The influence of learning value on learning management system use: An extension of UTAUT2

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Abstract
In this study the perceived value construct of the Unified Theory of Acceptance and Use of Technology (UTAUT2) is investigated in the context of a learning management system (LMS), in which the construct is redefined from its original price value conceptualization. It was found that many researchers simply ignore the price value construct when applying the UTAUT2 model in technology use studies in the educational context. This study extends the UTAUT2 framework by integrating the learning value construct and provides fresh insight about predictors of students’ intentions towards LMS and its use. A quantitative research approach was employed by utilizing a closed-ended questionnaire to collect data from Malaysian university students who were users of LMS. Probability proportional stratified sampling was employed to select an appropriate sample. The results indicated a good measurement and structural model fit and suggested the significant influence of performance expectancy, social influence and learning value on students’ intention towards LMS and also confirmed the influence of facilitating conditions and behavioral intention on LMS use. The extended UTAUT2 framework helps in understanding students’ perceived value in the LMS context. Furthermore, this study will help institutions to consider the factors for successful implementation of an LMS in an academic setting.

Keywords
UTAUT2, learning value, learning management system, e-learning, Malaysia

Performance expectancy, social influence, and learning value influence students’ intention towards learning management systems.

Introduction
Inevitably, information technology has brought about several changes in higher education by modifying earlier concepts of learning (Hassanzadeh et al., 2012). The learning management system (LMS) is one of the emerging information technology tools that facilitates e-learning and provides education without time and place constraints. It is a web-based system that allows instructors and students to interact via the web and share information and resources (Al-Busaidi and Al-Shihi, 2010; Lonn et al., 2011). WebCT, Blackboard, MOODLE (Modular Object-Oriented Dynamic Learning Environment) and Desire2Learn are some of the more popular examples of LMS used in various institutions (Iqbal and Qureshi, 2011; Waheed et al., 2015a).

Various educational institutions have invested plenty of resources to support the quality of teaching and learning process (Islam, 2013; Naveh et al., 2010; Waheed et al., 2015). However, the investment of ample resources is not beneficial if students do not use the system (Pituch and Lee, 2006). Therefore, for successful implementation of an LMS it is essential to...
understand the factors that impact students’ intention towards the LMS and its actual use.

Rationale of study

In previous studies, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) were frequently used to ascertain the antecedents of technology use (De Smet et al., 2012; Lin and Anol, 2008) in the LMS context. These studies discuss factors like usefulness, easiness, social influence and facilitating conditions. However, these studies lack in exploring the influence of students’ perceived value of LMS use in terms of learning gained from LMS, habitual LMS use and associated fun or pleasure. This is the key problem raised in this study, and the extended UTAUT framework, i.e. UTAUT2, has the theoretical groundings to fill this gap in the literature regarding the variables, price value, habit and hedonic motivation.

In the consumer setting, product use is influenced by price value (PV), which shows the product’s good/bad value for the price paid, referred to as good/bad value for money (Venkatesh et al., 2012). However, in an educational institution setting, students are not liable for the cost of using the LMS, thus, price value is assumed to be irrelevant, and this construct is often ignored. However, the time and effort devoted to using LMS learning-related activities is of value to the user. Prior studies lack in identifying this concept and do not explain the possible influence of learning value on LMS use.

An individual’s continuous use of technology makes the use habitual and builds a positive perception about technology (Bandyopadhyay and Fraccastoro, 2007). Studies have discussed the impact of habit on technology adoption (Ally and Gardiner, 2012; Lewis et al., 2013). However, in the educational setting, students’ habitual use of technology has received limited attention, even though it is essential to judge its influence on students’ intention towards LMS and its use.

Researchers conceptualize hedonic motivation as perceived enjoyment and have reported its influence on technology use or acceptance (Thong et al., 2006; Van der Heijden, 2004). Venkatesh et al. (2012) explained that the novelty of a particular technology is of key interest for consumers and is the reason for exploring and using that technology. The associated fun and pleasure in using that technology influence consumers’ technology use. This aspect of hedonic motivation is scantily discussed in the context of students’ LMS use. Students’ hedonic motivation plays an important role in predicting their intention towards LMS and its use and it is, therefore, essential to identify it.

Hence, there is a need for a framework that considers these aspects. Thus, to fulfill the above-mentioned research gap, this study is led by the following objectives:

- To extend the UTAUT2 framework by integrating the learning value concept in the LMS context.
- To explore the influence of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), learning value (LV), hedonic motivation (HM), and habit (HB) on students’ intention towards LMS and its use.

Theoretical background

Unified Theory of Acceptance and Use of Technology (UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) has been used as a baseline framework in various studies to measure technology use and adoption (Fidani and Idrizi, 2012; Maldonado et al., 2011). The aspects of consumer affect, automaticity and monetary costs were later integrated in the UTAUT2 model (Venkatesh et al., 2012) to overcome the limitations in UTAUT. The UTAUT2 framework comprises four constructs (performance expectancy, effort expectancy, social influence and facilitating conditions) from the UTAUT model and three new constructs (hedonic motivation, price value and habit) as antecedents of behavioral intention and use behavior (see Figure 1).

The literature map for UTAUT2 (see Table 1) shows that, to date, the UTAUT2 framework is employed in various contexts.

Researchers have utilized several or all of the UTAUT2 constructs and investigated the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value on: smart mobile acceptance (Ally and Gardiner, 2012), adoption of broadband Internet among inner-city residents (LaRose et al., 2012), use of e-governance technology (Krishnaraju et al., 2013; Vinodh and Mathew, 2012), e-prescribing technology acceptance (Cohen et al., 2013), and mobile social network services adoption (Nikou and...
Bouwman, 2013). Several studies in the educational context have employed the UTAUT2 framework and reported the influence of performance expectancy, effort expectancy, social influence and habit on teachers’ perception of adopting new technology (Lewis et al., 2013) and performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation on pre-service teachers’ acceptance of learning management software (Raman and Don, 2013).

The literature analysis (see Table 1) illustrates the applicability of the UTAUT2 framework in different contexts. However, studies lack in investigating the applicability of UTAUT2 in the educational context from the students’ perspective. Particularly, the literature excludes the price value construct but without introducing any other relevant construct. Therefore, the current study is conducted to consider the students’ perspective in using LMS, and the concept of learning value is taken into account as a price value alternative.

**Research model and hypothesis**

The constructs of the UTAUT2 framework fulfil the need of the study and are appropriate for investigating factors influencing students’ intention towards LMS and its use. However, the price value construct is replaced with learning value as the students do not bear any monetary costs. The proposed research model is presented in Figure 2.

**Performance expectancy.** Performance expectancy is concerned with individuals’ beliefs about the usefulness of the technology to perform different activities (Venkatesh et al., 2003; Waheed et al., 2015b). Sumak et al. (2010) reported a significant direct effect of performance expectancy on behavioral intention to use Moodle. Similarly, El-Gayar and Moran (2006) discussed the significant contribution of performance expectancy in influencing behavioral intention to accept tablet PCs. In the context of this study, it is believed that students’ behavioral intention to use LMS is built upon their positive perception about LMS’s usefulness in performing their educational activities. The following hypothesis is proposed to understand the relationship:

H1. Performance expectancy influences the behavioral intention to use LMS.
<table>
<thead>
<tr>
<th>Model</th>
<th>Domain of measure</th>
<th>Item used/Variables</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>UTAUT 2 (Ally and</td>
<td>Consumer acceptance of smart mobile technology</td>
<td>Hedonic motivation, Facilitating conditions, Habit, Social influence, Price value</td>
<td>Conceptual study</td>
</tr>
<tr>
<td>Gardiner, 2012)</td>
<td>Adopition of broadband Internet</td>
<td>Habit, Behavioral intention</td>
<td></td>
</tr>
<tr>
<td>(LaRose et al., 2012)</td>
<td>Role of web personalization in technology acceptance</td>
<td>Performance expectancy, Effort expectancy, Facilitating conditions, Hedonic</td>
<td>PE → BI</td>
</tr>
<tr>
<td></td>
<td>in consumer context (e-governance domain)</td>
<td>motivation, Price value, Habit, Behavioral intention</td>
<td></td>
</tr>
<tr>
<td>(Vinodh and Mathew,</td>
<td>Acceptance of e-prescribing technology in African</td>
<td>Performance expectancy, Effort expectancy, Social influence, Facilitating</td>
<td>PE →</td>
</tr>
<tr>
<td>2012)</td>
<td>context</td>
<td>conditions, Price value, Acceptance of e-prescribing technology</td>
<td>Acceptance</td>
</tr>
<tr>
<td>(Cohen et al., 2013)</td>
<td>Influence of web personalization on consumer</td>
<td>Performance expectancy, Effort expectancy, Facilitating conditions, Hedonic</td>
<td>PE → BI</td>
</tr>
<tr>
<td></td>
<td>technology acceptance in e-governent context</td>
<td>motivation, Price value, Habit, Behavioral intention</td>
<td></td>
</tr>
<tr>
<td>(Krishnaraju et al.,</td>
<td>Adoption of emerging information technology in</td>
<td>Performance expectancy, Effort expectancy, Social influence, Facilitating</td>
<td>PE → Use</td>
</tr>
<tr>
<td>2013)</td>
<td>higher education classrooms</td>
<td>conditions, Hedonic Motivation, Habit, Behavioral intention</td>
<td></td>
</tr>
<tr>
<td>(Lewis et al., 2013)</td>
<td>User’s acceptance and adoption of online music services</td>
<td>Performance expectancy, Effort expectancy, Social influence, Facilitating</td>
<td>PE → BI</td>
</tr>
<tr>
<td></td>
<td></td>
<td>conditions, Hedonic Motivation, Habit, Behavioral intention</td>
<td></td>
</tr>
<tr>
<td>(Martins, 2013)</td>
<td>Chinese user’s behavior towards the adoption of</td>
<td>Social influence, Habit, Behavioral intention</td>
<td>SI, HB → BI</td>
</tr>
<tr>
<td></td>
<td>mobile social network</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Nikou and Bouwman,</td>
<td>Pre-service teacher’s acceptance of leaning</td>
<td>Performance expectancy, Effort expectancy, Social influence, Facilitating</td>
<td>PE, EE,</td>
</tr>
<tr>
<td>2013)</td>
<td>management software</td>
<td>conditions, Hedonic Motivation, Habit, Behavioral intention</td>
<td>SI, FC,</td>
</tr>
<tr>
<td>(Raman and Don, 2013)</td>
<td></td>
<td></td>
<td>HB → BI</td>
</tr>
</tbody>
</table>

Effort expectancy. Effort expectancy represents individuals’ beliefs about the ease or effort associated with the technology use (Venkatesh et al., 2003; Waheed et al., 2015b). Vinodh and Mathew (2012) reported a significant relationship between effort expectancy and behavioural intention to use e-governance technology. Similarly, Raman and Don (2013) discussed the significant positive influence of effort expectancy on pre-school teachers’ acceptance of LMS. In the context of this study, the students’ perception that LMS use is free of effort leads to their positive intention to use LMS. Thus, the following relationship is hypothesized:

**H2.** Effort expectancy influences the behavioral intention to use LMS.

Social influence. Social influence reflects the impact of other people’s (peers, instructors and friends) beliefs on individuals’ intention or use behavior (Venkatesh et al., 2003). Al-Shafi et al. (2009) reported that employees are socially influenced by their peers’ beliefs about e-government services, which subsequently influences their behavioural intention to use e-government services. Similarly, Fidani and Idrizi (2012) also confirmed the significant relationship between social influence and behavioral intention to accept LMS. This study asserts that students’ intention towards LMS use is influenced by their friends’ or teachers’ beliefs about LMS. The following hypothesis is proposed to investigate the relationship:

**H3.** Social influence influences the behavioral intention to use LMS.

Facilitating conditions. This aspect relates to the availability of enough resources and support for individuals to use the technology (Venkatesh et al., 2003). Lack of availability of assistance, no timely support, incomplete information, and limited resources could hinder students in their acceptance of web-based technology (Nanayakkara, 2007). Deng et al. (2011) also reported a significant relationship between facilitating conditions and actual use of web-based question-answer services. Students need technical and teachers’ support, as this influences their LMS use.

UTAUT was proposed in the organizational context, where facilitating conditions have a direct influence on behavior (actual use of technology) (Venkatesh et al., 2003) because invariant support and training was available to each individual (Venkatesh et al., 2012). In contrast, UTAUT2 was proposed in the mobile technology acceptance context from the consumers’ perspective, where a new link between facilitating conditions and intention towards mobile technology use was proposed. The link is employed because individuals have different mobile phones and services that influence differently on their intention towards using mobile phones (Venkatesh et al., 2012).
In the context of this study, each student was provided with the same set of facilitating conditions; however, students were allowed to use the LMS off-campus as well. Thus, there may have been variance in facilitating conditions for different students who were using LMS via different Internet connections and technological devices (e.g., laptop, desktop computer, tablets). Venkatesh et al. (2003) explained that the core concept of facilitating conditions is related to effort expectancy, and effort expectancy captures the facilitating conditions effect. Thus, facilitating conditions do not influence behavioural intention because of the presence of effort expectancy in the model. In compliance with these concepts, this research hypothesizes two links:

H4. Facilitating conditions influence the behavioral intention to use LMS.

H5. Facilitating conditions influence LMS use.

Learning value. To consider the monetary costs and benefits associated with consumers’ technology use, Venkatesh et al. (2012) used the construct of ‘price value’, referred to as ‘consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them’ (Dodds et al., 1991; Venkatesh et al., 2012). It means that a consumer’s positive perception about a technology’s benefits influences their intention to bear the purchase cost of that technology. This is a benefit-cost relationship which impacts on consumers’ intention to use the technology (Venkatesh et al., 2012). The consumer statement ‘good value for money’ captures the price value concept. Positive price value perception influences consumers’ technology use intention.

From the consumers’ perspective, the product or service holds a ‘value’ if it provides the associated benefits or quality, while from the students’ perspective, the value is associated with the learning gained from LMS (the achieved benefit), which determines the perceived value of LMS. In the institutional context, students are not liable to pay any cost to gain benefits from LMS technology. However, students devote time and effort to gain benefit from LMS. The students’ positive perceptions about learning from LMS influence their intention to devote more time and effort to explore and obtain the required knowledge from LMS. The current study refers to this as the Learning – Time & Effort relationship and terms it Learning Value, which impacts on students’ intention to use LMS. Table 2 presents the conceptualization of the learning value construct based on the price value relationship and the ‘value’ concept.

Students’ perception that the time and effort put in for learning represents good value or, in other words, the perception of positive learning value, impacts on students’ LMS use intention. Acknowledging Venkatesh et al.’s (2012) price value definition, learning value is defined as the ‘cognitive trade-off between the perceived value of LMS, and time and effort spent for using it’. The following hypothesis is proposed to understand the learning value and intention to use LMS relationship:

H6. Learning value influences the behavioral intention to use LMS.

Hedonic motivation. The associated fun or pleasure experienced in using a technology is explained as individuals’ hedonic motivation. Hedonic motivation has been conceptualized as perceived enjoyment in information system (IS) research and has been found to have a direct effect on technology use (Thong et al., 2006; Van der Heijden, 2004). Brown and Venkatesh (2005) also reported hedonic motivation as a key predictor of behavioral intention to use technology. The current study asserts that students derive fun and pleasure from using LMS, which influences their intention to use LMS.

H7. Hedonic motivation influences the behavioral intention to use LMS.
**Habit.** Habit relates to individuals’ habitual or automatic behaviors using technology. It can also be conceptualized as “a perceptual construct that reflects the results of prior experiences” (Venkatesh et al., 2012). After an extended period of time, “continuous technology use becomes habitual, which means that well-learned action sequences may be activated by environmental cues and then repeated without conscious intention” (Bandyopadhyay and Fraccastoro, 2007). Prior research reported habit to be an important factor in predicting behavioral intention towards technology and its use (Kim et al., 2005; Lim et al., 2007; Venkatesh et al., 2012). In the context of this study, repeated use and regular checking of various LMS features (course content, assignments submission links, discussion forums, blogs, and grade checking) over an extended time period encourages students to build a positive intention towards LMS that subsequently influences its use in the long run. The following hypotheses are proposed to understand the concept:

**H8.** Habit influences the behavioral intention to use LMS.

**H9.** Habit influences LMS use.

**Behavioral intention.** Individuals’ intention to use a particular technology for different tasks is explained as behavioral intention. Moreover, the strength of individuals’ commitment to engage in a specific behavior can be evaluated though behavioral intention (Ngai et al., 2007). A number of studies have reported that behavioral intention to use significantly impacts actual system use (Davis, 1989; Motaghian et al., 2013; Raman and Don, 2013; Wang and Wang, 2009). In consistency with prior research, this study also expects a positive relationship between behavioral intention to use and actual use in the context of students’ LMS use, and proposes the following hypothesis:

**H10.** Behavioral intention to use LMS influences LMS use.

**Methodology**

**Sampling and survey administration**

The quantitative research approach was used to collect data from the largest government university in Kuala Lumpur, Malaysia. The selected university uses a LMS powered by Moodle, called Spectrum (Student Powered e-Collaboration Transforming UM). Spectrum is a learning platform that enables students to access course content and relevant resources (Waheed et al., 2016). Undergraduate and postgraduate students who were using LMS (SPECTRUM) were selected for data collection, which utilized a closed-ended quantitative questionnaire. Krejcie and Morgan’s (1970) formula for known population was used to determine the estimated sample size from four faculties (Faculty of Computer Science & Information Technology, Faculty of Business & Accountancy, Faculty of Languages & Linguistics, and Faculty of Arts & Social Science). Later, probability proportional stratified sampling was used to determine an equal number of participants from each faculty. The targeted population found in four faculties was N = 4484 and the calculated sample size was n = 354, which was in accord with the suggested sample size for structural equation modeling (Hair et al., 2006; Kline, 2011). A cover letter was attached to each questionnaire ensuring respondent confidentiality. The questionnaire was comprised of 30 items for nine variables and measured on a 5-point Likert scale. The questionnaire was distributed among n = 708 students, and 349 questionnaires were returned, yielding a response rate of 49.3%. The returned questionnaires were further checked for missing values and erroneous data, which reduced the useable number of questionnaires to 328; these were then used for data analysis using IBM SPSS (Statistical Package for the Social Sciences) and AMOS 20.0 software.

**Measures**

The measurement instrument used in the study was built upon validated scales from previous studies. In Table 3, the relevant sources for the scale adaptation of each variable are presented in detail. Details of the survey items used in the study are available in Table 6.

**Analysis and results**

Analysis of data was performed through confirmatory factor analysis (CFA) to evaluate the measurement model fit, and structural equation modeling (SEM) was used to evaluate the hypothesized relationships. Details of respondents’ characteristics are presented in Table 4. Analysis of respondents’ profiles shows an almost equal number of male (49.9%) and female (50.6%) respondents. The majority of respondents were in the 18-21 (54.6%) age group and were undergraduates (65.5%). The same statistics were...
confirmed by respondents’ semester enrolled status, where the majority of respondents were enrolled in 5th semester (21.6%) and 2nd semester (20.1%). This is because, at postgraduate level, LMS is used only by course work students (not in research mode), thus reducing the total number of students. Further, it should be noted that the majority of the responses came from the Faculty of Business and Accountancy (34.8%).

Considering the SEM sensitivity to data multicollinearity, collinearity diagnostics were performed. Two separate regression models were applied. In the first regression model, collinearity statistics for seven independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, learning value, and habit) and one dependent variable (Behavioral intention to use LMS) are shown. The second regression model shows statistics for one independent variable (Behavioral intention to use LMS) and one dependent variable (LMS use) (See Table 5).

The associated variance inflation factor (VIF) and tolerance values for both models are presented in Table 4. The range of 1.00 to 4.13 for VIF indicates acceptable values according to the suggested benchmark i.e. VIF <10. Similarly, associated tolerance values ranging from .242 to .981 were also within the acceptable threshold values i.e. tolerance > 0.1 (Howitt and Cramer, 2011). Thus, the model does not indicate any multicollinearity issues.

### Analysis of measurement model

The analysis of measurement model was used to evaluate the reliability and validity of 30 items for nine distinct latent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, learning value, habit,
behavioral intention, and LMS use). It was found that two items had low loadings (performance expectancy (PE4) = 0.42) and (facilitating conditions (FC4) = 0.28), these were removed for further analysis. It was also noticed that the standardized loading of the first item of habit (item1: 0.54) was slightly lower which might affect the construct validity but the other two items of habit (item 2: 0.90, item 3: 0.76) were comparatively higher, which increased the overall validity of the habit construct. The remaining standardized factor loadings for 28 items were higher than the suggested benchmark value of 0.50 (Hair et al., 2010) (See Table 6).

The reliability was assessed through the alpha and composite reliability method. The Cronbach’s alpha coefficient values for all variables were higher than the suggested benchmark value of 0.70 (Churchill, 1979) ranging from 0.74 to 0.94, which confirmed constructs reliability. The linear relationship between constructs was confirmed through composite reliability, which was within the acceptable threshold value of 0.70 (Werts et al., 1974).

Convergent and discriminant validity was evaluated to judge the constructs’ validity. Average Variance Extracted (AVE) values were used to assess the convergent validity. Table 7 shows that AVE values range from 0.50 to 0.818 which is higher than the suggested threshold value i.e. > 0.50 (Fornell and Larcker, 1981). The values of AVE square root should be higher than the correlation between any pair of variables to confirm discriminant validity. The AVE square root value (bold values in diagonal in Table 7) confirmed the constructs’ discriminant validity (Jöreskog, 1993).

Initially, fit between the data and proposed model was not achieved. The values for TLI = 0.80, CFI = 0.80 and AGFI = 0.71 were less than 0.90. The \( \chi^2/df = 4.1 \) was higher than the suggested threshold value of 2. Similarly, RMSEA = 0.09 was higher than the threshold value of 0.05 (Byrne, 2013). Thus, to improve the fit statistics, modification index values were reviewed and possible covariance among error terms was created.

Required fit was attained after covariance adjustment among error terms. Final values of fit indices \( \chi^2/df = 1.3, \text{GFI} = .91, \text{TLI} = .97, \text{AGFI} = .90, \text{CFI} = .97, \text{RMSEA} = .03 \) were within a good threshold range (Bentler and Bonett, 1980; Byrne, 2013), hence presenting good measurement model fit.

Overall, assessment of all results provided an indication for the measurement model to proceed for further analysis of hypothetical relationship testing.

Analysis of structural model

Structural model analysis was examined using SEM to evaluate (a) the data fit with the structural model and (b) hypothesized relationships. The results revealed fit values: \( \chi^2/df = 1.4, \text{GFI} = .91, \text{TLI} = .95, \text{AGFI} = .90, \text{CFI} = .96, \text{RMSEA} = .04, \text{SRMR} = .0542 \), which were in accord with the suggested benchmark values for good structural model fit. Thus, good fit of the data with the structural model was achieved. The relationship between proposed structural paths was assessed through their level of statistical significance and their standardized loadings (see Figure 3).

Table 8 represents a summary of the structural model results and proposed hypothetical relationships for the variables.

The structural model results showed that three hypothesized relationships between performance expectancy, social influence, learning value and behavioral intention to use LMS were supported. Further, three hypothesized relationships between facilitating conditions, behavioral intention and LMS use were supported.

Discussion

The major key objectives set at the initial stage of the study were accomplished. The UTAUT2 framework was extended by introducing the learning value concept, and students’ perceived value of LMS use in terms of learning gained from LMS was adequately examined. Additionally, the proposed relationships between key constructs were examined and the five hypothesized structural paths were supported.

The analysis of the hypothetical relation between performance expectancy and behavioral intention produced a significant result at \( \beta = .13, p < .05 \), which confirms that H1 is supported. This explains students’ belief that if they find LMS useful in performing educational activities, they will tend to use LMS as part of their study courses (Islam, 2013). The results were consistent with previous studies, which supported performance expectancy and behavioral intention relationship in the context of Moodle (Sumak et al., 2010) and tablet PCs (El-Gayar and Moran, 2006).

The results for the second hypothesis H2 did not support an effort expectancy and behavioral intention
### Table 6. Standardized Factor Loadings.

<table>
<thead>
<tr>
<th>Items</th>
<th>Coefficient Alpha</th>
<th>Composite Reliability</th>
<th>$R^2$</th>
<th>Standardized Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance Expectancy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I find SPECTRUM useful for my studies</td>
<td>.790</td>
<td>0.794</td>
<td>0.60</td>
<td>0.78</td>
</tr>
<tr>
<td>SPECTRUM allows me to accomplish class activities more quickly</td>
<td></td>
<td></td>
<td>0.68</td>
<td>0.82</td>
</tr>
<tr>
<td>SPECTRUM increases my learning productivity</td>
<td></td>
<td></td>
<td>0.42</td>
<td>0.65</td>
</tr>
<tr>
<td><strong>Effort Expectancy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPECTRUM is easy to use</td>
<td>.902</td>
<td>0.903</td>
<td>0.70</td>
<td>0.85</td>
</tr>
<tr>
<td>Learning how to use SPECTRUM is easy for me</td>
<td></td>
<td></td>
<td>0.80</td>
<td>0.90</td>
</tr>
<tr>
<td>My interaction with SPECTRUM is clear and understandable</td>
<td></td>
<td></td>
<td>0.77</td>
<td>0.86</td>
</tr>
<tr>
<td><strong>Social Influence</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My peers who influence my behaviour think that I should use SPECTRUM</td>
<td>.755</td>
<td>0.757</td>
<td>0.48</td>
<td>0.69</td>
</tr>
<tr>
<td>My friends who are important to me think that I should use SPECTRUM</td>
<td></td>
<td></td>
<td>0.47</td>
<td>0.68</td>
</tr>
<tr>
<td>My instructors whose opinions that I value prefer that I should use SPECTRUM</td>
<td></td>
<td></td>
<td>0.59</td>
<td>0.77</td>
</tr>
<tr>
<td><strong>Facilitating Conditions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I have resources to use SPECTRUM</td>
<td>.820</td>
<td>0.820</td>
<td>0.64</td>
<td>0.76</td>
</tr>
<tr>
<td>I have knowledge to use SPECTRUM</td>
<td></td>
<td></td>
<td>0.61</td>
<td>0.78</td>
</tr>
<tr>
<td>A specific person (or group) is available to assist when difficulties arise with SPECTRUM</td>
<td></td>
<td></td>
<td>0.60</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Learning value</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning through SPECTRUM is worth more than the time and effort given to it.</td>
<td>.863</td>
<td>0.864</td>
<td>0.54</td>
<td>0.74</td>
</tr>
<tr>
<td>In less time, SPECTRUM allows me to quickly and easily share my knowledge with others (e.g. chat session, forums, blogs, etc.)</td>
<td></td>
<td></td>
<td>0.69</td>
<td>0.83</td>
</tr>
<tr>
<td>SPECTRUM gives me the opportunity to decide about the pace of my own learning</td>
<td></td>
<td></td>
<td>0.64</td>
<td>0.80</td>
</tr>
<tr>
<td>SPECTRUM gives me the opportunity to increase my knowledge and to control my success (e.g., via quizzes and assignments/assessments, etc.)</td>
<td></td>
<td></td>
<td>0.58</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>Hedonic Motivation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I feel fun using SPECTRUM</td>
<td>.782</td>
<td>0.800</td>
<td>0.36</td>
<td>0.64</td>
</tr>
<tr>
<td>I enjoy using SPECTRUM</td>
<td></td>
<td></td>
<td>0.79</td>
<td>0.86</td>
</tr>
<tr>
<td>Using SPECTRUM is very entertaining</td>
<td></td>
<td></td>
<td>0.57</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>Habit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The use of SPECTRUM has become a habit for me</td>
<td>.776</td>
<td>0.786</td>
<td>0.30</td>
<td>0.54</td>
</tr>
<tr>
<td>I am addicted to using SPECTRUM to accomplish my study tasks</td>
<td></td>
<td></td>
<td>0.77</td>
<td>0.90</td>
</tr>
<tr>
<td>I must use SPECTRUM for my studies</td>
<td></td>
<td></td>
<td>0.61</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>Behavioural Intention</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I intend to continue using SPECTRUM</td>
<td>.747</td>
<td>0.747</td>
<td>0.46</td>
<td>0.68</td>
</tr>
<tr>
<td>For my studies, I would use SPECTRUM</td>
<td></td>
<td></td>
<td>0.60</td>
<td>0.78</td>
</tr>
<tr>
<td>I will continue to use SPECTRUM on a regular basis</td>
<td></td>
<td></td>
<td>0.43</td>
<td>0.65</td>
</tr>
<tr>
<td><strong>LMS Use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use SPECTRUM frequently during my academic period</td>
<td>.753</td>
<td>0.763</td>
<td>0.70</td>
<td>0.83</td>
</tr>
<tr>
<td>I use many functions of SPECTRUM (e.g. discussion forum, chat session, messaging, download course contents, upload assignments, etc.)</td>
<td></td>
<td></td>
<td>0.41</td>
<td>0.64</td>
</tr>
<tr>
<td>I depend on SPECTRUM</td>
<td></td>
<td></td>
<td>0.45</td>
<td>0.68</td>
</tr>
</tbody>
</table>
link (β = .10, ns). This may be due to the fact that students place more importance on usefulness and learning from the LMS. They do not consider it a complex system because a set pattern is available for using LMS (Spectrum). The results from Al-Shafi et al.’s (2009) study were also consistent with this finding. They reported an insignificant relationship between effort expectancy and behavioral intention while investigating e-government services adoption.

A significant result for the social influence and behavioral intention relationship, H3, at β = .21 and p = <0.001 was reported. As per the scope of the study, the use of LMS was mandatory for students; however, instructors’ and peers’ explanations about the usefulness and value of LMS influenced students to build a positive intention towards LMS use. It was also noted that peer influence was very influential in every technology adoption decision. Similarly, Fidani and Idrizi (2012) reported that social influence significantly affects behavioral intention to accept LMS.

The fourth hypothesized relationship, H4, between facilitating conditions and behavioral intention towards LMS was not supported (β = .10, ns). This may be because of the effort expectancy effect on facilitating conditions, where the facilitating conditions effect was captured by effort expectancy (Venkatesh et al., 2003). This result was consistent with the effort expectancy result, which also did not support H2. Hsu (2012) reported an insignificant relationship between facilitating conditions and students’ behavioral intention towards Moodle acceptance.

Hypothesis H5, linking facilitating conditions and LMS use, was supported at β = .13, p = <.05. The facilitating conditions served as the actual behavioral control’s proxy which directly influenced actual use (Ajzen, 1991). The link was supported because invariant facilities (regardless of their level) were freely provided to all students, which influenced their use of LMS. The study results were consistent with Deng et al.’s (2011) findings i.e. a significant relationship between facilitating conditions and actual use of web-based question-answer services.

The path analysis for hypothesis H6 revealed a highly significant relationship between learning value and behavioral intention towards LMS at β = .25, p = <0.001. This shows that students feel that learning through LMS is worth more than the time and effort that is devoted to using it for different activities. Thus, learning value influences intention towards LMS. A similar link was reported by Dodds et al. (1991) where it was asserted that perception of value has a direct influence on consumers’ willingness to buy a product.

The hypothesized relationship between hedonic motivation and behavioral intention towards LMS, H7, was insignificant at β = -.07. This shows that students do not perceive enjoyment and fun while using LMS. It may be because LMS is more task-oriented and students do not seek novelty in the system, only using it for course-related activities e.g. to access course content, online quizzes, assignment submissions, group discussions on a particular topic via the discussion forum, classroom group activities, downloading/uploading course related files, etc. Krishnaraju et al. (2013) also reported similar findings and explained that hedonic motivation significantly influenced consumers’ intention towards acceptance of e-government technology.
The subsequent hypotheses H8 and H9 for a relationship between habit-behavioral intention towards LMS ($\beta = -.04$) and habit-LMS use ($\beta = -.05$) were not supported. A plausible reason for this insignificant relationship may be that students perform routine tasks frequently using LMS but their frequent behavior may not be habitual (Nilsen et al., 2012). As it was mandatory for students to use LMS on a daily basis for course related activities, they might have accessed the system to perform educational activities due to compulsion and social pressure. Raman and Don (2013) also found habit an insignificant determinant of pre-service teachers’ behavioral intention to use Moodle and its actual use.

Finally, hypothesis H10 on the relationship between behavioral intention towards LMS and its actual use was supported at $\beta = .30$, $p < .001$. Students consider LMS to be a useful and beneficial tool for their learning, and social influence also encourages a positive perception towards LMS, which subsequently influences LMS use. This result was consistent with previous studies, which report a significant relationship between behavioral intention and actual Moodle use (Sumak et al., 2010) and classroom technology use behavior (Lewis et al., 2013).

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**Figure 3.** Proposed Structural Model Results: (Significant at the $p < 0.05 = $*, $p < 0.001 = $$$*, a = Not Significant).

**Table 8.** Statistical results for Structural Model.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Structural coefficient</th>
<th>Hypothesized Relationships</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE → BI</td>
<td>.13*</td>
<td>H1: Performance expectancy influences the behavioral intention to use LMS</td>
<td>Supported</td>
</tr>
<tr>
<td>EE → BI</td>
<td>.10</td>
<td>H2: Effort expectancy influences the behavioral intention to use LMS</td>
<td>Not Supported</td>
</tr>
<tr>
<td>SI → BI</td>
<td>.21***</td>
<td>H3: Social influence influences the behavioral intention to use LMS</td>
<td>Supported</td>
</tr>
<tr>
<td>FC → BI</td>
<td>-.09</td>
<td>H4: Facilitating conditions influence the behavioral intention to use LMS</td>
<td>Not Supported</td>
</tr>
<tr>
<td>FC → Use</td>
<td>.13*</td>
<td>H5: Facilitating conditions influence LMS use</td>
<td>Supported</td>
</tr>
<tr>
<td>LV → BI</td>
<td>.25***</td>
<td>H6: Learning value positively influences the behavioral intention to use LMS</td>
<td>Supported</td>
</tr>
<tr>
<td>HM → BI</td>
<td>-.07</td>
<td>H7: Hedonic motivation influences the behavioral intention to use LMS</td>
<td>Not Supported</td>
</tr>
<tr>
<td>HB → BI</td>
<td>.04</td>
<td>H8: Habit influences the behavioral intention to use LMS</td>
<td>Not Supported</td>
</tr>
<tr>
<td>HB → Use</td>
<td>-.05</td>
<td>H9: Habit influences LMS use</td>
<td>Not Supported</td>
</tr>
<tr>
<td>BI → Use</td>
<td>.30***</td>
<td>H10: Behavioral intention to use LMS influences LMS use</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Note: ***p < 0.001; **p < 0.01; *p < 0.05

Theoretical and practical implications
Research done based on students’ perspectives often omits the price value construct, justifying this by considering the fact that students do not bear any costs in using the technology provided (Lewis et al., 2013; Raman and Don, 2013). As such, the framework creates a gap and is unable to measure the perceived value of a particular technology. Thus, in this regard, the key theoretical contribution of this study is the extension of the UTAUT2 framework by incorporating the learning value construct in order to understand the perceived value of LMS. Students’ belief that learning from LMS is worth more than the time and effort spent significantly influences their positive intention towards LMS. Additionally, the investigation of the impact of performance expectancy, social influence, and facilitating conditions on students’ intention towards LMS and its use validate the UTAUT2 framework’s applicability in the LMS context. This study highlights the importance of the encouraging and supporting role of instructors, peers and friends in building a positive intention towards LMS use (Lai et al., 2012). It also suggests that usefulness and facilitating conditions, like necessary resources, organizational infrastructural support and technical assistance, significantly influence students’ intentions and LMS use.

From the academic perspective, the study’s contribution is noteworthy for administration, instructors, and teaching assistants as it will help them understand the factors necessary for successful implementation of LMS and how to facilitate students’ needs (Fidani and Idrizi, 2012). The practical implications of the current study are also noteworthy, especially for decision makers at the managerial level in educational institutions. To improve LMS acceptability and its positive perception, decision makers should consider the efforts associated with LMS use and provide support, a facilitating environment, discussion and sharing features to create a collaborative environment (Hsu, 2012). This will not only improve students’ satisfaction but also improve the institution’s technological reputation.

Conclusion
Drawing on the UTAUT2 framework, this study investigated the antecedents of LMS use from the students’ perspective. The gap in the literature from omitting the price value construct was highlighted in this study, and the learning value construct was introduced to consider the perceived value of LMS. The extended framework was validated in the LMS context and it showed a good measurement model fit. Furthermore, the structural model fit confirmed the fit between the data and the model and supported the five hypothesized relationships. The results showed that performance expectancy, social influence, and learning value influence students’ intention towards LMS. Additionally, facilitating conditions and behavioral intention have an impact on LMS use.

Limitations and further research
Although the results provide fresh insight into LMS use from the students’ perspective, the study’s limitations could not be avoided. The study took a single university as its target scope, which might have affected the generalizability of the results. The influence of other environmental, system and organizational factors was not taken into account, which may have altered LMS use.

The framework was extended by introducing the learning value construct, but although the results are significant, it is necessary to validate the framework in other organizational contexts in further studies. Additionally, the cultural influence of different developing and developed country perspectives may produce different results, thus this needs to be investigated. Furthermore, factors like hedonic motivation and habit require more attention, and further research is needed to explore their impact on students’ learning.

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References


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