An investigation of user perceptions and attitudes towards learning objects

Siong-Hoe Lau and Peter C. Woods

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Abstract
This study empirically evaluates the technology acceptance model drawn from Information Systems (IS) literature to investigate how user beliefs and attitudes influence learning-object use among higher education learners by evaluating the relationships between perceived usefulness, perceived ease of use, attitude, behavioural intentions and actual use. In the study, 601 potential learning-object users were presented with an introductory demonstration of learning objects for a Digital Systems course. Following the demonstration and practice, data on user beliefs, attitudes and intention to use learning objects were gathered, while data on actual use of learning objects was collected at the end of the semester. Subjects with prior experience using the learning objects were eliminated from further analysis, resulting in a final sample of 481 users. Structural equation modelling was employed to test the hypothesised study model. The analysis showed that both the user beliefs and attitudes have significant positive relationships with behavioural intention and that behavioural intention accurately predicted the actual use of learning objects. The results extend the validity of the TAM into a learning object context and clearly pointed out that it can be used to predict users’ future behaviour.

Introduction
Computer and Internet technologies, in particular the World Wide Web, provide educators and learners with an innovative learning environment to stimulate and enhance the teaching and learning process. The increased use of new educational technologies such as learning object technology in higher education institutions (Bannan-Ritland, Dabbagh & Murphy, 2000; Bratina, Hayes & Blumsack, 2002; Wiley, 2001) has made user acceptance an increasingly critical issue, as the end users are crucial for the effective use of the information technologies (Cheney & Dickson, 1982).
Although user acceptance has received fairly extensive attention in prior research, the majority of these studies have focused on specific information systems in Management Information Systems (MIS) fields, other than education. Some examples are Internet-based systems (Adams, Nelson & Todd, 1992; Gefen & Straub, 1997; Koufaris, 2002), office applications (Davis, Bagozzi & Warshaw, 1989); Mathieson, 1991; Szajna, 1996) and telemedicine technology (Hu, Chau, Liu Sheng & Tam, 1999). There is scarce research literature that addresses learner intention to use, and acceptance of educational technologies, especially in a learning-object context. The measurement of the user perception (McMahon, Gardner, Gray & Mulhern, 1999) and an understanding the factors that promote the effective use of systems (Mun & Hwang, 2003) become increasingly important to enhance our understanding and prediction of the acceptance and utilisation of educational technologies.

This study used the technology acceptance model (TAM) as the baseline model to predict the likely usage of learning objects as supplementary learning resources for traditional face-to-face classes in a higher-education context. To accomplish the purpose, structure equation modelling was employed to examine and validate the hypothesised relationships of user perceptions and attitudes towards the behavioural intention to use and actual use of learning objects.

**Theoretical background**

Information technology has been widely implemented in education to augment traditional face-to-face teaching and learning (Ho, Savenye & Haas, 1986; Reader & Hammond, 1994). In an attempt to make the instructional resources more efficient and to meet the diverse needs of learners, many organisations and institutions have been investing considerable amounts of financial resources for the integration and utilisation of learning objects into their e-learning systems (Urden & Weggen, 2000). The Institute of Electrical and Electronics Engineers (IEEE) formed the Learning Technology Standards Committee (LTSC) to create the common standards for the description, interchange and management of learning objects (LTSC, 2002). The goal is to develop an open architecture for online learning that will allow teaching to be centred around the needs of the learner and to allow for greater customisation and flexibility in the learning environment.

This concept has since filtered into the broader field of education (Bannan-Ritland et al, 2000; Bratina et al, 2002; Wiley, 2001), with more and more instructional content being developed as learning objects because of their potential for reusability, interoperability, discoverability and manageability (Singh, 2000). Like any other trend involving information systems, this has made user acceptance an increasingly critical issue, as the success of the information systems largely depends on user satisfaction and acceptance (Bharati, 2003; DeLone & McLean, 1992; Doll & Torkzadeh, 1992; Seddon, 1997). Stokes (2001) indicated that the issue of learner satisfaction and acceptance in the digital environment is very important. A high level of learner satisfaction and acceptance reflects that the users are more willing to continue to use the technology (Biner, Dean & Mellinger, 1994; Chute, Thompson & Hancock, 1999; Tallman, 1994).
Several intention-based theories and models have been proposed and empirically tested in the last decade in understanding user adoption and usage of information technology (IT) innovations. For example, the theory of reasoned action—TRA (Fishbein & Ajzen, 1975), TAM (Davis et al., 1989), the theory of planned behaviour (Ajzen, 1991), innovation diffusion theory (Roger, 1995), and the Information Systems (IS) success model (DeLone & McLean, 1992). Those frameworks have been applied to a variety of information technologies in different contexts and populations (Gefen, Karahanna & Straub, 2003; Hassan, 2003; Ong, Lai & Wang, 2004; Saade & Bahli, 2005; Tetiwat & Huff, 2002; Venkatesh, Speier & Morris, 2002). Among them, the TAM (Davis, 1986) is one of the most influential and frequently tested models, and is widely applied to explain general IT adoption in the IS literature (Jong-Ae, 2005; Ma & Liu, 2004; Saga & Zmud, 1994).

The TAM is a specific model developed to explain and predict users’ computer usage behaviour. Derived from the TRA (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), it predicts user acceptance based on the influence of two user beliefs: perceived usefulness (PU) and perceived ease of use (PEU). Both PU and PEU are posited as having significant impact on a user’s attitude (AT) towards using the system. Behavioural intentions (BI) to use is jointly determined by a person’s attitude towards using the system and its perceived usefulness. BI then determines the actual use (AU) of the system. Using different methodologies, numerous studies have found that PU and PEU correlate well with IT acceptance across a wide range of information systems (Gefen et al., 2003; Hassan, 2003; Ong et al., 2004; Saade & Bahli, 2005; Tetiwat & Huff, 2002; Venkatesh et al., 2002). Likewise, empirical research has also shown that BI is the strongest predictor of AU (Fred. D. Davis et al., 1989; Taylor & Todd, 1995).

Research model and hypotheses

In this study, the TAM was used as the baseline model to verify the following hypothesised relationships in the context of learning-objects usage among higher educational learners. Figure 1 shows the studied model that posits that behavioural intention determines actual use and behavioural intention is determined by both attitude and perceived usefulness. Perceived usefulness and perceived ease of use both have direct relationships with attitude. Perceived ease of use also influences perceived usefulness. This study model involves testing of six hypotheses as shown in Figure 1.

![Research model and hypotheses (H1–H6)](image-url)
H1: PEU of learning objects will have a positive, direct relationship with PU of learning objects.

H2: PEU of learning objects will have a positive, direct relationship with AT towards using learning objects.

H3: PU of learning objects will have a positive, direct relationship with AT towards using learning objects.

H4: PU of learning objects will have a positive, direct relationship with BI to use learning objects.

H5: AT towards using learning objects will have a positive, direct relationship with BI to use learning objects.

H6: BI to use learning objects will have a positive, direct relationship with AU of learning objects.

Research design and procedures

This study utilises a web-based survey to collect data for quantitative testing of the research model. A review of the IS literature was used to identify existing measures for constructs, which had been used in previous MIS research. The scales for PU, PEU, AT and BI were adapted from literature studies (F. D. Davis, 1989; Davis et al., 1989; Mathieson, 1991; Szajna, 1996; Venkatesh & Davis, 2000). Items were rewritten as necessary to fit the context of this study. Details of all questions used in measuring constructs for this study are presented in the Appendix.

The target population for the study consists of undergraduate IT students who were enrolled in the Faculty of Information Science and Technology (FIST), Multimedia University. This study sought experienced online-learning users who are familiar with Web technologies in the general sense and who have the basic ability to use online learning systems. In this regard, the in-house developed an online multimedia learning system (MMLS) so that they could evaluate the learning objects based on their current online-learning experience. All students enrolled in the Digital Systems course agreed to participate in this study, resulting in a sample of 601 potential users of learning objects. Subjects with prior experience using the learning objects were eliminated from further analysis resulting in a final sample of 481 users.

The Digital Systems course is a core subject for the 1st-year IT students who enrol in FIST. It introduces the student to the field of digital technology elements such as logic gates, combination logic circuits, memory devices and digital signal processing. In this study, relevant learning objects for this course were retrieved from various general repositories (e.g., Connexions—http://cnx.org/; Multimedia Educational Resource for Learning—http://www.merlot.org/; and Online Teaching and Wisconsin Online Resource Centre—http://www.wisc-online.com), which provided higher education-level learning objects that anyone may view and use. These repositories were selected for being among the few learning-object repositories that permit public access, which made the study possible. In order to produce cohesive and pedagogically sound learning materials, and to effectively search for relevant learning objects, the researcher designed a generic structure of the Digital Systems course consisting of a series of
electronic folders, similar to traditional course hierarchy (chapters, lessons and topics) to hold the retrieved learning objects. Some of the learning objects were authored in Macromedia Flash, which uses animation and interactive simulations to provide visual examples of digital-systems concepts. Others were text-based objects authored as web pages. Relevant learning objects were linked into the syllabus each week from the lecture notes with the aim of helping students to understand the more abstract and complex aspects of learning content.

At the beginning of the semester, emails were sent to the instructors to seek permission and to arrange time for their class students to participate in the study. First, respondents were told the purpose of the study, followed by a 15-minute brief in-class introduction of learning objects to the respondents, describing the nature and benefits of learning objects and their relevance to their curriculum. Second, during the demonstration session, each student had one desktop computer to use. The instructor guided them through some of the learning objects related to logic gates (e.g., AND, OR, NOT, NAND, NOR, XOR and XNOR gates). It took about 45 minutes to complete the tasks. Having the opportunity to explore the learning objects, respondents could feel the use of learning objects and appreciate the functionality attributes made available by the study learning objects before they shaped their perceptions, attitudes and intentions to use the learning objects. Following the demonstration session, all subjects received and completed the questionnaire designed to capture learning objects’ perceived usefulness, perceived ease of use, students’ attitude towards using learning objects, and their intentions to use learning objects over the remainder semester. At the end of the semester, the researchers returned to the class and had subjects estimated the frequency and number of learning objects referred to over the 3-month interval since initial exposure.

**Instrument validation**

In this study, scale reliability and validity were assessed via confirmatory factor analysis (CFA). Convergent validity of scale items were assessed using three criteria (reliability, composite reliability and average variance extracted) as recommended by Fornell and Larcker (1981). The standardised CFA loadings for all scale items exceeded the minimum loading criterion of 0.70, and the composite reliabilities of all factors also exceeded the required minimum of 0.70. Further, average variance-extracted values of all constructs exceeded the threshold value of 0.50. Hence all three conditions for convergent validity were met, as shown in Table 1.

Evidence of discriminant validity was obtained by comparing the square root of the average variance extracted of each latent construct with the correlations between factors (Segars & Grover, 1998). All the square roots of the average variance extracted were greater than the correlations between factors, as shown in Table 2.

Hence, the discriminant validity criterion was also met for CFA models, giving further confidence in the adequacy of the measurement scales. Therefore, the derived CFA model was incorporated into the analysis of a structural equation model with latent variables.
Data analysis and results
Demographics data
The population of interest was learners enrolled in the Digital Systems course and who used learning objects as supplementary learning resources in their face-to-face classes. The sample consisted of 601 undergraduate students who had prior experience with the use of computers and the Internet. Majority of the subjects have 2 to 4 years of

<table>
<thead>
<tr>
<th>Constructs / Factors</th>
<th>Indicators</th>
<th>Standardised loadings ($&gt;0.707$)</th>
<th>Reliability ($r^2$) ($&gt;0.50$)</th>
<th>Composite reliability ($&gt;0.70$)</th>
<th>Average variance extracted ($&gt;0.50$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual use (AU)</td>
<td>AU1</td>
<td>0.910</td>
<td>0.828</td>
<td>0.947</td>
<td>0.857</td>
</tr>
<tr>
<td></td>
<td>AU2</td>
<td>0.914</td>
<td>0.835</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AU3</td>
<td>0.952</td>
<td>0.906</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioural intention (BI)</td>
<td>BI1</td>
<td>0.944</td>
<td>0.891</td>
<td>0.964</td>
<td>0.898</td>
</tr>
<tr>
<td></td>
<td>BI2</td>
<td>0.950</td>
<td>0.903</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BI3</td>
<td>0.949</td>
<td>0.901</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attitude (AT)</td>
<td>AT1</td>
<td>0.861</td>
<td>0.741</td>
<td>0.935</td>
<td>0.783</td>
</tr>
<tr>
<td></td>
<td>AT2</td>
<td>0.915</td>
<td>0.837</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>AT3</td>
<td>0.881</td>
<td>0.776</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AT4</td>
<td>0.881</td>
<td>0.776</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived usefulness (PU)</td>
<td>PU1</td>
<td>0.921</td>
<td>0.848</td>
<td>0.970</td>
<td>0.843</td>
</tr>
<tr>
<td></td>
<td>PU2</td>
<td>0.925</td>
<td>0.856</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU3</td>
<td>0.909</td>
<td>0.826</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU4</td>
<td>0.925</td>
<td>0.856</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU5</td>
<td>0.911</td>
<td>0.830</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PU6</td>
<td>0.919</td>
<td>0.845</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived ease of use (PEU)</td>
<td>PEU1</td>
<td>0.884</td>
<td>0.781</td>
<td>0.946</td>
<td>0.747</td>
</tr>
<tr>
<td></td>
<td>PEU2</td>
<td>0.869</td>
<td>0.755</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PEU3</td>
<td>0.855</td>
<td>0.731</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PEU4</td>
<td>0.877</td>
<td>0.769</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PEU5</td>
<td>0.843</td>
<td>0.711</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PEU6</td>
<td>0.856</td>
<td>0.733</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Discriminant validity

<table>
<thead>
<tr>
<th>Construct</th>
<th>AU</th>
<th>BI</th>
<th>AT</th>
<th>PU</th>
<th>PEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual use (AU)</td>
<td>0.926</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioural intention (BI)</td>
<td>0.485</td>
<td>0.948</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attitude (AT)</td>
<td>0.332</td>
<td>0.685</td>
<td>0.885</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived ease of use (PU)</td>
<td>0.348</td>
<td>0.717</td>
<td>0.708</td>
<td>0.918</td>
<td></td>
</tr>
<tr>
<td>Perceived usefulness (PEU)</td>
<td>0.363</td>
<td>0.543</td>
<td>0.648</td>
<td>0.672</td>
<td>0.864</td>
</tr>
</tbody>
</table>

Note. Diagonals represent the square root of average variance extracted, and the other matrix entries are the factor correlation.

Data analysis and results
Demographics data
The population of interest was learners enrolled in the Digital Systems course and who used learning objects as supplementary learning resources in their face-to-face classes. The sample consisted of 601 undergraduate students who had prior experience with the use of computers and the Internet. Majority of the subjects have 2 to 4 years of

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computer experiences and spent about 2 to 4 hours everyday on the Internet. Overall, of the 601 that were distributed, only 481 respondents with no initial experience using learning objects were used for analysis, giving a response rate of 80%. Detailed descriptive statistics relating to the respondents’ characteristics are shown in Table 3.

After a 3-month interval since initial exposure, at the end of the semester, all 481 respondents had hands-on experience on the learning objects, as shown in Table 4. On average, the respondents spent about 3 to 4 hours on learning objects weekly and used about 10 to 15 learning objects per week.

**Descriptive statistics**

The means and standard deviations for all constructs were determined and are displayed in Table 5. The highest mean of 5.052 was for the mediating construct, attitude, which on a scale of 1 to 7 indicates that, on the whole, students have a positive attitude towards learning objects. The means for perceived usefulness, perceived ease of use and behavioural intention were 4.958, 4.929 and 4.815, respectively, while the mean for actual use was 4.380.

**Test of the structure model and hypotheses**

The next step in data analysis was to examine the significance and strength of hypothesised relationships in the research model (Figure 1). The results of the analysis of the structural model, including path coefficients, path significances, and variance explained ($r^2$ values) for each dependent variable are presented in Figure 2.

PEU had significant positive relationships with both PU ($\beta = 0.672, p < 0.001$), and AT ($\beta = 0.314, p < 0.001$). Therefore, H1 and H2 were supported. Likewise, PU had significant positive relationships with both AT ($\beta = 0.672, p < 0.001$) and BI ($\beta = 0.467$).
Thus, H3 and H4 were also supported. PEU explained about 45\% of the variance in PU and about 56\% of the variance in AT was jointly explained by PU and PEU. The total relationships of PEU and PU with AU were 0.263 and 0.312. The impacts of these variables were transmitted indirectly, through the BI. About 58\% of the variance in BI could be explained by AT ($\beta = 0.354$, $p < 0.001$) and PU ($\beta = 0.467$, $p < 0.001$). Therefore, H4 and H5 were supported. The total relationships of AT with AU was 0.172, solely as a result its significant indirect relationship. Finally, BI had a significant positive relationship with AU ($\beta = 0.485$, $p < 0.001$). The proposed model accounted for 24\% of the variance in AU.

According to the path coefficient, the BI exhibited the strongest direct relationship (0.487) with AU. Additionally, PU, PEU and AT had also positive significant total relationships, but the impact of these variables were transmitted through BI, as the direct

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**Table 4: Actual use of learning objects**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Items</th>
<th>Frequency</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>On average, how much time do you spend on the learning objects weekly?</td>
<td>None</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>Less than 1 hour</td>
<td>12</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>1–2 hours</td>
<td>116</td>
<td>24.1</td>
</tr>
<tr>
<td></td>
<td>3–4 hours</td>
<td>123</td>
<td>25.6</td>
</tr>
<tr>
<td></td>
<td>4–5 hours</td>
<td>156</td>
<td>32.4</td>
</tr>
<tr>
<td></td>
<td>More than 5 hours</td>
<td>74</td>
<td>15.4</td>
</tr>
<tr>
<td>On average, how often do you use learning objects?</td>
<td>Not at all</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>About once a week</td>
<td>19</td>
<td>4.0</td>
</tr>
<tr>
<td></td>
<td>two to three times a week</td>
<td>81</td>
<td>16.8</td>
</tr>
<tr>
<td></td>
<td>four to six times a week</td>
<td>115</td>
<td>23.9</td>
</tr>
<tr>
<td></td>
<td>About once a day</td>
<td>183</td>
<td>38.0</td>
</tr>
<tr>
<td></td>
<td>More than once a day</td>
<td>83</td>
<td>17.3</td>
</tr>
<tr>
<td>On average, how many learning objects do you use every week?</td>
<td>None</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>Less than five learning objects a week</td>
<td>16</td>
<td>3.3</td>
</tr>
<tr>
<td></td>
<td>five to 10 learning objects a week</td>
<td>102</td>
<td>21.2</td>
</tr>
<tr>
<td></td>
<td>10 to 15 learning objects a week</td>
<td>154</td>
<td>32.0</td>
</tr>
<tr>
<td></td>
<td>15 to 20 learning objects a week</td>
<td>126</td>
<td>26.2</td>
</tr>
<tr>
<td></td>
<td>More than 20 learning objects a week</td>
<td>83</td>
<td>17.3</td>
</tr>
</tbody>
</table>

**Table 5: Descriptive statistics**

<table>
<thead>
<tr>
<th>Construct (# Items)</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived ease of use (six items)</td>
<td>4.929</td>
<td>1.144</td>
</tr>
<tr>
<td>Perceived usefulness (six items)</td>
<td>4.958</td>
<td>1.066</td>
</tr>
<tr>
<td>Attitude (four items)</td>
<td>5.052</td>
<td>1.121</td>
</tr>
<tr>
<td>Behavioural intention (three items)</td>
<td>4.815</td>
<td>1.032</td>
</tr>
<tr>
<td>Actual use (three items)</td>
<td>4.380</td>
<td>1.029</td>
</tr>
</tbody>
</table>

$p < 0.001$).
relationships of the use beliefs and AU were not statistically significant. Consistent with the previous results, BI to use appears to have a positive relationship with AU, a result that strongly supports H6.

The predicting variables of the four endogenous constructs and their direct, indirect and total relationships to the target endogenous construct were summarised in Table 6. In summary, the test results firmly supported the hypotheses derived from the TAM. In addition, the amount of variance explained ($r^2$) for each variable was medium to high, ranging from about 20 to 60%.

**Discussion, implications and limitations**

The study results clearly pointed out that the TAM appears to provide researchers a theoretically sound and parsimonious model which can be used to predict the users’ behavioural intention to use and subsequent actual use of learning objects after being introduced to them. In this study, learners evaluated and rated their use perceptions, attitudes and behavioural intentions to use after being introduced and followed by the use of learning objects as supplementary learning resources.

An individual’s attitude towards the use of the learning objects is significantly influenced by the individual’s perception about ease of use and usefulness. User perceptions of usefulness had even stronger influences on attitudes than user perceptions of the learning objects’ ease of use. Judged by its direct relationship with attitude and behavioural intention to use, perceived usefulness was found to be the most significant factor influencing users’ acceptance of learning objects. At the same time, behavioural intentions to use the learning objects is highly related to the attitude and perceived usefulness. As suggested by the TRA (Fishbein & Ajzen, 1975), an individual’s behavioural intention is the strongest predictor of future behaviour. Such was the case in this study, as learners’ intentions to use learning objects accurately predicted their actual use of the learning objects as supplementary learning resources.

The importance of the user perceptions and attitudes in influencing behavioural intention and actual use of learning objects have several implications for researchers and
Table 6: The direct, indirect, and total relationship of dominants on actual usage

<table>
<thead>
<tr>
<th>Direct relationship</th>
<th>Indirect relationship</th>
<th>Total relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PU</td>
<td>AT</td>
</tr>
<tr>
<td>PEU</td>
<td>0.672</td>
<td>0.314</td>
</tr>
<tr>
<td>PU</td>
<td>0.497</td>
<td>0.467</td>
</tr>
<tr>
<td>AT</td>
<td></td>
<td>0.354</td>
</tr>
<tr>
<td>BI</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

PU, perceived usefulness; AT, user’s attitude; BI, behavioural intentions; AU, actual use; PEU, perceived ease of use.
practitioners. First, the study model, TAM can be used as a cost-effective instrument to predict the future use of learning objects. It has the potential for practical application in the conceptual-design stages of learning objects, which provides instructional designers a practical tool for early use-acceptance testing by collecting data at various stages to forecast user acceptance as early as possible in the design and development lifecycle. Ultimately, with a series of user-acceptance tests performed early in the design stage, the risk of user rejection could be reduced and predictive measures could be taken to ensure future user acceptance. In short, the findings suggest that educators and instructional designers of learning objects should carefully consider the needs and values of learning-object users and ensure that the learning objects effectively meet their needs and demands. Such compatibility between learning objects and user needs has been found to enhance IT adoption in other contexts (Carswell & Venkatesh, 2002; Davis et al. 1989; Moore & Benbasat, 1991).

Second, according to the innovation-diffusion process theory outlined by Rogers (1995), adoption is not a momentary, one-time decision, but rather a stage-based process that can be studied, facilitated and supported (Leonard-Barton, 1988; Rogers, 1995). Potential adopters must first learn about the innovation and be persuaded to try it out before deciding to adopt or reject it. Persuasion has been shown to be one of the most important strategies for influencing beliefs and behaviour (Ajzen & Fishbein, 1980). In addition, empirical IS study suggests that training provides users with conceptual and procedural knowledge, which in turn influences perceived ease of use (Venkatesh & Davis, 1996), attitudes (Raymond, 1988) and usage (DeLone, 1988; Igbaria, Pavri & Huff, 1989; Kraemer, Danziger, Dunkle & King, 1993). As such, where feasible, educators should introduce and describe the benefits of learning objects and their relevance to the curriculum. Additionally, educators should demonstrate the use of learning objects more frequently to help learners form the initial positive beliefs and attitudes which in turn will positively influence the behavioural intention and actual use of learning objects.

Although the findings provide meaningful insights for learning-object context, the study has some limitations. The sample was fairly homogeneous in terms of age and of computer and Internet experience, but as different ethnic and culture groups are moving towards learning-object use, further generalisation could be achieved by examining more diverse users from different backgrounds in other degree programmes and at other universities. Second, this study was conducted with a snapshot research approach focused on public, free learning-object repositories, but a longitudinal approach at further intervals with learning objects from more specific institutional or disciplinary learning-object repositories would provide a better way of assessing the influence of beliefs and attitudes on the intention to use, and thus should be considered.

**Conclusion**

This study has validated the TAM in the context of the learning objects and has provided a further understanding into the users’ possible perceptions about learning...
objects. In predicting learning-object acceptability among higher education learners, it suggests that early user beliefs and attitudes have a very powerful influence on whether users will actually use learning objects in the future. Behavioural intention is a good predictor of future behaviour. User perceptions of usefulness had stronger influences on attitudes than user perceptions of the learning objects’ ease of use. Therefore, educators and instructional designers must consider not only the ease of use of learning objects, but also their usefulness, in order to promote and encourage end-user acceptance of learning objects. In future work, the intention is to investigate the antecedents of perceived usefulness and perceived ease of use of the TAM to gain a better understanding of factors that influence user intention to use learning objects and, further, to use a longitudinal study to investigate the extended TAM in a learning-object context to gain more insight about how learners’ beliefs and attitudes towards learning objects usage change over time as they experience learning objects usage first-hand.

References


**Appendix: Questionnaire**

**Perceived ease of use (PEU):**

PEU1 Learning to use learning objects would be easy for me.

PEU2 I would find it easy to get learning objects to do what I want it to do.

PEU3 My interaction with learning objects would be clear and understandable.

PEU4 I would find learning objects flexible to interact with.

PEU5 It would be easy for me to become skilful at using learning objects.

PEU6 I would find learning objects easy to use.

**Perceived usefulness (PU):**

PU1 Using learning objects would make it easier to learn course content.

PU2 Using learning objects would improve my learning performance.

PU3 Using learning objects would enhance my effectiveness in learning.

PU4 Using learning objects would increase my learning productivity.

PU5 Using learning objects would help me to accomplish learning tasks more quickly.

PU6 I would find learning objects useful in my learning.

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**Attitude toward use (AT):**

- **AT1** Using learning objects for learning would be a very good/very bad idea.
- **AT2** In my opinion it would be very desirable/very undesirable for me to use learning objects.
- **AT3** It would be much better/much worse for me to use learning objects.
- **AT4** I like/dislike the idea of using learning objects for learning.

**Behavioural intention to use (BI):**

- **BI1** I intend to use the learning objects whenever possible.
- **BI2** I intend to increase my use of the learning objects in the future for learning.
- **BI3** I would adopt the learning objects in the future.

**Actual use (AU):**

- **AU1** How frequently do you use learning objects?
- **AU2** How many times do you use learning objects during a week?
- **AU3** How many learning objects do you use every week?