An Investigation to Examine Factors Influencing University Students' Behavioral Intention Towards the Acceptance of Brightspace LMS: Using SEM Approach

Lilian Yap, Wawasan Open University, Malaysia
Geok Ling Khoo, Wawasan Open University, Malaysia

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Abstract
Students' perceived usefulness (PU) and ease of use (PEOU) of Brightspace by D2L Learning Management System were evaluated (LMS). Brightspace, a new cloud-based LMS were subscribed at University W in January 2021, is a virtual learning environment with no space or time constraints between instructors and students. It has interactive material, assessment, curated resources, video upload, and student progress tracking. The Google Survey Questionnaire was created online and sent to around 300 pupils through email. Online classes were conducted in July 2021 in the small private education institution, University W. Tutors were asked to assist to encourage students to complete the survey. Approximately 200 student responses were solicited. The structural model analysis revealed that students' extrinsic values influenced perceived usefulness positively. Also, intrinsic values had a beneficial impact on perceived usability. Similarly, perceived usefulness and ease of use positively influenced behavioral intention.

Keywords: Technology Acceptance Model, Intrinsic Motivation, Extrinsic Motivation, System Acceptance

1. Introduction

Technology is prompting colleges and universities to accelerate their use in higher education (Hernández et al., 2017). Because of this, instructors are challenged to utilize new technologies to increase students' experiences and academic learning outcomes (Parkman et al., 2018).

A learning management system (LMS) is a web-based tool that allows students to learn online (Wichadee, 2015). By allowing the students to access the LMS 24/7, it is considered as an effective means to deliver course content and instructions to the students, while enabling instructors to create, plan implement, assess and manage course content (Bousbahi & Alrazgan, 2015).

1.2 Research Problem

Education institutions globally spends millions to build and maintain their e-learning system platform. Moodle and Blackboard are the more popular e-learning platforms, while other institutions developed their own (Puteh, 2008). In Malaysia, the senior management of a small private education institution, University W, decided to move away from Moodle and to partner with D2L Brightspace to integrate all aspects of online learning. University W was the first education institution in Malaysia to partner the cloud based D2L Brightspace LMS in January 2021. D2L Brightspace is able to provide access anytime (24/7), anywhere, create a variety of assessment; quizzes, assignments, online grade book, personalized feedback (Miller et al., 2020) and has an analytic component which will generate reports to help the institution to better engage the students (Peters, 2021).

While an e-learning system may benefit students, its effectiveness is determined by their acceptance.

1.3 Research Objectives

i. To review the literature on the use of TAM to measure e-learning system acceptability.
ii. To create a technology enhanced approach to assess student acceptability of Brightspace LMS e-learning platform.
iii. To study students' adoption of Brightspace LMS e-learning platform. (Four motivation factors connected to system focus and user attributes were found. The variables are incorporated into the TAM to examine hypotheses.)

2. Literature Review

2.1 Theory of Reasonable Action (TRA) and Theory of Planned Behavior (TPB)

The Technology Acceptance Model (TAM) is based on the psychology-based theory of reasonable action (TRA) and theory of planned behavior (TPB) (Marangunić & Granić, 2015).

Fishbein & Ajzen (1980) assumed humans are logical and process information methodically.

An understanding of individual conduct and attitude was therefore created. The TRA uses behavioural intents rather than attitudes to predict behavior. In their theoretical model, Ajzen and Fishbein argued that an individual's actual action could be predicted based on their prior purpose and desire for the given activity (Davis, 1986). Behavioral intention is the fundamental predictor of conduct, and the influence of attitude on behavior is mediated by intention. It was acknowledged that the theory was competent but had some drawbacks. One of the flaws was that people couldn't regulate their own conduct and attitudes. Ajzen (1985) explained behavior and attitude as being on a continuum of control. Illogical, complicated, or socially supported behavior is unaccountable (Wright, 1998).

To address the individual's non-volatile control, Azjen added a third element, perceived behavioural control, to the original theory, resulting in a new theory known as the Theory of Planned Behavior (TPB). TPB is TRA's extension. TPB is used to alleviate TRA inadequacies.

For example, a person's willingness to exert effort in knowledge, information, and skills impacts whether or not they will engage in a certain action (Gist & Mitchell, 1992; Carr 2005).

In other words, the intention to do an action determines the individual's performance.

TPB has been severely criticized due to a significant flaw: it only works when some parts of behavior are not within voluntary control. The theory assumes humans are rational and will evaluate and systematize based on available facts, thereby ignoring hidden and undiscovered needs. Other issues include the assumption that perceived behavioural control predicts actual behavioural control, which may not be the case (Mathieson, 1991). Despite their flaws, both models can explain and predict human behavior. However, it failed to explain system (technology) acceptance or rejection in most research (Marangunić & Granić, 2015).

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed by Davis (1989) to predict individual's acceptance of information technology by measuring their behavioral intention. The theory proposes that perceived usefulness (PU) and perceived ease of use (PEOU) of information technology are two important determinants in predicting individuals' acceptance and use of information technology; (1) perceived usefulness (PU) which is defined as *"the degree to which a person believes that using a particular system would enhance his or her job performance"*, and (2) perceived ease of use (PEOU) which is defined as *"the degree to which a person believes that using a particular system would be free of effort"* (Davis, 1989). User's behavioral intention is defined as "*a measure of the strength of one's intention to perform a specified behavior*" (Davis et al., 1989).

TAM has been extensively investigated, extended, and demonstrated to be effective in management information systems, information systems, and information technology adoption (Abbad et al., 2009; Mao & Palvia, 2006; Munguatosha et al., 2011). Studies by Asianzu (2012) found a substantial link between perceived usefulness and behavioural intention to use the system. The findings were statistically significant. Koutromanos et al. (2015) found strong support for TAM as a model for predicting students' adoption behavior.

TAM has both strengths and weaknesses. One major flaw was its inability to reveal independent variable determinants (perceived usefulness and perceived ease-of-use). TAM's other flaw is that it focuses on voluntary information systems, with no regard for mandatory use. (Chuttur, 2009).

The key concern in TAM study is to get a better understanding of potential variables that can influence information system acceptance, such as variables that can be used to extend the TAM and solve the research's unique element.

The current Covid-19 pandemic situation has changed education forever, giving a distinct rise to e-learning where learning is conducted remotely and on digital platforms (Li, C. & Lalani, F., 2020). Higher education institutions, continue to struggle with the use of e-learning systems, such as the obstacles students' face in their learning process; s decreased motivation in the students arising from delayed feedback or assistance as instructors may not be available during the time when the students need help; the feeling of isolation due to lack of physical presence (Yusuf & Al-Banawi, 2013). However, according to Park (2009), little study has been done on why students accept e-learning. To improve e-learning efficacy, teachers must first understand student motivations.

2.3 Motivation

Motivation is thought to influence people's actions. To perform a given behavior, people must be motivated (Lin, 2007). Extrinsic and intrinsic motivations exist. Extrinsic motivation refers to *"the performance of an activity because it leads to instrumental rewards"* (R. Saadé & Bahli, 2005), while Intrinsic motivation refers to the *"engagement motivated by pleasure or enjoyment"* (Henderson & Lepper, 2002).

This study looked into the extrinsic and intrinsic factors that influence learners' acceptance of LMS. Students' characteristics and system factors were divided into two groups in the study. Beyond the TAM three constructs, the study found four external variables (i.e. perceived ease of use, perceived usefulness and behavioural intention).

<table>
<tr><th>Dimension</th><th>Variable</th><th>Group</th><th>Type</th></tr>
<tr><td rowspan="2">Extrinsic</td><td>Information Quality</td><td>System Characteristic</td><td>Independent</td></tr>
<tr><td>Functionality</td><td>System Characteristic</td><td>Independent</td></tr>
<tr><td rowspan="2">Intrinsic</td><td>Enjoyment</td><td>System Characteristic</td><td>Independent</td></tr>
<tr><td>Learning Goals Orientation</td><td>User Characteristic</td><td>Independent</td></tr>
<tr><td rowspan="3">TAM</td><td>Perceived usefulness</td><td>TAM</td><td>Independent</td></tr>
<tr><td>Perceived ease of use</td><td>TAM</td><td>Independent</td></tr>
<tr><td>Behavioral intention</td><td>TAM</td><td>Dependent</td></tr>
</table>

Table 1: The Developed Model Variables

TAM research required hypotheses to guide model variable interactions (Al-Harbi, 2011; Cho et al., 2009; M. K. Lee et al., 2005; Y.-H. Lee et al., 2013; Liu et al., 2010; Padilla-Meléndez et al., 2013; Park, 2009; Sánchez & Hueros, 2010; Udo et al., 2012; Venkatesh & Davis, 2000). The combined hypotheses governed the direction of each relationship between variables in the created model.

2.3.1 Information Quality

Information quality is defined as *quality of outputs the information system produces* (DeLone & McLean, 1992). Huh et al. (1990) defined information quality as correctness, completeness, consistency, and currency. The importance of information quality in determining user pleasure has been proven (Katerattanakul & Siau, 1999; Y.-C. Lee, 2006; McKinney et al., 2002). Hughes et al. (2004) found that students appreciated online content and functionality up to 58 percent, whereas website usability and look were regarded at 20% and 10%, respectively.

An excellent e-learning content allows students to see its value (Tseng & Hsia, 2008). Unreliable or inaccurate data may jeopardize student acceptance (Liao et al., 2006). However, students' acceptance may be influenced by the information quality provided by Brightspace LMS. Students' adoption of Brightspace LMS is hypothesized in this study.

Hypothesis (H1): Information quality has a positive effect on the students' perceived usefulness of Brightspace LMS.

2.3.2 Functionality

Functionality is defined as *the functions provided by an information system, i.e., an e-learning system in this study, that enable the user/ e-learner to effectively achieve their goals* (Cho et al., 2009). The system's usability affects student acceptability (Hong et al., 2005). Perception of usefulness precedes functionality, according to Davis (1989). The strongest predictor of perceived usefulness, according to Hong et al. (2005). concluded that functioning was the most important criterion of perceived usefulness.

An LMS can customize a learning environment. The LMS functional parts may provide online course content, assignments, quizzes, and exams. This study sought to determine whether the functioning of Brightspace LMS affects students' acceptance or perceived usefulness. So the study hypothesizes a hypothesis to examine functioning.

Hypothesis (H2): Functionality has a positive effect on the students' perceived usefulness of the Brightspace LMS.

2.3.3 Enjoyment

Enjoyment is defined as "*the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use*" (Venkatesh, 2000). The intrinsic characteristics do alter students' perceptions, which is why researchers in technology acceptance study use enjoyment (Venkatesh & Bala, 2008). Enjoyment was reported to diminish the perception of activities performed by users on novel systems (R. G. Saadé et al., 2008). To better understand student technology acceptance, a desire for a thorough understanding of the intrinsic and extrinsic factors was suggested. Therefore, the research hypothesizes a hypothesis to investigate the effect of enjoyment.

Hypothesis (H3): Enjoyment has a positive effect on the students' perceived ease of use of the Brightspace LMS.

2.3.4 Learning Goals Orientation

Learning goal orientation is an intrinsic motivation that refers to the *“motivation to constantly improve one's competencies”*(Runhaar et al., 2010). Learning goal orientation refers to the difficult task of improving knowledge and skills. Learning difficulties were to be considered as part of their learning (Mun & Hwang, 2003). Student acceptance of web-based information systems is determined by perceived ease of use (Mun & Hwang, 2003). In order to study the influence of learning goal orientation, the research hypothesizes.

Hypothesis (H4): Learning goal orientation has a positive effect on the students’ perceived ease of use of the Brightspace LMS.

2.3.5 Perceived Ease of Use & Perceived Usefulness

The TAM model's two primary parts are perceived usefulness and perceived ease of use. (Davis, 1989; Venkatesh, 2000; Venkatesh & Bala, 2008). Perceived usefulness is defined as *"the degree to which a person believes that using a particular system would enhance his or her job performance"* (Davis, 1989). Perceived ease of use is defined as *"the degree to which a person believes that using a particular system would be free of effort"* (Davis, 1989).

Perceived usefulness has been used to anticipate word processor and spreadsheet system acceptability, user intentions, telecommuting technologies, online and wireless site usability, and system usage (Alrafi, 2007). The validity of perceived usefulness as a predictor of propensity to use IT was validated by (Davis et al., 1989).

Researchers have commonly utilized perceived usefulness to assess the success of e-learning systems (Hsieh & Cho, 2011; Hussein et al., 2007; Johnson et al., 2008; Joo et al., 2011; J.-K. Lee & Lee, 2008; Limayem & Cheung, 2008).

A few studies have identified a link between perceived ease of use and e-learning behavior intention. It was either direct or indirect. (Alharbi & Drew, 2014; Boateng et al., 2016; Farahat, 2012; Haryanto & Kultsum, 2016; Kanwal & Rehman, 2017; Mahmodi, 2017; Martínez-Torres et al., 2008; Park, 2009; Vidanagama, 2016).

Thus, the study proposes two hypotheses to examine the effect of perceived usefulness and perceived ease of use.

Hypothesis (H5): Perceived ease of use has a positive effect on the students’ behavioral intentions to use the Brightspace LMS.

Hypothesis (H6): Perceived usefulness has a positive effect on the students’ behavioral intentions to use the Brightspace LMS.

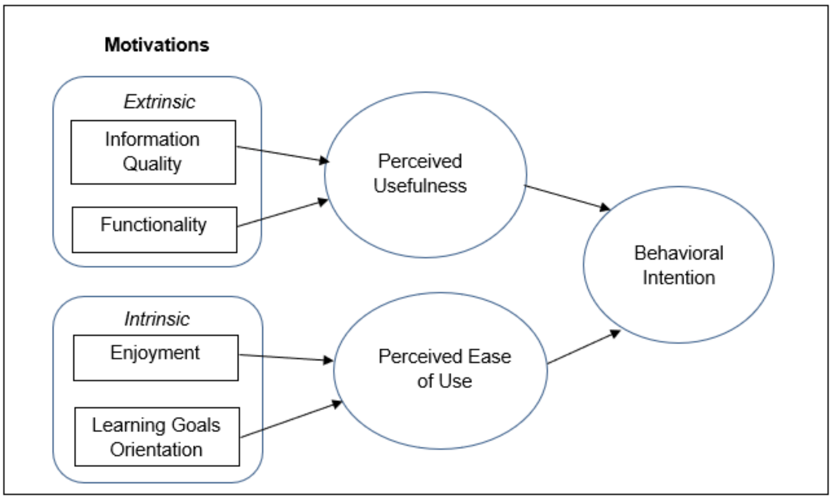


Figure 1: Theoretical Framework

3. Research Methodology

An online survey was conducted across University W during the May 2021 semester, to explore students' e-learning usage motivation and Brightspace LMS system acceptance. The online survey questionnaire was developed and created on Google Form and was distributed to approximately 300 students via email. Brightspace LMS was introduced to the University W's students since January 2021 semester, thus we deduced that students have little or some experience with D2L Brightspace LMS.

This study proposed an enhanced Technology Acceptance Model utilizing SEM with Smart PLS. The survey results were cleaned and four incomplete questionnaires were eliminated. Hair et al. (2013) said the suggested sample size for PLS-SEM depended on i) confidence interval of 5%, ii) statistical power of 80% iii) minimum coefficient of determination R^2 values of at least 0.25 and iv) the maximum number of arrows pointing to a latent variable. While Marcoulides & Saunders (2006) state that for maximum 2 arrows pointing a latent variable, a sample size of 52 is necessary. Prior studies indicated a sample size of 100-200. (Hoyle, 1995). SMARTPLS was used to evaluate roughly 200 questionnaire replies.

4. Findings

4.1 Common Method Variance (CMV)

Podsakoff et al. (2012) highlighted those estimated relationships could be biased if measured using a single survey instrument. Therefore, this study used the Harmon single-factor analysis and confirmatory factor analysis to assess the impact of CMV (Podsakoff et al., 2003). The principal axis factoring on all measurement items showed that the total variance explained was 49.75%. Also, the second test results using confirmatory factor analysis by modelling all items as the indicators of a single factor indicated a poor fit (CMIN/DF=5.846, p=0.000). In conclusion, this study does not suffer from the CMV problem.

4.2 Assessment of Measurement Model

Three assessments were used to assess the goodness of the measurement model: internal consistency reliability, convergent validity, and discriminant validity. Hair et al. (2011)

proposed that composite reliability (CR) should be above 0.7 to indicate internal consistency reliability. On the other hand, outer loading and average variance extracted (AVE) has been computed to assess the convergent validity. Loading values equal or greater than 0.7 and AVE value greater than 0.5 demonstrate convergent validity has been achieved (Hair et al., 2011). Lastly, Heterotrait-Monotrait Ratio of Correlations (HTMT) approach proposed by Henseler et al. (2015) was adopted in this study to analyze the discriminant validity issues. Gold et al. (2001) mentioned that $HTMT_{.90}$ value should be lower than 0.90 to indicate no discriminant validity issues. On top of that, Henseler et al. (2015) further emphasized that the confidence interval of HTMT values should not include a zero value to indicate any potential discriminant validity issues. Table 2 and Table 3 present the measurement model and HTMT analysis results. The results showed that the measurement model in this study is valid and reliable.

Constructs	**Loadings**	**AVE**	**CR**
(Threshold value)	*≥0.7*	*>0.5*	*>0.7*
Information Quality			
INFOQTY1	0.898	0.812	0.928
INFOQTY2	0.913		
INFOQTY3	0.893		
Functionality			
FUNCTION1	0.781	0.683	0.896
FUNCTION2	0.873		
FUNCTION3	0.835		
FUNCTION4	0.814		
Enjoyment			
ENJOY1	0.942	0.861	0.949
ENJOY2	0.919		
ENJOY3	0.922		
Learning Goals Orientation			
LEARNGOALS1	0.842	0.698	0.902
LEARNGOALS2	0.842		
LEARNGOALS3	0.853		
LEARNGOALS4	0.803		
Perceived Usefulness			
PUSEFUL2	0.934	0.916	0.956
PUSEFUL3	0.913		
Perceived Ease of Use			
PEOU2	0.916	0.768	0.908
PEOU3	0.890		
Behavioral Intention			
BINTENTION4	0.848	0.805	0.943
BINTENTION2	0.920		
BINTENTION3	0.923		
BINTENTION4	0.897		

Notes: AVE, average variance extracted; CR, composite reliability. PUSEFUL1 was dropped due to low loading value and PEOU1 was dropped to improve the discriminant validity.

Table 2. Measurement Model Analysis Results

	1	2	3	4	5	6	7
1. Enjoyment							
2. Functionality	0.717 CI.90 (0.623-0.798)						
3. Information Quality	0.593 CI.90 (0.485-0.690)	0.859 CI.90 (0.790-0.921)					
4. Behavioral Intention	0.781 CI.90 (0.703-0.847)	0.756 CI.90 (0.662-0.835)	0.595 CI.90 (0.476-0.698)				
5. Learning Goals Orientation	0.414 CI.90 (0.250-0.561)	0.633 CI.90 (0.496-0.748)	0.617 CI.90 (0.458-0.750)	0.502 CI.90 (0.356-0.623)			
6. Perceived Ease of Use	0.699 CI.90 (0.607-0.778)	0.654 CI.90 (0.537-0.751)	0.607 CI.90 (0.477-0.716)	0.770 CI.90 (0.677-0.850)	0.425 CI.90 (0.262-0.571)		
7. Perceived Usefulness	0.815 CI.90 (0.751-0.869)	0.769 CI.90 (0.680-0.849)	0.727 CI.90 (0.637-0.809)	0.803 CI.90 (0.733-0.869)	0.469 CI.90 (0.290-0.627)	0.662 CI.90 (0.561-0.753)	

Table 3: HTMT Analysis

4.3 Assessment of Structural Model

4.3.1 Assessment of Coefficient of Determination, R^2

The model's predictive accuracy in this study was evaluated using the coefficient of determination, R^2. The R^2 indicated that information quality and functionality demonstrated a moderate level of predictive accuracy on perceived usefulness (R^2 = 0.501). Meanwhile, enjoyment and learning goals orientation showed a weak level of predictive accuracy on perceived ease of use (R^2 = 0.431). Despite that, both perceived usefulness and perceived ease of use illustrated a moderate level of predictive accuracy on behavioral intention (R^2 = 0.650).

4.3.2 Level of Path Coefficients Analysis

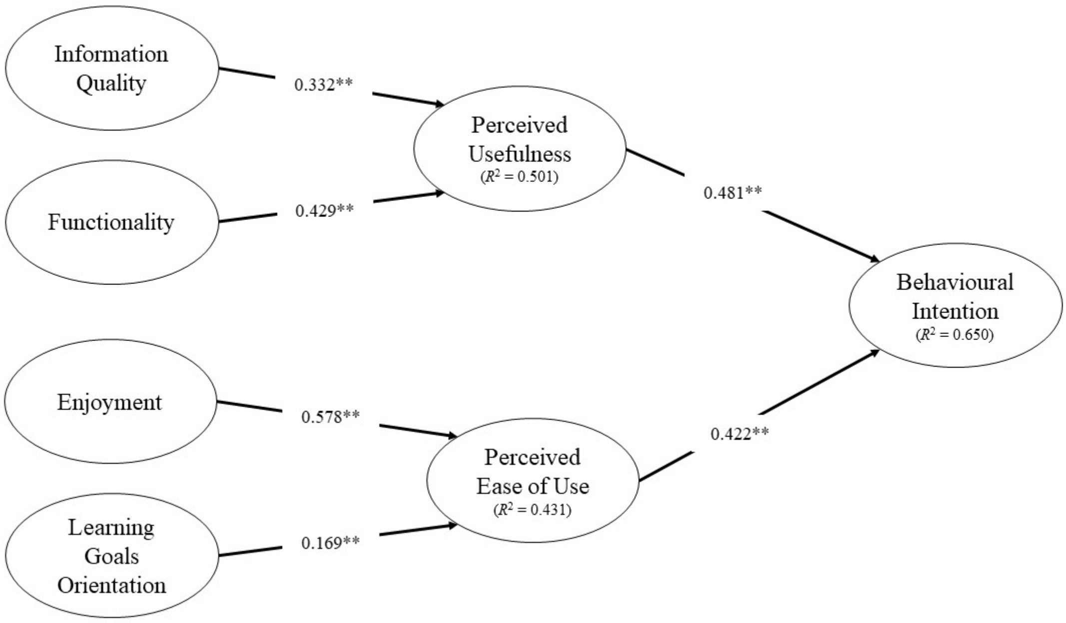
Bootstrapping procedure with 5000 subsamples was conducted to estimate the level of path coefficients. Similarly, Cohen's f^2 was computed as well to examine the effect size. f^2 values of 0.35, 0.15, and 0.02 are considered large, medium, and small effect sizes (Cohen, 1988). Results from the bootstrapping procedure showed that information quality (β=0.332, p<0.01; f^2=0.099) and functionality (β=0.429, p<0.01; f^2=0.165) both showed a positive influence on perceived usefulness. Also, enjoyment (β=0.578, p<0.01; f^2=0.506) and learning goals orientation (β=0.169, p<0.01; f^2=0.043) exerted a positive influence on perceived ease of use. Likewise, perceived ease of use (β=0.422, p<0.01; f^2=0.329) and perceived usefulness (β=0.481, p<0.01; f^2=0.425) is found to influence behavioral intention positively. As a result, all the hypothesis proposed in this study was supported. Table 3 showed the structural model analysis results. Figure 2 showed the main effects.

Hypothesis	Relationship	Std Beta	Std Error	*t*-value	Decision	f^2	5% CI LL	95% CI UL
H1	Information Quality → Perceived Usefulness	0.332	0.085	3.914**	Supported	0.099	0.030	0.213
H2	Functionality → Perceived Usefulness	0.429	0.085	5.052**	Supported	0.165	0.072	0.330
H3	Enjoyment → Perceived Ease of Use	0.578	0.056	10.399**	Supported	0.506	0.306	0.773

H4	Learning Goals Orientation → Perceived Ease of Use	0.169	0.066	2.571**	Supported	0.043	0.006	0.128
H5	Perceived Usefulness → Behavioral Intention	0.481	0.063	7.618**	Supported	0.425	0.237	0.730
H6	Perceived Ease of Use → Behavioral Intention	0.422	0.067	6.275**	Supported	0.329	0.164	0.599

Notes: **$p < 0.01$ (one-tailed)

Table 4. Structural Model Analysis Results



Notes: **$p < 0.01$ (one-tailed)

Figure 2. Results of the Main Effect

5. Conclusion

This research aims to address the gap in the technology acceptance research by extending the technology acceptance model to explain students' acceptance of Brightspace LMS in University W. The developed model consisted of four motivation variables and three TAM constructs. The research also focused on examining the effect of extrinsic and intrinsic motivation variables on the students' acceptance of Brightspace LMS.

Research Objective 1:

i. To review the literature on the use of TAM to measure e-learning system acceptability.

Literature review was conducted to discuss the evolvement from TRA to TPB and finally the TAM was developed.

Research Objective 2:

ii. To create a technology enhanced approach to assess student acceptability of Brightspace LMS e-learning platform.

Four motivation variables were added to enhanced the Technology Acceptance Model; two extrinsic motivation variables – information quality and functionality, and two intrinsic motivation variables – enjoyment and learning goal orientation, to study University W's students' acceptance of Brightspace LMS.

Research Objective 3:

iii. To study students' adoption of Brightspace LMS e-learning platform. (Four motivation factors connected to system focus and user attributes were found. The variables are incorporated into the TAM to examine hypotheses.)

The coefficient of determination, R^2 demonstrated that information quality and functionality was able to predict the accuracy of perceived usefulness at 50.1% while enjoyment and learning goal orientation was able to predicated perceived ease of use at 43.1%. However, both perceived usefulness and perceived ease of use were able to predict the accuracy on behavioral intention at 65%.

The results showed significance of the intrinsic variables towards students' acceptance of Brightspace LMS. Enjoyment was perceived as the stronger important determinant of the system ease of use. Enjoyment (H3) was the strongest determinant of behavioral intention ($\beta = 0.578$, P-value ≤ 0.01). This was further confirmed by Davis et al. (1992) that enjoyment as an intrinsic motivation is critical towards user intention to use information systems. The html interface design and its functions may have contributed to students' enjoyment of the Brightspace LMS. According to Cyr et al. (2006), the system interface design determines the satisfaction level. Enjoying the LMS increases student acceptability (R. G. Saadé et al., 2008). Perceived ease of use influenced both enjoyment and learning goal orientation.

Extrinsic characteristics were also found to be significant in determining students' approval of Brightspace LMS, with functionality being the strongest determinant of system usefulness. Functionality (H2) effect perceived usefulness ($\beta = 0.429$, P-value ≤ 0.01). Students achieved their learning outcomes with the support of an online quiz, online assignment evaluation, learning forums, and html online course content with url connections to audios, videos, and internet content. Students will learn more effectively and appreciate the system's usefulness if it is fully working (Cho et al., 2009). Functionality and information quality had an indirect effect on behavioral intention via perceived usefulness.

From the TAM model constructs, perceived usefulness had the stronger determinant towards students' behavioral intention to use Brightspace LMS. Perceived ease of use (β=0.422, p<0.01; f^2=0.329) and perceived usefulness (β=0.481, p<0.01; f^2=0.425). Perceived usefulness is the more important determinant of students' behavioral intention because students would be able to achieved the course learning outcomes by performing fundamental tasks such as reading online course content, participating in the course quiz and assignment assessment, discussion forums and online chats forums (Van Raaij & Schepers, 2008). By achieving these course learning outcomes, the students will perceive the Brightspace LMS as useful and thus leading them towards system acceptance.

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Contact Email: llyap@wou.edu.my
glkhoo@wou.edu.my