as an assessment of the degree of consistency between multiple measurements of a variable. Their studies assesses the consistency of the entire scale with Cronbach's alpha and its overall reliability of each factor of efficiency values (Cohen, 1988; Westland, 2010).

A research model including seven or fewer constructs, modest commonalities, and no unidentified constructs for structural equation modeling (SEM) technique (Cohen, 1988; Westland, 2010; Hair et al., 2010). To ensure content validity, an examination was made of the relevant literature. In order to reduce the possibility of non-random errors, a pilot has conducted in March 2020 to examine the questionnaire for validity, completeness, and readability/ understandability. As a result, several suggested changes to the questionnaire items have incorporated into this study. AMOS has used as the major statistical tool for model testing. The entire data analysis process engaged a two-stage approach recommended by Anderson and Gerbing (1988). At the first stage, we developed a measurement model using confirmatory factor analysis (CFA) to assess the extent to which indicators specified for each measure refer to the same conceptual construct. After an acceptable measurement model had been obtained, we built the structural equation model and examined the hypothesized causal paths among the constructs by performing a simultaneous test. This test helped us to observe whether the recommended conceptual framework had provided an acceptable fit to the empirical data.

Findings and Discussion

This part of the study includes descriptive findings, results of the measurement, structural model validities and discussion on hypothesis testing result.

1. **Descriptive Statistics**

The results of the demographic sections illustrated some interesting points; the three questions represented the initial idea of the participants' characteristics, which include gender, age groups, and graduate student's level (Table 1). The results indicated that participants are graduate students and they have great awareness to use remote learning systems as screening questions shown at the beginning of the questionnaire. When asking about gender, the rate of the male group was 46% while the female was 54 %. Next, age group, the number of participants is greater and equal 18 years old to 25 years old was representing 11% and they are students at the graduate studies in the universities, 43% from the age group between 26 years old to 35 years old, 25% from the age group between 36 years old to 45 years old, 17% from the age group between 46 years old to 55 years old, then lastly the age group greater and equal 56 years old was 4%.

Table 1. Demographic distribution of participants

Variables		n	%
Gender:	Male	97	46
	Female	113	54
	Total	**210**	**100**
Age Group:	≥ 18 yrs - 25 yrs	23	11
	26 yrs - 35 yrs	91	43
	36 yrs - 45 yrs	52	25
	46 yrs - 55 yrs	36	17
	≥ 56 yrs	8	4
	Total	**210**	**100**
Graduate students' level:	Master Degree	192	91
	Doctoral Degree	18	9
	Total	**210**	**100**

2. **The measurement model**

A normality check was first performed to ensure suitability of the empirical data for predetermined statistical analysis procedures. Of all the variables in the measurement model, univariate skewness values range from -1.676 to 0.458, with a mean of -0.464; univariate kurtosis values range from -1.147 to 3.352, with a mean of 0.244. According to Kline (1998), absolute values of univariate skew indexes greater than 3.0 and absolute values of the univariate kurtosis indexes greater than 8 are indications of extreme cases of violating normality assumption; the present data set is in the tolerable range for non-severe violation. Therefore, Structural Equation Modeling (SEM) procedures assuming multivariate normality are followed. All the nine constructs in the model are believed to exhibit very good internal consistency as evidenced by their reliability scores. A CFA measurement model has created to check the model fit and convergent validity of each construct in the proposed model. This CFA model allows each construct to correlate freely with every other construct but with no causal relationships specified between the latent constructs. The measures used to assess model fit include Chi-square, degree of freedom, the X^2/df ratio, Normed Fit Index (NFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). Since the sample size in this study is commonly considered small (> 250), the Chi-square value and the related p-value are neglected for their over sensitivity to the sample size (Joreskog & Sorbom, 1993). All the other criteria meet the recommended level for a reasonably good fit (Table.2).

Table 2. Display statistical values to assess the coherence of the model with empirical data

Index	Criterion	References	Statistical values obtained from analysis
χ/2df)CMIN/df(	<3	(Hair et al., 2010)	1.737
GFI	$\geq$0.85	(Schumacker & Lomax, 2004; Baumgartner & Homburg, 1996; Doll et al., 1994)	.851
AGFI	$\geq$0.80	(Baumgartner & Homburg, 1996; Marsh et al., 1988; Doll et al., 1994)	.804
CFI	$\geq$0.90	(Bentler, 1990; Baumgartner & Homburg, 1996)	.948
NFI	$\geq$0.85	(Browne & Cudeck, 1993;_Garson, 2015)	.886
RMSEA	<0.08	(Hu & Bentler, 1999; McDonald & Moon-Ho, 2002; Schermelleh-Engel et al., 2003; Thompson, 2000)	.059
Model summary			**Appropriate fit coherence of the model with empirical data**

Remark: 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, normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residua

3. **Model Estimation**

Composite Reliability measure (CR) was used to determine reliability. It worked in the same way as the previously mentioned determinants. It gave accurate values with the help of factor loadings, and they were used in the given formula. The Average Variance Extracted (AVE) can show the latent construct, which is the average amount of difference or variations in each variable. AVE can be used when there is discriminate validity, and it is greater than one factor. It can examine each factor's convergence. According to Table 3, the outcome of consequence and the questionnaire reliability and convergent validity have surpassed the requirements. In Table 3, the basic requisites for the reliability and validity of the questionnaire are presented and the results obtained for every factor is shown by the variables obtained from the questionnaire.

The SEM represent an extension of related to statistical tests of variables efficiency. The SEM focuses to test if the Theoretical Model is valid, and by studying and evaluating linear relations between the Constructs to see the strength relationship between them through hypothesis testing in the model, which helps to ensure the validity of the model (Shah & Goldstein, 2006). Hence, the Measurement Model is testing output that focuses on measuring relationships between variables and Constructs, which can be used to determine whether the Constructs were measure accurately or not. The reliability test of the all model Constructs by using more accurate test, which called Composite Reliability Scale (CR). The CR test is alternative test to Cronbach's alpha, while the CR refers to the degree of two variables or more to involve for build the constructs and model (Lu et al., 2007). If CR was more than 0.6, that is the CR degree can be acceptable (Bagozzi & Yi, 1988). Thus, this shows that all the factors in the model are statistically significant and measure the same Construct. The CR can be calculated by the following equation (Hair et al., 2010; Fornell & Larcker, 1981): Average Variance Extracted (AVE), it is used to calculate the variance between the variables in the Constructs separately (Koufteros, 1999). The recommend values of AVE is more than 0.5, this mean the variables are represent the Constructs a really. AVE can be calculated according to the following equation (Hair et al., 2010).

Table 3. Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Constructs	Items	Factor Loading		Cronbach's Alpha	CR	AVE
(1) Perceived ease of use	3	PEOU1	0.867	0.802	0.860	0.673
		PEOU2	0.829			
		PEOU3	0.812			
(2) Perceived usefulness	3	PU1	0.916	0.829	0.889	0.728
		PU2	0.843			
		PU3	0.797			
(3) Effort expectancy	3	EE1	0.890	0.744	0.839	0.637
		EE2	0.739			
		EE3	0.756			
(4) Lecturers' influence	3	LI1	0.903	0.762	0.847	0.650
		LI2	0.729			
		LI3	0.777			
(5) Facilitating condition	3	FC1	0.897	0.797	0.856	0.665
		FC2	0.785			
		FC3	0.758			
(6) Performance expectancy	3	PE1	0.891	0.823	0.869	0.689
		PE2	0.758			
		PE3	0.836			

Constructs	Items	Factor Loading		Cronbach's Alpha	CR	AVE
(7) Personal innovativeness	3	PI1	0.861	0.756	0.845	0.645
		PI2	0.785			
		PI3	0.760			
(8) Relative advantage	3	RA1	0.862	0.712	0.828	0.618
		RA2	0.789			
		RA3	0.698			
(9) Behavioral intention to adopt / use cognitive load optimization (CLO)	3	CLO1	0.868	0.810	0.866	0.684
		CLO2	0.792			
		CLO3	0.820			

Note: CR = Composite Reliability, AVE = Average Variance Extracted; (Factor loading, Cronbach's Alpha, CR ≥ 0.70 & AVE > 0.5).

The Table 3 indicates that the Factor extracted values in the Constructs were recorded higher than 0.5 and the value of the AVE was higher than 0.5. The AVE values were ranging 0.618 and 0.728 then the CR values ranged between 0.828 and 0.889. Then, these indicators are pointing to the differentiation in the used scales, and that should be enough to validate students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems in this study. Moreover, the Factor loading values were between 0.698 and 0.916. In addition, all of them were significant at p <0.001. No factors have been excluded in this stage of analysis, because the accepted values and compatible among the factors. The results of this part indicate the convergence between the values in the tests, which lead to the reliability of the variables in the model constructs.

Table 4. Discriminant Validity

Variables	Factor Correlations								
	PEOU	PU	EE	LI	FC	PE	PI	RA	BI-CLO
PEOU	**0.82**								
PU	0.565	**0.853**							
EE	0.343	0.59	**0.798**						
LI	0.368	0.712	0.38	**0.806**					
FC	0.562	0.734	0.546	0.703	**0.815**				
PE	0.186	0.655	0.349	0.334	0.64	**0.83**			
PI	0.585	0.615	0.618	0.649	0.755	0.613	**0.803**		
RA	0.724	0.721	0.613	0.749	0.625	0.615	0.745	**0.786**	
BI-CLO	0.801	0.55	0.728	0.429	0.606	0.71	0.591	0.629	**0.827**

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

From Table 4, one measuring aspect that is used to measure the discriminant validity between the factors is compared the square root of the AVE values with each Constructs in the Model (Fornell & Larcker, 1981). If the square roots of AVE values are bigger than other constructs values, which means each Constructs are closely linked other

Constructs (Fornell & Larcker, 1981). The squared root of AVEs is larger than the correlation of each constructs. The numbers with dark blue is the square root of the AVEs at level of 0.001.

Table 5. Hypothesis testing results of the Structural Model

Hypothesis / Paths	Standardized path coefficients (β)	S.E.	t-value	Testing result
H1: PEOU → PU	0.082	0.039	2.028*	Supported
H2: PU → BI-CLO	0.836	0.088	5.778*	Supported
H3: EE → BI-CLO	0.727	0.166	3.591*	Supported
H4: LI → BI-CLO	0.912	0.136	7.769*	Supported
H5: FC → BI-CLO	0.627	0.164	3.489*	Supported
H6: PE → BI-CLO	0.597	0.177	3.191*	Supported
H7: PI → BI-CLO	0.885	0.182	7.398*	Supported
H8: RA → BI-CLO	0.036	0.064	0.671	Not Supported

*Remark: *p<0.05*

After that, the relationships between the constructs were calculated by three main indicators, which are t-value, p-value, and Standardized regression coefficient. The Constructs result was shown proportionate and significant for all model hypotheses from H1 to H8. The value of Standardized regression coefficient was between 0.597 and 0.912 and the p-value was significant in the level 0.05 and the R^2 values between 7.769 and 0.671 which is recommended more than 1.96 ranged. As shown in the Table 5 all, the modelling fit indicators in the acceptable level as presented in the path coefficient structure model. The result of previous statistical tests shows all the model constructs (PE, EE, LI, FC, PU, PEOU, and PI) have positive effects on BI-CLO to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems, except RA has no positive effect in this study in H8. As mentioned in the Table 5.

Table 6. Direct, Indirect and Total Effects of Relationships

Dependent Variables	Effect	Independent variables							
		PEOU	PU	EE	LI	FC	PE	PI	RA
Behavioral intention to	DE	-	0.836*	0.727*	0.912*	0.627*	0.597*	0.885*	0.036
adopt / use cognitive	IE	0.079*	-	-	-	-	-	-	-
load optimization (BI-	TE	0.079*	0.836*	0.727*	0.912*	0.627*	0.597*	0.885*	0.036
CLO)	R^2	.571							
Perceived usefulness	DE	0.082*	-	-	-	-	-	-	-
(PU)	IE	-	-	-	-	-	-	-	-
	TE	0.082*	-	-	-	-	-	-	-
	R^2	0.239							

*Remark: DE =Direct Effect, IE =Indirect Effect, TE =Total Effect)DE+IE(, *p<0.05*

4. Discussion

The result from Table 5 and Table 6 can be explained that the proposed model adequately explains patterns of the factors influencing of students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems. H1 of Perceived ease of use (PEOU) has significant direct effect to perceived usefulness (PU) with the standard coefficient value of 0.082 and thus leading to indirect effect to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems (0.079). On perceived usefulness (PU) itself, H2 is also supported that there is a significant direct effect to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with the standard coefficient value of 0.836. The result of this finding aligns with research papers of Davis (1986), Liu et al. (2009), and Abdullah et al. (2016).

For H3, effort expectancy (EE) has significant direct effect on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with the standard coefficient value of 0.727. This is consistent to the finding of Al-Gahtani et al. (2007) and Chong (2013) that performance expectancy plays a crucial role in affecting individuals' behavioral intention to use or perform a task.

H4 is hypothesized on the significance of lecturers' influence (LI) on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems. The hypothesis is supported with standard coefficient value of 0.912. This significance as strengthen the previous research conducted by Miller et al. (2003) and Rodprayoon et al. (2017).

H5 of facilitating condition (FC) has a supported hypothesis that it has significant direct effect of facilitating condition (FC) on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with standard coefficient value of 0.627. This finding has also supported by previous research of Lin and Anol (2008) and Jones et al. (2002). This behavioral intention can be fostered by facilitating condition of such as study guidance, technical instructions and personal assistant from the lecturers (Thompson et al., 1991).

H6 is supported that performance expectancy (PE) has significant direct effect on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with standard coefficient value of 0.597. The finding is supported by the previous research by Al-Gahtani et al. (2007) and Wang et al. (2009).

In H7, the hypothesis is supported that personal innovativeness (PI) has significant direct effect on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with standard coefficient value of 0.885. As the research of Agarwal and Karahanna (2000) states that individual traits of liveliness and personal innovativeness are important determinants of cognitive absorption.

Lastly, H8 of relative advantage (PI) has insignificant direct effect on students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems with standard coefficient value of 0.036. This finding has contradicted with previous papers that the more student perceived benefits and advantage of STEM, the more students would accept and intent to learn through cognitive load optimization (Venkatesh et al., 2003; Chitungo & Munongo, 2013; Shaikh and Karjaluoto, 2015).

To summarize, most factors regarding to independent variables (performance expectancy, effort expectancy, lecturers' influence, facilitating condition, perceived usefulness, perceived ease of use, and personal innovativeness) were significant variables in influencing of students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems, excluding, relative advantage was presented insignificant effect in this study. In particular, three factors (lecturers' influence, personal innovativeness, perceived usefulness) added to the TAM and the UTAUT model demonstrated high levels of statistical significance. In studies where the course matter is complex and requires a high level of technical background, it is found that the influence of the lecturer plays an important role in the digestion of the course contents for students to understand more easily. So there will affect performance expectancy and perceived usefulness in better motivation to adopt and use CLO to expand their learning outcomes. Graduate students believe that the adoption and usage of cognitive load optimization for teaching STEM disciplines via remote learning systems will substantially improve their learning performance. This finding would seem to provide clear evidence for the adoption and usage of this technique in courses. The adoption and usage of cognitive load optimization for teaching STEM should be designed with the criterion of graduate students' behavioral context which based on lecturers' influence, personal innovativeness, and perceived usefulness.

Conclusion and Recommendation

The present research has explored the factors influencing of students' behavioral intention to adopt and use cognitive load optimization for teaching STEM disciplines via remote learning systems, which are actively seeking to adopt and use the CLO technique for students in level of graduate studies in Bangkok. The Cognitive Load Optimization (CLO) technique provides a quantitative metric for measuring Intrinsic Cognitive Load (ICL) which is a measure of complex knowledge that is hard to teach. CLO will provides guidelines to assist in the presentation of information in order to optimize intellectual performance. Using this technique, it is conceivable to produce the simplest learning sequence with the minimum ICL. This study has consistently shown that adopting and using CLO results in significant improvements in learning outcomes in considerably less time. Some business courses, such as IT technology management, require students to study STEM technical subjects such as IT infrastructure. However, business students typically do not have a technical background. The result is likely to be superficial learning which is easily forgotten and of limited value in the workplace. The main research objective of this study is to investigate students' behavioral intention to adopt CLO to teach STEM disciplines in graduate studies in Bangkok. A quantitative, questionnaire-based approach was used to collect relevant data. The questionnaire was distributed across a wide range of institutions to graduate students at different levels (e.g. master degree, doctoral degree/Ph.D. degree). More than 210 participants, studying through e-learning (either partly or wholly) in graduate studies in the private university, responded to the questionnaire. Online invitation by university learning management system channels such as NEOLMS, Moodle, and Google Classroom were used to invite participation. As a theoretical framework, the TAM and the UTAUT model were adopted to study the factors influencing of students' behavioral intention to adopt and use cognitive load optimization for teaching STEM via remote learning systems. In this reverence, the existing study bridges a significant gap in the collected works. The study has identified factors influencing students' behavioral intention to adopt and use cognitive load optimization for teaching STEM, identifying needs among the target population as well as the challenges they face in this regard. To improve the experience of graduate students and to increase the numbers of university students adopting and using cognitive load optimization for teaching STEM in the future. This research contributes to clarifying current trends, helping all stakeholders to face the major challenges in the developing teaching new technique (CLO) thru remote learning systems in general, and of M-learning in particular.

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