E-learning motivation and educational portal acceptance in developing countries

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Abstract

Purpose – The purpose of this paper is to: empirically validate a modified unified theory of acceptance and use of technology (UTAUT) model by adding an “e-learning motivation” construct in the South American context; try to determine the role of e-learning motivation in the use and adoption of e-learning systems and conversely the effect of technology on students’ e-learning motivation; and to test region and gender as moderators in the model.

Design/methodology/approach – A survey method was used to collect data from 47 schools located at different regions: the coast, Andes, and jungle of Peru. The partial least square technique was used for data analysis.

Findings – It was found that “e-learning motivation” and “social influence” had a positive influence on behavioural intention, while “facilitating condition” had no effect on e-learning portal use. Furthermore, use behaviour had a positive influence on e-learning motivation. Also found was the moderating role of “region”.

Research limitations/implications – The analysis is carried out in a single country, thus, caution should be taken in generalisation of the results.

Practical implications – The findings will help policy makers and practitioners in developing countries to better understand students’ e-learning motivation.

Originality/value – By adopting the UTAUT model, a new construct of “e-learning motivation” is added, and applied to the South American context.

Keywords Acceptance sampling, E-learning, Developing countries, Information technology, Peru

Paper type Research paper

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Introduction
Organisations and educational institutions have been investing in information technologies to improve education and training through electronic learning, known as e-learning (Bates, 2001). E-learning refers to the education and training delivered through ICTs (information and communications technologies), specially designed to support individual learning or organisational performance goals (Clark and Mayer, 2003; Sun et al., 2008). E-learning has been identified as an enabler for people and organisations to keep up with changes in the global economy, particularly in the internet era. Being economical, flexible, and easy to deliver without the constraints of time and distance (Carey and Blatnik, 2005), e-learning is an attractive option for developing countries.

Following the path of its counterparts (Bates, 2001), the Peruvian government formed The General Direction of Educational Technologies in 2007 with the aim to incorporate ICTs in education. It has the following main objectives (MinEdu, 2007a):

- develop and execute a trustworthy network capable of accessing all sources of information, and to broadcast multimedia content to improve educational quality in the rural and urban regions;
- guarantee connectivity in schools under the criterion of equity and provide facilities according to their needs;
- articulate and coordinate inter-sector actions with other organisations that facilitate expansion of educational services through ICT and media;
- establish guidelines for implementing technological platforms in educational institutions such as innovative classrooms and other educational facilities using ICT; and
- promote e-learning initiatives by incorporating learning strategies and multimedia technologies into the educational process.

The national educational portal called “Peru EDUCA” is one of several initiatives of the Peruvian government aimed at modernising education utilising ICT. The Peruvian government has invested and continues investing money and effort in the Peru EDUCA e-learning portal (MinEdu, 2007b; BFPE, 2008). However, there is no empirical proof regarding students’ motivation to adopt and use the national educational portal, and the portal’s effect on the students’ motivation toward technology, particularly in the South American context.

Therefore, the aim of this research is to:

- empirically validate a modified unified theory of acceptance and use of technology (UTAUT) model, by adding an “e-learning motivation” (ELM) construct in the South American context, especially in the case of Peru;
- try to determine the role of e-learning motivation in the adoption of the e-learning system and conversely technology’s effect on students’ e-learning motivation (Allen and Kishore, 2006); and
- consider “region” and “gender” as moderator variables in our model.

The rest of the paper is organised as follows. In the next section we provide a brief but comprehensive literature review related to e-learning, technology adoption, and
motivation to learn constructs alongside our research model and hypothesis. Then we discuss the research method employed in this study followed by analysis of the results. Finally, we draw conclusions about our findings.

**Theoretical background**

E-learning or learning through web based information and communication technological tools has a profound effect on performance, academic achievements, and students’ satisfaction (Katz, 2002). Several models have been employed to address the issues of e-learning and to identify the cause and effect of different variables in the technology acceptance and use literature. For instance, perceived usefulness, perceived ease of use, and flexibility (Arbaugh, 2000, 2002), satisfaction and academic achievements (Katz, 2002), motivation, being comfortable with technology, and availability (Piccoli et al., 2001), computer skills and initial knowledge about e-learning technology (Thurmond et al., 2002), interpersonal behaviours, motivating aims, and cognitive modes (Kanuka and Nocente, 2003), have all been linked with web based learning and ICT utilisation for educational purposes.

In e-learning a student’s motivation plays an important role (Conati, 2002). Motivation to learn is a “student’s tendency to find academic activities meaningful and worthwhile and try to derive the intended academic benefits from it” (Brophy, 2004, p. 249). There are different research streams dealing with motivation in e-learning. Marzano (2003) for example outlined five lines of research on student motivation:

1. drive theories (Hull, 1935) – students are either driven by striving for success or fear of failure;
2. attribution theory (Weiner, 1992, 1980) – students attribute success to ability, luck, effort, and task difficulty;
3. self-worth theory (Covington, 1984) – self-acceptance is one of our highest priorities as humans;
4. emotions (Conati, 2002; Kort and Reilly, 2001); and
5. self-efficacy and self-regulation, freedom, meaningful individual goals, and self-awareness (McCombs and Whisler, 1989; Bandura, 1986; Pintrich and Schunk, 2002).

Other research streams related to students’ motivation include the motivational planner approach (Del Soldato and Du Boulay, 1995), which deals with practical strategies and tactics to be employed based on the e-learner’s motivational state. Another is the attention, relevance, confidence, and satisfaction approach (Keller, 1987) based on motivational design of instructions. This approach argues that these four elements of motivation that should be considered in order to facilitate successful learning. Similarly social cognitive learning theory and theories of intrinsic and extrinsic motivation are well known (Ryan and Deci, 2000a).

So far students’ motivation to learn has been widely studied in the traditional classroom environment, but not its influence on technology adoption, nor has the effect of technology on e-learning motivation been tested (Ryan and Deci, 2000a, b). We argue that e-learning motivation can play an important role in technology acceptance and conversely technology use will affect a student’s e-learning motivation (Kim and Malhotra, 2005). In addition, we suggest that e-learning motivation is different from
conventional learning motivation, which is based on an instruction design approach (Keller, 1987). For e-learning motivation, technology characteristics such as effort expectancy must also be considered (Arbaugh, 2000) as shown in our research model (Figure 1). Our research model is based on UTAUT Model (Venkatesh et al., 2003), but we modified the original model by adding the “e-learning motivation” construct.

**E-learning motivation and technology use**

The UTAUT model (Venkatesh et al., 2003) aims to explain user intentions to use an information system and the usage behaviour; it was developed through a review and merger of different theories, which include the theory of reasoned action (Ajzen, 1985), technology acceptance model (Davis, 1989a), the theory of planned behaviour (Ajzen, 1991), a combined theory of planned behaviour/technology acceptance model (Taylor and Todd, 1995), a model of PC utilisation behaviour (Thompson et al., 1991), innovation diffusion theory (Rodger et al., 1996), and social cognitive theory (Compeau et al., 1999). The model states that four key constructs – performance expectancy, effort expectancy, social influence, and facilitating conditions – predict technology usage intention and behaviour (Venkatesh et al., 2003).

UTAUT defines performance expectancy as “the degree to which an individual believes that using the system will help him or her gain the desired performance” and effort expectancy as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, pp. 447, 450). The performance expectancy construct is composed of perceived usefulness adopted from Davis (1989) and Taylor and Todd (1995), extrinsic motivation (Davis et al., 1992; Thompson et al., 1991), and relative advantage and outcome expectation from Compeau et al. (1999). Effort expectancy comprises three constructs:

1. perceived ease of use (Davis, 1989);
2. complexity associated with the task derived from the model of PC utilisation (Thompson et al., 1991); and
3. ease of use (Davis, 1989).

In contrast the conventional motivation construct includes intrinsic motivation, extrinsic motivation, goal orientation, self-determination, self efficacy, and assessment
anxiety (Glynn and Koballa, 2006). Intrinsic motivation comes from the rewards inherent to a task or activity (Ryan and Deci, 2000a, b) while motivation that comes from outside the performer is mainly extrinsic (Pintrich and Schunk, 2002). Similarities among performance expectancy, effort expectancy, and the motivation construct have been observed in prior research (Davis et al., 1989; Thompson et al., 1991; Moore and Benbasat, 1991). The motivation and performance expectancy constructs address these concepts: usefulness and extrinsic motivation, usefulness and outcome expectation, satisfaction and beliefs about one’s capabilities, and beliefs about attaining the gains. These concepts are common to both constructs (Davis et al., 1989, 1992; Thompson et al., 1991; Moore and Benbasat, 1991). The following concepts are unique to each construct: intrinsic motivation, effort expectancy, and perceived enjoyment. Therefore, we introduce a new construct of “e-learning motivation” (ELM) by the merger of performance expectancy, effort expectancy, and the motivation construct. However, according to UTAUT assessment anxiety and self-efficacy are not direct determinants of intention, so they are not considered in our model either. Based on Agarwal and Prasad’s (1999) recommendations we removed the items that were very similar to other items. We define the e-learning motivation construct as a student’s tendency to find an e-learning system useful, easy to use, and to try to derive the intended academic benefits from it. The e-learning motivation construct is composed of items adopted from the motivation, performance, and effort expectancy constructs which have a direct influence on intention to use (Davis et al., 1992; Moon and Kim, 2001) as shown in our proposed research model (Figure 1).

Previous studies (Davis et al., 1992; Moon and Kim, 2001) have reported that both extrinsic and intrinsic motivation have a significant effect on intentions to use information technology systems (Coovet and Goldstein, 1980). Similarly, Pintrich and Schrauben (1992) suggested that a student’s motivation is affected by the value they associate with the outcome and this motivation leads to cognitive engagement, which in turn, leads to the use behaviour. According to Pintrich and Schrauben (1992) cognitive engagement represents the amount of effort spent in either studying or completing assignments. Incentive theories of motivation, for example Rotter et al. (1972) and Overmier and Lawry (1979), suggest that people will carry out an act only when the desired outcome is to be attained, or they will perform an action that is of value to them. Furthermore, perceived usefulness, perceived ease of use, intention to use, and usage behaviours have a circular rather than linear relationship (Allen and Kishore, 2006; Kim and Malhotra, 2005). Based on the above reasoning we propose the following two hypotheses:

\[ H1. \] E-learning motivation will positively influence a student’s behavioural intentions to use an educational portal.

\[ H2. \] Educational portal use will positively influence a student’s e-learning motivation (ELM).

Social influence, facilitating conditions, behaviour intention, and technology use

Social influence (SI) has been examined as an important factor in predicting technology use behaviour and intention to use (Venkatesh and Davis, 2000). According to the theory of reasoned action, people’s behaviour is influenced by the way in which they believe others important to them think certain behaviour should or should not be
followed. Where use is mandatory the role of social influence weakens over time and eventually becomes irrelevant with constant technology usage; however, it is important in the early stage of technology usage (Venkatesh and Davis, 2000). UTAUT also postulates that facilitating conditions (FC) have a direct influence on use behaviour (UB); it is composed of perceived behavioural control (Ajzen, 1991; Taylor and Todd, 1995), facilitating conditions (Thompson et al., 1991) and compatibility. Social influence is defined by UTAUT as: “the degree to which an individual perceives that important others believe he or she should use the new system”, while facilitating conditions are defined as “the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, pp. 451, 453). Based on the above reasoning the following hypotheses are constructed:

**H3.** Social influence will positively affect a student’s behavioural intention to use an educational portal.

**H4.** Facilitating conditions will positively influence educational portal use behaviour.

**H5.** A student’s intention to use an educational portal will positively influence their use of an educational portal.

### Moderating effects

In addition UTAUT hypothesises the role of four key moderator variables: gender, age, experience, and voluntariness of use. However, the knowledge gap literature argues that people with higher socio-economic status may acquire political and scientific knowledge at a faster rate than people with lower socio-economic status (Trichenor et al., 1970). The impact of culture, family income, practice of religion, political activities, personal relationships, individual habits, and race on technology adoption, have been widely studied (Hoffman and Novak, 1998; Eamon, 2004; Mehra et al., 2004). Peru is geographically divided into three regions – coast, Andes and jungle – with each region having diverse cultures, income levels, infrastructure, and race (see Ministry of Commerce and Tourism web portal, www.mincutur.gob.pe/newweb/Default.aspx?tabid = 1581). Therefore, in the context of Peru while applying the UTAUT model we introduce region and gender as moderating variables keeping in consideration the political differences, race, family income, and geographical location of the students, and the effects of gender and cultural differences on technology adoption (Minton and Schneider, 1980; Weiner et al., 2003). We eliminated voluntariness of use and experience due to their irrelevance in the school context; most of the students in our sample are of the same age group and have the same level of use experience. Thus, the following hypotheses are designed to test the moderating effects:

**H6.** Region will negatively moderate the effect of social influence on intention to use an educational portal.

**H7.** Region will negatively moderate the effect of facilitating conditions on educational portal usage behaviour.

**H8.** Region will negatively moderate the effect of e-learning motivation on intention to use an educational portal.
Gender will positively moderate the effect of social influence on intention to use an educational portal.

Gender will positively moderate the effect of e-learning motivation on intention to use an educational portal.

Research method

The portal

The national educational portal, Peru EDUCA (2009), is one of several initiatives taken in order to achieve the goals of modernising education through promoting e-learning and to increase the supply of education in Peru, especially in the rural areas. The portal is used by more than 3,000 students from schools throughout Peru. The portal provides course materials of instant audio and video content related to a wide range of subjects including physics, religious education, history, economics, geography, English, and mathematics. Apart from the academic content Peru EDUCA provides access to other online services such as chat, forums, and customised desktop services.

Instrument development

The research instrument was developed based on the items adopted from the Venkatesh et al. (2003) model and motivational theories (Brophy, 1988, 2004; Tuckman and Sexton, 1992; Glynn and Koballa, 2006). To fully represent the “e-learning motivation” construct and to keep the length of the instrument reasonable, five items were adopted from the motivation construct (MC), four items from performance expectancy (PE), and three from effort expectancy (EE). However, based on Agarwal and Prasad’s (1999) recommendations we removed the items that were not relevant to the study, and we deleted items that were very similar to other items leaving eight items in total representing the e-learning motivation construct. By using these criteria the items selected ensure complete coverage of the e-learning motivation construct. Furthermore, the items for measuring social influence, facilitating conditions, behavioural intention, and use behaviour were also adopted from Venkatesh et al. (2003).

The back translation method (Brislin, 1970, 1986) was used for translating the English version of the original survey items into Spanish. Every effort was made to present the items in a way that could be understood by the respondents while preserving the original meaning of the items until both the versions converged (Werner and Campbell, 1970). A total of 21 question items (see Appendix) were used and respondents had to rate each item on a Likert scale ranging from “totally disagree” (1) to “totally agree” (5) in order to measure the latent constructs.

Data collection

We randomly identified 47 secondary schools located in different regions – the coast, Andes and jungle of Peru – which were connected to the Peru EDUCA national educational portal. The survey instrument was administered to all the students for data collection with the help of the Peruvian Engineering Collegiate Association (www.cip.org.pe) and some assistance from the Ministry of Education’s website. Initially, 240 students responded to the survey. After excluding cases with missing or incomplete responses 150 complete and usable surveys were retained for quantitative analysis. Among the respondents 70 per cent were male and 30 per cent were female students. Most (62 per cent) of the responses were from the coast region while 38 per
cent were from the Andes region. We were unable to receive enough responses from the jungle region; therefore we eliminated it from our analysis. The demographic profile of the respondents is shown in Table I.

**Data analysis and results**

The partial least square (PLS) technique was used for the data analysis. PLS is a structured equation modelling technique that can analyse structural equation models involving multiple-item constructs, with direct and indirect paths. PLS has several advantages over other analysis tools; for instance it uses component-based estimation, maximises the variance explained in the dependent variable, does not require multivariate normality of the data, and is less demanding as regards sample size (Chin, 1998). PLS analysis is a two-stage process. First, the test of the measurement model includes the estimation of internal consistency (composite reliability) and the convergent and discriminant validity of the instrument items. The second stage comprises the assessment of the structural model.

**Reliability and validity tests**

The reliability results are depicted in Table II. The data indicates that all reliability measures are robust and well above the recommended level of 0.70 (Nunnally, 1978), thus indicating adequate composite reliability (internal consistency). The average variance extracted (AVE) was also calculated. AVE measures the amount of variance that a construct captures from its indicators relative to the variance

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Frequency</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>105</td>
<td>70</td>
</tr>
<tr>
<td>Female</td>
<td>45</td>
<td>30</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-18</td>
<td>150</td>
<td>100</td>
</tr>
<tr>
<td><strong>Region</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td>93</td>
<td>62</td>
</tr>
<tr>
<td>Andes</td>
<td>57</td>
<td>38</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student</td>
<td>150</td>
<td>100</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School</td>
<td>150</td>
<td>100</td>
</tr>
</tbody>
</table>

Table I. Demographic profile of the respondents

<table>
<thead>
<tr>
<th>Variable constructs</th>
<th>Composite reliability</th>
<th>Average variance extracted/explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-learning motivation (ELM)</td>
<td>0.937</td>
<td>0.654</td>
</tr>
<tr>
<td>Social influence (SI)</td>
<td>0.955</td>
<td>0.877</td>
</tr>
<tr>
<td>Facilitating conditions (FC)</td>
<td>0.938</td>
<td>0.836</td>
</tr>
<tr>
<td>Behavioural intention (BI)</td>
<td>0.934</td>
<td>0.825</td>
</tr>
<tr>
<td>Use behaviour (UB)</td>
<td>0.955</td>
<td>0.875</td>
</tr>
</tbody>
</table>

Table II. Reliability
contained in measurement error; it is interpreted as a measure of reliability for the construct, and as a means of evaluating discriminant validity. The average variance extracted (AVE) for each measure exceeded the recommended level of 0.50 (Fornell and Larcker, 1981).

For satisfactory discriminant validity the AVE from the construct should be greater than the variance shared between the construct and other constructs in the model. Table III shows the results of testing the discriminant validity of the measured scales. The elements in the matrix diagonals, representing the square roots of the AVEs, are greater in all cases than the off-diagonal elements in their corresponding row and column, supporting the discriminant validity of our scales. Convergent validity is demonstrated when items load highly (> 0.50) on their associated factors. Table IV shows that all the measures have significant loadings that load much higher than the suggested threshold. Furthermore, each item’s factor loading on its respective construct was highly significant (p < 0.0001) as the values of t-statistics were between 63 and 730.

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>ELM</th>
<th>BI</th>
<th>SI</th>
<th>UB</th>
<th>FC</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-learning motivation</td>
<td>0.817</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioural intention</td>
<td>0.734</td>
<td>0.945</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social influence</td>
<td>0.737</td>
<td>0.744</td>
<td>0.914</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use behaviour</td>
<td>0.585</td>
<td>0.735</td>
<td>0.536</td>
<td>0.917</td>
<td></td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>0.584</td>
<td>0.648</td>
<td>0.653</td>
<td>0.537</td>
<td>0.944</td>
</tr>
</tbody>
</table>

Table III. Discriminant validity (inter-correlations) of variables

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>ELM</th>
<th>Social influence</th>
<th>Facilitating conditions</th>
<th>Behaviour intention</th>
<th>Use behaviour</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELM1</td>
<td>0.890</td>
<td>-0.066</td>
<td>-0.055</td>
<td>-0.108</td>
<td>0.757</td>
</tr>
<tr>
<td>ELM 2</td>
<td>0.805</td>
<td>0.207</td>
<td>-0.140</td>
<td>-0.130</td>
<td>0.372</td>
</tr>
<tr>
<td>ELM 3</td>
<td>0.661</td>
<td>-0.047</td>
<td>0.143</td>
<td>0.396</td>
<td>0.102</td>
</tr>
<tr>
<td>ELM 4</td>
<td>0.801</td>
<td>0.354</td>
<td>0.038</td>
<td>-0.125</td>
<td>-0.041</td>
</tr>
<tr>
<td>ELM 5</td>
<td>0.837</td>
<td>-0.036</td>
<td>-0.083</td>
<td>0.471</td>
<td>-0.086</td>
</tr>
<tr>
<td>ELM 6</td>
<td>0.836</td>
<td>0.325</td>
<td>-0.048</td>
<td>0.096</td>
<td>-0.324</td>
</tr>
<tr>
<td>ELM 7</td>
<td>0.790</td>
<td>0.408</td>
<td>-0.030</td>
<td>-0.280</td>
<td>-0.013</td>
</tr>
<tr>
<td>ELM 8</td>
<td>0.889</td>
<td>-0.054</td>
<td>-0.136</td>
<td>0.293</td>
<td>-0.107</td>
</tr>
<tr>
<td>SI1</td>
<td>0.146</td>
<td>0.859</td>
<td>-0.105</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI2</td>
<td>0.228</td>
<td>0.834</td>
<td>-0.139</td>
<td>-0.010</td>
<td>-0.180</td>
</tr>
<tr>
<td>SI3</td>
<td>0.115</td>
<td>0.892</td>
<td>-0.049</td>
<td>0.200</td>
<td>0.059</td>
</tr>
<tr>
<td>FC1</td>
<td>0.224</td>
<td>0.108</td>
<td>0.791</td>
<td>-0.072</td>
<td>-0.149</td>
</tr>
<tr>
<td>FC2</td>
<td>0.325</td>
<td>0.206</td>
<td>0.797</td>
<td>-0.349</td>
<td>-0.148</td>
</tr>
<tr>
<td>FC3</td>
<td>0.178</td>
<td>-0.100</td>
<td>0.786</td>
<td>-0.053</td>
<td>0.084</td>
</tr>
<tr>
<td>BI1</td>
<td>0.119</td>
<td>-0.160</td>
<td>0.019</td>
<td>0.842</td>
<td>0.230</td>
</tr>
<tr>
<td>BI2</td>
<td>0.077</td>
<td>0.005</td>
<td>0.254</td>
<td>0.870</td>
<td>-0.113</td>
</tr>
<tr>
<td>BI3</td>
<td>0.264</td>
<td>-0.039</td>
<td>-0.090</td>
<td>0.809</td>
<td>0.258</td>
</tr>
<tr>
<td>UB1</td>
<td>-0.099</td>
<td>-0.028</td>
<td>0.412</td>
<td>-0.140</td>
<td>0.808</td>
</tr>
<tr>
<td>UB2</td>
<td>-0.190</td>
<td>0.016</td>
<td>0.458</td>
<td>0.006</td>
<td>0.865</td>
</tr>
<tr>
<td>UB3</td>
<td>-0.206</td>
<td>-0.064</td>
<td>0.480</td>
<td>0.119</td>
<td>0.874</td>
</tr>
</tbody>
</table>

Table IV. Loadings and cross loadings
Assessment of the structural model

The test of the structural model was performed using a PLS graph. The test includes:

- estimating the goodness of fit indices, which indicates how well the model is performing;
- estimating the path coefficients, which indicate the strengths of the relationships between the dependent variables and independent variables; and
- the $R^2$ value, which represents the amount of variance explained by the independent variables.

The path coefficients in the PLS model represent standardised regression coefficients. The suggested lower limit of substantive significance for regression coefficients is 0.05.

The structural model results without moderating effects are shown in Figure 2. All beta path coefficients are positive and statistically significant (at $^* p < 0.0005$) except in the case of the relationship between facilitating conditions and use behaviour ($\beta = 0.09, \text{ns}$). E-learning motivation and social influence both had a positive influence ($\beta = 0.43, p < 0.0005$) on behavioural intention and accounted for 64 per cent of the variance in intention. Furthermore, behavioural intention had a positive influence ($\beta = 0.69, p < 0.0005$) on use behaviour. As predicted, use behaviour had a positive influence ($\beta = 0.59, ^* p < 0.0005$) on e-learning motivation in a cyclic manner and accounted for 40 per cent of the variance in e-learning motivation.

The structural model with significant moderator effects is shown in Figure 3. Initially, we considered gender and region as moderator variables in our model (see Figure 1). However, we found that only region had a negative ($\beta = -0.23, ^* p < 0.1$) significant interacting effect with the social influence upon behavioural intention. Furthermore, both with and without moderating effects the model explains 64 per cent of the variance in behavioural intention and 60 per cent of the variance in use behaviour. In the cyclic effect, the variance observed was as much as 40 per cent in e-learning motivation with and without moderating

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**Figure 2.** Structural model results (without moderating effect)
effects in our model. A summary of the findings after the introduction of moderating variables is shown in Table V.

**Discussion and implications**

The goal of this study was to empirically extend the understanding of students’ e-learning motivation and e-learning portal usage. The findings of this study provide a preliminary test of the viability of the research model and are consistent with the proposed theoretical foundation within the context of developing countries, especially in the case of Peru. We found that e-learning motivation had a positive influence on behavioural intention toward the e-learning portal. As predicted, use behaviour had a positive influence on e-learning motivation in a cyclic way and accounted for as much as 40 per cent of the variance in e-learning motivation. Also, we found that social influence had a significant effect on behavioural intention and accounted for 64 per cent of the variance in behavioural intention. Similarly, we found that facilitating conditions had no effect on use behaviour. Regarding moderation effects, we found that region moderated the relationship between social influence (SI) and behavioural intention.

Several implications can be drawn from our findings. We can conclude from the positive cyclic relation between e-learning portal use and e-learning motivation that motivation plays a significant role in the adoption and use of e-educational portals in a school context. Conversely, the more students use educational portals the higher will be their motivation toward e-learning. The role of educational portals in enhancing students’ motivation toward e-learning gives us a clear indication that we must encourage students to use educational portals. Similarly, for the students to be motivated to use the e-educational system, technology characteristics such as ease of use and effort expectancy must also be considered while designing educational portals, apart from conventional motivational factors such as intrinsic and extrinsic motivation, goal orientation, self-determination, and self efficacy. The positive
<table>
<thead>
<tr>
<th>Independent variables and interactions terms</th>
<th>Dependent variables</th>
<th>Beta</th>
<th>t-statistic</th>
<th>Sig. level</th>
<th>Conclusions</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-learning motivation</td>
<td>Behavioural intention</td>
<td>0.43</td>
<td>4.50</td>
<td>0.0005</td>
<td>E-learning motivation influences behavioural intention</td>
</tr>
<tr>
<td>Behavioural intention</td>
<td>Use</td>
<td>0.71</td>
<td>8.97</td>
<td>0.0005</td>
<td>Behavioural intention strongly influences use</td>
</tr>
<tr>
<td>Social influence</td>
<td>Behavioural intention</td>
<td>0.60</td>
<td>4.80</td>
<td>0.0005</td>
<td>Social influence on behavioural intention</td>
</tr>
<tr>
<td>Use</td>
<td>Behavioural intention</td>
<td>0.59</td>
<td>9.80</td>
<td>0.0005</td>
<td>Use influence on e-learning motivation</td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>Use</td>
<td>0.08</td>
<td>0.14</td>
<td>No</td>
<td>Facilitating conditions do not influence use behaviour</td>
</tr>
<tr>
<td>Region*Social influence</td>
<td>Behavioural intention</td>
<td>−0.27</td>
<td>1.16</td>
<td>0.10</td>
<td>Region negatively moderates the effect of social influence on behaviour intention</td>
</tr>
<tr>
<td>Region</td>
<td>Use</td>
<td>−0.15</td>
<td>0.15</td>
<td>No</td>
<td>Direct effect of region on use is not significant</td>
</tr>
<tr>
<td>Region*Facilitating conditions</td>
<td>Use</td>
<td>0.18</td>
<td>0.06</td>
<td>No</td>
<td>Region negatively moderates the relationship of facilitating conditions on educational portal usage behaviour</td>
</tr>
<tr>
<td>Region</td>
<td>Behavioural intention</td>
<td>0.142</td>
<td>1.19</td>
<td>0.10</td>
<td>Direct effect of region on behavioural intention is significant</td>
</tr>
<tr>
<td>Gender</td>
<td>Behavioural intention</td>
<td>0.19</td>
<td>0.22</td>
<td>No</td>
<td>Direct effect of gender on behavioural intention is not significant</td>
</tr>
<tr>
<td>Region*E-learning motivation</td>
<td>Behavioural intention</td>
<td>−0.10</td>
<td>0.17</td>
<td>No</td>
<td>Region does not moderate the effect of e-learning motivation on intentions to use educational portal</td>
</tr>
<tr>
<td>Gender*E-learning motivation</td>
<td>Behavioural intention</td>
<td>−0.25</td>
<td>0.06</td>
<td>No</td>
<td>Gender does not moderate the effect of e-learning motivation on intentions to use educational portal</td>
</tr>
<tr>
<td>Gender*Social influence</td>
<td>Behavioural intention</td>
<td>0.05</td>
<td>0.11</td>
<td>No</td>
<td>Gender does not moderate the effect of social influence on intentions to use educational portal</td>
</tr>
</tbody>
</table>

Table V: Moderating variables
relationship between social influence and behavioural intention is consistent with prior literature that stresses the role of social influence in adoption and usage of technology (McInerney, 2005). In the school context these findings explain the role of teachers, parents, and other peers in the adoption and diffusion of an e-educational portal. Also during the data collection phase we came across several schools and students who were not aware of the Peru EDUCA portal or who did not want to use it; this suggests that either they are not aware of the cyclic benefit of using e-portals or maybe they are not influenced by their teachers, family members, or other peers to use the portal. We can conclude that in developing countries such as Peru where technology diffusion and awareness is low, the students must be influenced through teachers, parents, and other peers to adopt and use educational portals.

In addition, we can conclude from the negative moderating effect of region on the relationship of social influence and behavioural intention that the level of social influence for students in the Andes region is stronger than that of students in the coastal region of Peru. Simply put, technology can be more easily adopted by the students in the Andes region, due to the stronger influence of teachers, friends, and family. This socially influenced behaviour must be reflected in government policies for motivating students to use e-learning portals. This also implies that different strategies must be used by authorities to motivate students toward e-learning system use depending on the region. The limited response rate from the jungle region during our data collection phase reflects the lack of awareness of the students about the e-learning portal. So there is a need for creating awareness regarding use of the e-learning portal in the jungle region of Peru. In addition, we did not find gender as a moderator in our model. These findings suggest that, in Peru, male and female students can be equally motivated toward use of e-learning portals and similar polices can be used to motivate both genders toward e-learning. Furthermore, this implies that in the Peruvian context while using e-learning systems male and female students who live in the same regions have the same level of social influence. The lack of a correlation between facilitating conditions and e-learning portal use suggests that making all resources available does not necessarily guarantee the adoption of e-learning portals. These findings further highlight the importance of e-learning motivation in educational portal use among students.

In order to further elaborate our findings we collected qualitative data from secondary sources about e-learning initiatives in Peru and compared it with the empirical findings of this study. As expected the qualitative data fully support the findings. For example, basic infrastructure such as computers and the internet is available in more than 41 per cent of the schools in the coastal and Andes regions of Peru (Escale, 2008). However, our findings indicate that even though basic infrastructure is available in Peru it does not guarantee educational portal use, although the authorities believe that making infrastructure available may promote internet use. Furthermore, our findings indicate that contextual policies must be enacted in different regions for motivating students toward e-learning portal use, but the government of Peru has not made such policy differentiation and initiated similar policies and projects irrespective of the regions (MinEdu, 2007b). This further elaborates our findings regarding the lack of awareness and use of the e-learning portal in the jungle region of Peru, as most of the infrastructure and policies are directed toward the coastal and Andes regions rather than the jungle region (MinEdu, 2007b; Escale, 2008). Our empirical findings regarding the lack of awareness and motivation
among students in the jungle region can also be reflected in the number of schools having internet connectivity by region, for example, 46.3 per cent schools from urban areas and only 15 per cent from rural areas had internet connectivity (Escale, 2008). Our research demonstrates that student e-learning motivation plays a significant role in educational portal use and adoption, but the data from the Peru government indicate that there are no special policies and projects designed to encourage students' motivation toward educational portal use (MinEdu, 2009). We found that social influence plays an important role in fostering educational portal use and people in the Andes region are more likely to adopt technology due to comparatively strong social influence; which is consistent with the fact that people in the Andes region have close ties and the level of embeddedness is high compared to the coastal region, mainly due to the cultural and ethnic differences among these regions (Degregori, 1977).

This study has some limitations that must be mentioned. We carried out our analysis in only one country, but which can be representative of the South American context; thus caution should be taken in generalisation of the study. Also the sample size ($N = 150$) was not large enough due to no responses from the jungle region of Peru. Furthermore, we could not include the jungle area in our analysis due to limited responses from this area. Future research may extend the study to other South American countries for testing the effect of e-learning motivation on use of educational portals, and vice versa while utilising a larger sample size. Moreover, future research can use the e-learning motivation construct for exploring other e-learning technologies’ acceptance in schools, for instance e-learning delivered through mobile, digital TV, and IP TV in developing countries.

**Conclusion**

Adopting and modifying the UTAUT model, we added a new construct of e-learning motivation and applied it to the Peruvian context for predicting the role of e-learning motivation in educational portal adoption and use. We found that e-learning motivation plays a crucial role in the adoption and use of e-educational portals; we demonstrated that it is different from conventional learning motivation by adding technology characteristics (effort expectancy) to the traditional motivational construct. In addition we examined the cyclic effect of the technology use on e-learning motivation; we found that e-educational portal use simulates students’ e-learning motivation. We also demonstrated the importance of the influence of teachers, parents, and other peers in the adoption of educational portals in schools. In addition, we used region and gender as moderating variables in our study. Based on the findings we provided some useful suggestions to policy makers and practitioners in developing countries.

**References**


Brophy, J. (2004), Motivating Students to Learn, 2nd ed., Lawrence Erlbaum, Mahwah, NJ.


Appendix. Peruvian predictor latent construct items

E-learning motivation (Five-point Likert scale from “totally disagree” to “totally agree”):

ELM 1: I enjoy learning by using the Peru EDUCA portal. (MC).

ELM 2: I find the Peru EDUCA portal useful in my studies. (MC, PE).

ELM 3: Using the Peru EDUCA portal in my studies enables me to accomplish tasks more quickly. (MC, PE).

ELM 5: Using the Peru EDUCA portal helps me do better than others in my studies. (MC, PE).

ELM 6: My interactions with the Peru EDUCA portal are clear and understandable. (EE).

ELM 7: Learning by using the Peru EDUCA portal is easy for me. (EE).

ELM 8: It is easy for me to learn more using the Peru EDUCA portal. (EE).

Social influence (Five-point Likert scale from “totally disagree” to “totally agree”):

SN 1: Most people who are important to me think I should use the Peru EDUCA portal.

SN 2: Most people who are important to me would want me to use the Peru EDUCA portal.

SN 3: People whose opinions I value would prefer me to use the Peru EDUCA portal.

Facilitating conditions (Five-point Likert scale from “totally disagree” to “totally agree”):

FC 1: I have the resources and the knowledge and the ability to make use of the Peru EDUCA portal.

FC 2: Central support was available to help with the Peru EDUCA portal’s problems.

FC 3: Management provided most of the necessary help and resources for use of the Peru EDUCA portal.

Behavioural intention (Five-point Likert scale from “strongly disagree” to “strongly agree”):

BI 1: I predict I will continue to use the Peru EDUCA portal on a regular basis.

BI 2: What are the chances in 100 that you will continue as a Peru EDUCA portal user? 1) 0; 2) 1-10%; 3) 11-30%; 4) 31-50%; 5) 51-70%; 6) 71-100%.
BI 3: To do my work, I would use the Peru EDUCA portal rather than any other means available.

Use behaviour

USE 1: On an average working day, how much time do you spend using the Peru EDUCA portal? 1) Almost none; 2) less than 30 minutes; 3) from 30 minutes to 1 hour; 4) from one to two hours; 5) from two to three hours; and 6) more than three hours.

USE 2: On average, how frequently do you use the Peru EDUCA portal? 1) Less than once a month; 2) once a month; 3) a few times a month; 4) a few times a week; 5) about once a day; and 6) several times a day.

USE 3: How many different applications of the Peru EDUCA portal have you worked with or used in your studies? 1) None; 2) one; 3) two; 4) three to five applications; 5) 6 to 10 applications; and 6) more than 10 applications.

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