This article was originally published in a journal published by Elsevier, and the attached copy is provided by Elsevier for the author’s benefit and for the benefit of the author’s institution, for non-commercial research and educational use including without limitation use in instruction at your institution, sending it to specific colleagues that you know, and providing a copy to your institution’s administrator.

All other uses, reproduction and distribution, including without limitation commercial reprints, selling or licensing copies or access, or posting on open internet sites, your personal or institution’s website or repository, are prohibited. For exceptions, permission may be sought for such use through Elsevier’s permissions site at:

http://www.elsevier.com/locate/permissionusematerial
The computer attributes for learning scale (CALS) among university students: Scale development and relationship with actual computer use for learning

Johan van Braak a,*, Penni Tearle b,1

a Department of Education, Ghent University, Henri Dunantlaan 2, 9000 Ghent, Belgium
b School of Education and Lifelong Learning, University of Exeter, UK

Available online 6 October 2006

Abstract

The purpose of this study was twofold. First to develop an instrument, the computer attributes for learning scale (CALS) for assessing how university students perceive the attributes of computer use for learning, and secondly to examine the predictive value of the CALS in relation to the actual use students made of a computer for learning. The research was based on innovation diffusion theory, and was set in the context of higher education in Flanders, the Dutch speaking part of Belgium. The first step in the development of the computer attributes for learning scale, was to draw on the literature to determine a set of attributes which could be used in relation to the use of computers for learning. Secondly, working with a stratified sample of university students (n = 237), exploratory factor analysis was used to develop a one-dimensional nine item-scale for measuring students’ perceptions towards these specified attributes of a computer for learning. Next, using another similar stratified sample of the same size, confirmatory factor analysis was used to assess the stability of the one-factor structure. Finally, having developed the instrument, the predictive value of the CALS was assessed by examination of the relationship of the CALS with actual computer use for learning, when controlling for related computer variables, including computer self-efficacy, perceived usefulness of computers and computer use for personal purposes. The CALS was found to have a significant predictive value in terms of computer use for learning. In view of this it is argued that the
CALS is an instrument which can be used in the future to assess the likely use students will make of a computer application in relation to their learning.

© 2006 Elsevier Ltd. All rights reserved.

Keywords: Computer use; Diffusion theory; Innovation; University students; Scale development

1. Introduction

This study sets out to develop an instrument for assessing how university students perceive the attributes of computer use for learning and then to examine the predictive value of this scale in relation to the actual use the students made of a computer in relation to their studies. The research is underpinned by innovation diffusion theory, and focuses on the use of perceived attributes of an innovation as a key variable in explaining and predicting the acceptance and utilisation of information technologies. This approach has been taken by a number of authors (e.g. Agarwal & Prasad, 1997; Greer & Murtaza, 2003; Lee, 2004) whose research was also situated within the domain of innovation diffusion theory, one of the many theories with its roots in social sciences which addresses the need to describe and understand human action.

Building on an initial study by Ryan and Gross (1943), cited in Surry and Farquahar (1997), Rogers (1995) work has underpinned and provided a theoretical basis for much of the research in the field of innovation diffusion. He defines diffusion as ‘the process by which an innovation is communicated through certain channels over time among members of a social system’ (Rogers, 1995, p. 5). Innovation diffusion then can be considered to be ‘the reasons why, and the process by which, an innovation is adopted by people in a specific setting or community. Innovation diffusion theory offers some insights into different aspects of this process.

Rogers (1995) identified and structured his work on four aspects of the diffusion of an innovation: the diffusion process, people’s individual characteristics which impact on their adoption of an innovation, people’s perceptions of the characteristics by which an innovation can be described, and the pattern of the changing rate of adoption of an innovation as it passes through different stages. Of these four elements, it is the third, which is often referred to as the ‘theory of perceived attributes’ (Surry & Farquahar, 1997) on which this study draws most directly. More recent work by Rogers (2003) continues to emphasise the importance of understanding the attributes of an innovation, since he asserts that perceptions towards these attributes have a significant impact on predicting future adoption of the particular innovation. Rogers (1995) identified five attributes of an innovation which he postulated impacted on its adoption: relative advantage, compatibility, complexity, trialability, observability. Descriptions of these attributes can be found in the original text (Rogers, 1995, p. 208).

Dearing and Meyer (1994), building on Rogers early work (Rogers, 1983), refer to these attributes as ‘innovation attributes’, and describe them as ‘the perceived characteristics of a new idea, process, or technology’ (Dearing & Meyer, 1994, p. 47). They proposed a set of eleven attributes which they postulated ‘profile’ an innovation and help to determine to what degree an innovation would be adopted. These attributes comprised four of those noted above from Rogers (1995) work; compatibility, complexity, trialability and compatibility, and a further seven:
• **Economic advantage:** the degree to which an innovation is communicated as being more cost effective than the one it supersedes.
• **Effectiveness:** the degree to which an innovation is communicated as being relatively more capable in achieving an idea state.
• **Reliability:** the degree to which an innovation is communicated as being consistent in its results.
• **Divisibility:** the degree to which an innovation is communicated as allowing incremental implementation of its components.
• **Applicability:** the degree to which an innovation is communicated as having more than one use in more than one context.
• **Commutuality:** the degree to which an innovation is communicated as exhibiting a complementary relationship with other innovations.
• **Radicalness:** the degree to which an innovation is communicated as being different from existing innovations (Dearing & Meyer, 1994, p. 46).

It will be noted that Dearing and Meyer describe each attribute in terms of the way it was communicated by the innovator. They found this to be an influential part of the adoption process. Given the nature of an innovation as something ‘new’, and hence when it is in the early, or ‘pre-diffusion’ stage; the users/potential adopters may have little or no prior experience to draw on. Rogers also noted the importance of first ‘learning about the innovation’ and then the need to ‘be persuaded as to the merits of it’ (Surry & Farquhar, 1997, p. 2). As the process continues however the user is better placed to (also) draw on their own perceptions of the attributes of an innovation, but the early communication remains influential. Most studies which examine the importance of the perceived attributes of the innovation do not focus on or specify how these perceptions were reached, they simply seek further understanding of possible association between perceived innovation attributes and adoption (Chew, Grant, & Tote, 2004; Oh, Ahn, & Kim, 2003). It is also noted that many ‘innovations’, including the introduction, adoption and implementation of technology into an organisation or workplace, are termed innovations, as from the organisational viewpoint and context, and from a collective consideration, they are indeed new. Individual adopters however may be quite familiar with the innovation focus in other settings and for other purposes. This is usually true of use of computers; something which is very commonplace for many people, but may still be the focus of an innovation in the workplace. This degree of familiarity with an innovation focus makes it possible and reasonable to ask participants directly about their perceptions of an innovation at an early stage of the process. This is the approach used in this research and has been adopted in the majority of studies focussing on the adoption of technology over recent years (e.g. Davis, Bagozzi, & Warshaw, 1989; Oh et al., 2003; van Braak, 2001; Wozney, Venkatesh, & Abrami, 2006).

Some of the studies in the field of technology adoption are firmly rooted within innovation diffusion theory, whilst others integrate theoretical insights from innovation diffusion theory with those from other theoretical streams, such as social and cognitive psychology. For example, Vishwanath and Goldhaber (2003) synthesise the psychological perspective from the Technology Acceptance Model (Davis et al., 1989) with innovation diffusion theory. Similarly, Oh et al. (2003) theorise innovation attributes as antecedents of attitudes toward technology, mediated through perceived ease of use and perceived usefulness; the two constructs at the heart of Davis and Bagozzi’s Technology Acceptance
Model. It is noted that these two constructs are not dissimilar to complexity (in the reverse sense; i.e. lack of complexity), and relative advantage which are identified in Rogers (1995) model of the diffusion of an innovation.

The work of Dearing and Meyer (1994) is particularly significant as until this time innovation theory had been used almost exclusively in a post hoc manner, to explain the adoption of an innovation which had already taken place. Theirs was one of the first studies to attempt to develop an instrument which was to be used prior to an innovation, and thus take on a predictive role. The ability to make an informed prediction about the likely adoption of any innovation is important for a number of reasons, not least of which is that having profiled the innovation through the identification of innovation attributes and gained a better understanding of the probable perception people have of them, it may be possible to influence and improve either the degree of adoption or adoption rate by making adaptations to the innovation strategy.

In the context of this study, computer use for learning, it is argued that the ability to make an informed prediction about the likely adoption of technology as a learning tool, is of particular importance. The adoption of technology, particularly in education settings, has been a challenge for many years. Although the potential of computer use for learning and teaching was noted as long ago as 1966 (Suppes, 1966), and has been regularly reported since that time (e.g. Heppell, 1999; Papert, 1981; Selwyn, 2001) this high expectation has still not been fully realised, particularly in higher education (Jacobsen, 2000). In the UK, and many other European countries, there has been Government intervention in the schools sector (Tearle & Davis, 1999), including funding for equipment (DfEE, 1997, 2000), training programmes for teachers (NOF, 1999), and statutory and non-statutory curriculum requirements for computer use (DfEE/QCA, 1999). This support, encouragement and ‘requirement’ to use computers for teaching and learning in schools did not include the higher education sector, (with the exception of education departments involved in teacher training). Consequently the use of computers in higher education is less clear and less well researched (Casmar & Peterson, 2002). It is suggested that while there are many examples of contexts in higher education where use of computers is well acknowledged and fully embedded into courses, their use is still ‘patchy’ in this sector and not well established (Jacobsen, 2000). As initiatives are put in place to extend and fully integrate computer use for teaching and learning more widely in higher education, it will be an important step forward if an instrument is available which can play a role in predicting, or indicating likely adoption patterns, and hence highlight areas for pre-emptive action.

In this context of computers and education, less attention has been given to the role of perceived innovation attributes in explaining why technology is, or is not, used. van Braak (2001) introduced the computer mediated communication (CMC) attribution matrix for teachers, an instrument that assesses the perceived characteristics of CMC. It hypothesised that the higher the perceived congruency between the attributes of CMC as an innovation and teachers’ familiar teaching practice, the more likely teachers were to make use of CMC. The perceived attributes of CMC were found to be strongly related to technological innovativeness and attitudes toward the use of CMC (van Braak, 2001). Martins, Steil, and Todesco (2004) used perceived attributes of the Internet to predict the adoption of the Internet as a teaching tool. They based their work on a theoretical model derived from Rogers (1995) theory of perceived attributes of an innovation, and found that in their South American based educational (school) context, observability and trialability were the two most significant influences. Tearle (2004) also noted the particular importance
of *observability* and in addition found the *compatibility* of the innovation with the existing characteristics and features of the setting was a key factor. Outside the field of education, Chew et al. (2004) looked at the adoption of Internet technologies by doctors, and confirmed that the innovation attributes identified by Rogers (1995) were indeed good predictors of adoption of the technology. They recognised a number of stages the innovation passed through during its adoption, and identified *observability* and *low complexity*, as important first steps in adoption. These in turn allowed the importance of *relative advantage*, *triaibility* and *compatibility* to be seen.

In addition to the characteristics of the innovation, many studies focussing on technology adoption raise issues sometimes referred to as ‘practical factors’, e.g. resourcing, training and support (Mumtaz, 2000; Tearle, 2003), which it is argued play an important role in determining adoption of the innovation in the case of technology in an educational context. These practical factors are usually considered to be a subset of what are referred to as ‘external factors’ in the Technology Acceptance Model (Davis et al., 1989). Whilst no real interpretation of the term, or consideration of how this impacts on take-up of computer use is provided in that study, other subsequent studies based on the TAM model explored these factors in more depth and found them to be very influential (Preston, Cox, & Cox, 2000; Tearle, 2003).

This current study is situated in the tradition of innovation diffusion studies that identify perceived characteristics of technology as a key concept in user acceptance and behaviour towards technology. The innovation target under investigation is the use of a computer as a tool that supports study-related and learning tasks. Characteristics of a domain specific application of computers, e.g. the use of computers for supporting learning will be identified and the psychometric qualities of the items and the scale will be assessed. In a further phase, the *perceived attributes* of computers for learning will be related to the *actual use* of a computer for learning purposes in order to examine the predicative value of the scale. To eliminate the effect of other student characteristics, the impact of the perceived attributes of a computer for learning on students’ actual computer use for learning will be controlled for computer self-efficacy, perceived usefulness of a computer and student use of a computer for personal purposes.

### 2. Method

Based on prior studies (Dearing & Meyer, 1994; Rogers, 1995; van Braak, 2001; van Braak & Goeman, 2003), and taking into account the nature of the innovation as the adoption of computer use for learning and the specific higher education context, an item set on which to base the CALS was constructed. This led to the selection of nine different attributes with relevance to the context of higher education learning: relative advantage, effectiveness, observability, preferability, applicability, flexibility, economic advantage, specificity and necessity. Table 1 provides the interpretation of these items as used in this context, i.e. the item content.

Two of these attributes are taken directly from the five identified by Rogers (1995); relative advantage and observability. Three were adapted from Dearing and Meyer (1994): economic advantage, effectiveness, and applicability and two were adapted from van Braak (2001): flexibility and necessity. The final two items, preferability and specificity, have not been used under these particular ‘labels’ previously, but were derived from the outcomes of van Braak and Goeman’s (2003) study into perceived attributes of computers.
for professional purposes. Taken collectively, these nine items comprised those which in the various studies van Braak has undertaken in this field (van Braak, 2001; van Braak & Goeman, 2003), emerged as likely to be influential in this context of technology adoption in an educational context.

It is hypothesised in this research that all nine of the specified perceived attributes of using a computer for learning are interrelated. If this is the case, the item scores can be summarised into a scale score, which would indicate an individual’s overall perception of the attributes of using a computer for learning.

2.1. Participants and data collection

A sample of 500 students in a middle-sized, Dutch speaking university in Flanders (Belgium) was drawn. This was a representative sample which consisted of students within human sciences faculties (psychology and education, economics and social sciences, philosophy and arts, and law) and exact sciences (mathematics, natural sciences and applied sciences). All study programmes and all years of study were included (undergraduate, master and PhD students). The sample was stratified based on gender, faculty, study program, and study year. All students were contacted individually to assure a maximum response rate.

A questionnaire was used to collect the data. It comprised questions relating to the computer attribute items, i.e. what may be described as the ‘CALS items’ (see Table 1), student background variables (gender, age, faculty, study program, year of study) and computer related variables (computer use for learning, personal computer use, perceived usefulness of computers and computer self-efficacy). A paper version of the questionnaire was used and administered anonymously.

2.2. Procedures and data analysis

In order to test the psychometric qualities of the computer attributes for learning items, the student questionnaire responses were randomly divided into two equally sized sub-samples. Both sub-samples were equally matched based on age, gender, study year, faculty and study programme. Data from the first sub-sample \( n = 237 \) were subjected to an exploratory factor analysis (EFA) on the nine computer attribute items noted in Table 1. EFA was performed using the Maximum Likelihood method (Finch & West, 1997; Loehlin, 1992). Three methods were used to determine the number of factors to
retain: the K1-criterion (Kaiser, 1960), scree plot evidence (Cattell, 1966), and parallel analysis (O’Connor, 2000; Reise, Waller, & Comrey, 2000). In a parallel analysis, random data sets were generated on the basis of the same number of items and subjects as in the real data matrix. The scree plot of the eigenvalues from the real data was compared with the scree plot of the eigenvalues from the random data. The point where the two plots meet suggests the absolute maximum number of factors that should be extracted (Reise et al., 2000).

Data from the second sub-sample \( (n = 237) \) were used to verify the identified factor structure using confirmatory factor analysis. Statistical procedures for the confirmatory factor analysis were conducted using the AMOS 5.0 programme (Arbuckle, 2003; Arbuckle & Wothke, 1999). CFA models were tested using maximum likelihood estimates. Several fit indices were calculated to provide information on the adequacy of the fitted model: \( \chi^2 \), root mean square error of approximation (RMSEA), where a cutoff value close to 0.06 is needed before a relatively good fit can be concluded (Hu & Bentler, 1999). Brown and Cudeck (1993) however evaluated that values of RMSEA in the range from 0.05 to 0.08 indicate fair fit. Goodness of fit index (GFI), the adjusted goodness of fit index (AGFI) (Jöreskog & Sörbom, 1993), the normed fit index (NFI) and the comparative fit index (CFI) (Bentler, 1990). GFI, AGFI, NFI and CFI should each be above 0.90 to indicate adequate fit.

In a third phase, correlation analysis was used to assess relationships between CALS, computer use for learning and other variables that might predict computer use for learning, i.e. personal computer use, computer usefulness, and computer self-efficacy. Pearson correlations were also calculated to examine possible multicollinearity among the predictor variables. Next hierarchical regression analysis was used to examine the predictive value of the new CALS measure when correcting for the effect of other computer related variables. In a first step, personal computer use, computer usefulness and computer self-efficacy were entered in the model to predict the amount of computer use for learning. In a second step, the CALS measure was added to determine if the variable added significantly to the variance accounted for in the first model. For both the correlation and hierarchical analyses, a combination of both sub-samples \( (N = 454) \) is used.

2.3. Measures

Questions addressing the nine CALS items were rated on a five point Likert scale, ranging from ‘strongly disagree’ (0) to ‘strongly agree’ (4). Data on the quality of the computer related variables and descriptive results are presented in the results section.

2.3.1. Computer use for learning

The CALS, an attribute scale comprising the nine attributes listed in Table 1, was expected to be strongly related to the actual use of computers for learning; and the questionnaire sought to measure the actual use students made of computers for learning. Students from the different study programmes were asked about the amount of time they spend using a computer to support their own learning. The responses indicated that they used the computers for an average of 8.5 h a week \( (SD = 10.5) \). Significant differences were noticed between the different study programs. The highest use of computers for learning was by those in the faculty of science \( (n = 57, M = 12.6, SD = 13.8) \), whilst students in the faculty of medicine \( (n = 55) \) make the least use of computers to support their learning \( (M = 6.6, SD = 10.3) \).
2.3.2. Personal computer use

The time for personal computer use is expressed as the amount of hours students spend using a computer for a range of purposes (gaming, leisure activities, etc.). Students reported that they used the computer on average for 6.2 h a week (SD = 6.7). Again, this use of computers for purposes other than learning seems to be strongly related to faculty. Students in the faculty of sciences use computers the most for free time activities (n = 57, M = 9.2, SD = 6.8), whilst students in the faculty of medicine report the lowest degree of computer use for reasons other than learning (n = 54, M = 3.8, SD = 3.9). The Pearson product-moment correlation between computer use for learning and personal computer use was weak (r = .14, p < 0.01).

2.3.3. Usefulness of computers

The perceived usefulness of computers is an important variable in the Technology Acceptance Model (Davis et al., 1989) and seems to be an essential characteristic in understanding why people do, or do not, adopt computers. In view of this, Loyd and Gressard’s (1984) perceived computer usefulness scale was used to investigate the relationship with the computer attributes measure for learning under investigation in this research. All items were measured using a five point Likert scale varying from (0) ‘totally disagree’ to (4) ‘totally agree’. Eight of the ten original items were included in the questionnaire. Two items “Learning about computers is worthwhile” and “Anything that a computer can be used for, I can do just as well some other way” were not included because it was believed in this context all respondents would (strongly) (dis)agree with both items. In order to examine the psychometric quality of Loyd and Gressard’s instrument relating to the perceived usefulness of a computer, a confirmatory factor analysis was performed on the eight items. Two more items were removed before doing further analysis; “I can’t think of any way that I will use computers in my career” and “Learning about computers is a waste of time”. This was done for two reasons. First, these items showed high values for both skewness and kurtosis, an outcome which can be explained by the fact that students nowadays are convinced about the overall value of computers in society and hence tended to (strongly) agree with both statements. Over 90% of all respondents (totally) disagree on both items, indicating too low a variability among the respondents. Second, both items had low factor coefficients (<.32) on a one factor solution. Internal consistency for the remaining six items measured by Cronbach’s alpha (Cronbach, 1951) was α = .69, indicating fair reliability. The remaining six items are:

(i) I’ll need a firm mastery of computers for my future work.
(ii) Knowing how to work with computers will increase my job possibilities.
(iii) It is important to me to do well in computer classes.
(iv) Working with computers will be important to me in my future work.
(v) I will use computers in many ways in the future.
(vi) I expect to have little use for computers in my daily life.

2.3.4. Computer self-efficacy

Self-efficacy theory emerged as a part of social cognitive research. Perceived self-efficacy beliefs refer to ones capabilities to organise and execute the courses required to produce given attainments (Bandura, 1997). Efficacy beliefs influence how people feel,
think, motivate themselves, and behave (Bandura, 1993; Bandura, 1997). Computer self-efficacy can be defined as a part of self-perceived efficacy beliefs and refers to a set of beliefs a person has about their ability to perform with computers. It is not concerned with what one has done in the past, but rather with judgements of what could be done in the future (Compeau & Higgins, 1995). Barbeite and Weiss (2004) noted that participants with little confidence in their ability to use computers performed less well on computer-based tasks.

In this current study, the 10-item instrument of Compeau and Higgins (1995) was used to assess students’ degree of computer self-efficacy. The original instrument contained items on a 10-point scale, ranging from ‘not at all confident’ to ‘totally confident’. In this study, a 5-point scale was used instead, ranging from (0) not at all confident to (4) totally confident. In the original study (Compeau & Higgins, 1995), a high internal consistency of $\alpha = .95$ was found for the computer self-efficacy scale. In this study the internal consistency, also measured using Cronbach’s alpha, was similarly high ($\alpha = .90$).

3. Results

Four hundred and seventy four participants (94.8%) returned a completed questionnaire, with those who did not, mainly citing time constraints as their reason for not doing so. The sample consisted of 55.0% female and 45.0% male students and they had an average age of 22.6 years (SD = 4.9).

3.1. Item characteristics (sub-sample 1 and sub-sample 2)

Descriptive statistics comprising percentages, mean, standard deviation, skewness and kurtosis of the nine perceived attributes of computers for learning are presented in Table 2. Respondents rated all attributes on a 5-point scale, ranging from 0 = totally disagree to 4 = totally agree.

For all items, skewness and kurtosis values were within the $-1$ and $+1$ interval, indicating a good distribution of scores and allowing Maximum Likelihood estimation in the factor analysis (Finch & West, 1997).

Table 2
Descriptive statistics for the nine perceived attributes of computers for learning

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S1</td>
<td>S2</td>
<td>S1</td>
<td>S2</td>
</tr>
<tr>
<td>Relative advantage</td>
<td>2.8</td>
<td>2.8</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Effectiveness</td>
<td>2.7</td>
<td>2.7</td>
<td>0.9</td>
<td>1.0</td>
</tr>
<tr>
<td>Observability</td>
<td>2.3</td>
<td>2.3</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Preferability</td>
<td>3.0</td>
<td>3.1</td>
<td>1.0</td>
<td>0.9</td>
</tr>
<tr>
<td>Applicability</td>
<td>3.0</td>
<td>3.0</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>Flexibility</td>
<td>2.7</td>
<td>2.7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Economic advantage</td>
<td>2.9</td>
<td>3.0</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Specificity</td>
<td>3.0</td>
<td>3.0</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Necessity</td>
<td>2.8</td>
<td>2.9</td>
<td>1.1</td>
<td>1.1</td>
</tr>
</tbody>
</table>

Note: S1 = Sub-sample 1 ($n = 237$); S2 = Sub-sample 2 ($n = 237$).
3.2. Exploratory factor analysis

The data from sub-sample one were analysed using exploratory factor analysis (EFA) to determine the number of factors underlying the nine perceived computer attributes items. When conducting the exploratory factor analysis on the nine computer attributes for learning, the initial solution revealed only one factor with an eigenvalue greater than 1 (eigenvalue = 5.4, explaining 55.6% of the variance). The second highest eigenvalue was 0.8. Based on the commonly used K1 (Kaiser–Guttman) criterion, only one factor should be retained, but in view of concern that the K1-rule can sometimes lead to the retention of too few factors, alternative methods were also used, including a scree plot. The scree plot evidence also suggested a one-factor solution, since only one factor fell above the straight line. The scree plot is shown in Fig. 1 as a dotted line.

![Scree plot](image)

**Fig. 1.** Scree plot and parallel analysis evidence for the nine perceived attributes of computers for learning \((n = 237)\).

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative advantage: whether the computer improves the quality of learning</td>
<td>.76</td>
</tr>
<tr>
<td>Effectiveness: whether learning with the computer supports reaching goals</td>
<td>.72</td>
</tr>
<tr>
<td>Observability: perceptions about others seeing positive results when the computer is used</td>
<td>.49</td>
</tr>
<tr>
<td>Preferability: whether using a computer for learning is better than not using a computer</td>
<td>.80</td>
</tr>
<tr>
<td>Applicability: whether the use of a computer for learning serves different goals</td>
<td>.68</td>
</tr>
<tr>
<td>Flexibility: whether the computer allows more flexibility in learning</td>
<td>.75</td>
</tr>
<tr>
<td>Economic advantage: whether investing in computers for learning is worth the cost</td>
<td>.82</td>
</tr>
<tr>
<td>Specificity: whether using a computer for learning means goals can be reached which otherwise could not be reached</td>
<td>.81</td>
</tr>
<tr>
<td>Necessity: whether computer use for learning is a necessity</td>
<td>.80</td>
</tr>
</tbody>
</table>
The scree plot evidence in Fig. 1 was augmented by adding the results of a parallel analysis. As can be seen in Fig. 1, results from the parallel analysis with the 95th percentile as the comparison baseline also clearly suggested extracting one factor.

Results of the factor extraction are presented in Table 3. All computer attribute items revealed high loadings on the one-factor structure. Factor coefficients varied between .49 and .82.

The high correlation among the variables indicates it is appropriate to summarise the item scores into a scale score, labelled the computer attributes for learning scale (CALS).

3.3. Confirmatory factor analysis

Confirmatory factor analysis (CFA) was used on the second sub-sample to verify the stability of the factor structure found in the first sample. The results of the confirmatory factor analysis, showing the pattern coefficient for each attribute are presented in Fig. 2. The results show a good fit of the suggested structure obtained from the first sample and the observed data from the second sample. As can be seen in Fig. 2, each computer attribute item has a substantial loading on the latent CALS factor. No error terms were allowed to be correlated. All pattern coefficients were between 0.45 and 0.79 and all were statistically different from zero at the .001 level. The goodness of fit estimates were $\chi^2 = 51.6$, ($p = .003$, df = 27), GFI = .95, AGFI = .92, CFI = .98, NFI = .95, and RMSEA = .063.

![Diagram of factor analysis](image-url)
To improve the interpretation of the scores, scale values have been transformed into a theoretical minimum value of 0 and a maximum value of 100. Scale means are $M = 69.9$ (SD = 18.2) for the first sub-sample and $M = 70.6$ (SD = 17.0) for the second.

3.4. Scale characteristics

The next estimate of the psychometric quality of the computer attributes scale is the internal consistency (Cronbach, 1951), measured with Cronbach’s alpha coefficient. High item-scale correlations were found, ranging between .48 and .78 (sub-sample 1) and between .43 and .74 (sub-sample 2), with a high general internal consistency of $\alpha = .92$ (sub-sample 1) and $\alpha = .90$ (sub-sample 2). Internal consistency for the whole sample is $\alpha = .91$.

3.5. Predictive value of the CALS

The analysis above has revealed the psychometric qualities of the CALS, but ultimately it is imperative to determine the relationship of the CALS with the actual use of computers for learning, when controlling for other computer related variables.

First, an overview of all bivariate interrelationships among the variables is presented in Table 4.

These results suggest that there is a strong association between computer use for learning and CALS ($r = .41$). The association between computer use for learning and the other possible computer related predictors of computer use for learning is less significant: personal computer use ($r = .14$), computer usefulness ($r = .18$), and computer self-efficacy ($r = .18$). The strongest relationship among the predictor variables is between CALS and computer usefulness ($r = .40$). It is important to note that these correlation coefficients only reveal bivariate relationships among variables.

In Table 5, the results of the hierarchical regression model are presented. Step 1 accounted for 5% of the variance in computer use for learning entering personal computer use, computer usefulness, and computer self-efficacy. All four predictors had a significant impact on the dependent computer use for learning variable. Another 12% of the variance in computer use for learning was accounted for when adding CALS in step 2. The effect of CALS on computer use for learning is strongly significant ($\beta = .39$). The effect of the other computer related variables becomes non-significant when entering CALS into the model, except for personal computer use, although the strength of association is weak ($\beta = .11$).

Table 4
Pearson’s product moment correlation coefficients among the research variables ($N = 474$)

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Computer use for learning</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 CALS</td>
<td>.41***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Personal computer use</td>
<td>.14*</td>
<td>.06</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Computer usefulness</td>
<td>.18**</td>
<td>.40***</td>
<td>.11*</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5 Computer self-efficacy</td>
<td>.18**</td>
<td>.29**</td>
<td>.23**</td>
<td>.20**</td>
<td>1.00</td>
</tr>
</tbody>
</table>

* $p < .05$.
** $p < .01$.
*** $p < .001$. 
The effect of computer usefulness and computer self-efficacy completely disappears when controlling for CALS, indicating that CALS has a stronger association with computer use for learning compared to the other variables.

4. Discussion and conclusion

Initially, to inform the development of the CALS, it was necessary to identify the appropriate attributes to include on the scale which previous research suggested were most likely to influence the adoption of technology. This selection was based on the outcomes of prior research and then the selected attributes were critically examined, in particular by considering the inter-relationship of the attributes. Firstly, the different attributes were singled out in order to ensure the influences each may have were incorporated into the final instrument. Secondly, an exploratory factor analysis was performed; a process which revealed that all the attributes displayed high loadings on a one factor structure. Thirdly, a confirmatory factor analysis was run on a second sample (of similar structure and with the same number of participants) in order to test the hypothesis of the underlying one dimensionality found in the first sample, which could be accepted. It was interesting to note that although its factor coefficient was significant, the attribute observability had a noticeably lower influence in comparison to any of the other eight attributes, at least in terms of shared variance with the underlying factor. In many other studies (Chew et al., 2004; Martins et al., 2004; Tearle, 2004) it proved to be one of the most important innovation attributes, so this outcome is worth further reflection in any future study. Observability is the one attribute which has been interpreted in many different ways in previous work on the diffusion of innovations. In Rogers’ (1995) original work the emphasis was on the benefit to the adopter when he asked the question: “I am more likely to use the computer for learning if I can see positive results when others have done this”. It would therefore be interesting to review the phrasing of the question used in this study (“if I use the computer for learning, others can see the positive results”) to see if the outcomes were similar.

Although the internal validity and psychometric qualities of the CALS was shown to be good, it was noted that not all common innovation attributes were included in the measure, and in any further development of the scale it might be interesting to consider attri-

Table 5
Summary of hierarchical regression analyses for variables predicting computer use for learning (N = 474)

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal computer use</td>
<td>0.15</td>
<td>0.07</td>
<td>.10**</td>
</tr>
<tr>
<td>Computer usefulness</td>
<td>0.11</td>
<td>0.04</td>
<td>.14**</td>
</tr>
<tr>
<td>Computer self-efficacy</td>
<td>0.08</td>
<td>0.03</td>
<td>.13**</td>
</tr>
<tr>
<td>CALS</td>
<td>0.23</td>
<td>0.03</td>
<td>.39***</td>
</tr>
</tbody>
</table>

Note: $R^2 = .05$ for Step 1; $\Delta R^2 = .12$ for Step 2.
* $p < .05$.
** $p < .01$.
*** $p < .001$. 

The effect of computer usefulness and computer self-efficacy completely disappears when controlling for CALS, indicating that CALS has a stronger association with computer use for learning compared to the other variables.
butes such as trialability and complexity, both of which have proved relevant in prior research (Chew et al., 2004; Martins et al., 2004). In this study they were not included as in a prior study van Braak (2001), found these attributes showed a lack of interrelationship with other the other attributes.

The appropriateness of the nine item CALS developed for this study however received further endorsement when the confirmatory factor analysis using the data from sample two showed a good fit with this structure. Observability again was the attribute which could be singled out in that its pattern coefficient was statistically significant, but noticeably lower than those of the other attributes.

Having established the psychometric quality of the CALS, the focus shifted to its predictive value. The sensitive issue of recognising that it is association between the CALS and actual computer use for learning which was established as opposed to cause and effect is important to note if CALS is to be used in a predictive mode, since the instrument was developed on post hoc evidence. Since the work of Dearing and Meyer (1994), a number of studies have adopted a similar approach, each sharing one key characteristic; the importance of consideration of the attributes associated with the specific innovation under discussion. This is quite distinct from parallel studies (Marcinkiewicz, 1993; Vannatta & Fordham, 2004) which have focused more on the characteristics of the individual users/adopters, in terms of their beliefs and dispositions. This study with its focus on innovation attributes, adds strength to the growing arguments which suggest that post hoc evidence can contribute to assessing the predictive ability of an instrument. Having devised the CALS and shown it to have ‘predictive value’ it is felt that the natural progression from here is to assess how it can be used in an a priori capacity in future research to predict the likely use students will make of a computer for learning. For example the CALS could be administered at the beginning of the term and used to assess likely student participation rates in activities organised by the university which include computer use for learning.

In this research it is argued that perceptions of computer attributes have a stronger impact on computer use for learning than the impact of related behaviours (e.g. the personal use of computers). It is accepted that there is an undisputed relationship between both variables, but here it is argued that domain specific perceptions seem to be a stronger antecedent of a domain specific computer use, compared to the effect of computer related behaviour. There has been discussion regarding perceptions about attributes of an innovation (e.g. the use of computers to support learning), and that these perceptions contain a certain behavioural component, a certain familiarity, as attitudes do (“I like working with computers”). The stronger the behavioural overlap between the predictor and the dependent variable, the more likely it will be to find a high degree of shared variance. The latter does not however imply that attitudes and behaviour are similar constructs, or that attitudes cannot be viewed as strong determinants of behaviour.

In this study, when gathering data to assess each of the nine attributes in the CALS, a single item was used. It is believed further work in this area would be appropriate in order to consider whether a single item question is sufficient and is the most appropriate way of assessing each of the attributes. It is noted for example by Rogers (2003) that whilst he encourages researchers to devise for themselves a set of scale items to assess innovation attributes so they are specific to their context, he also draws attention to the work of Moore and Benbasat (1991). They initially proposed a set of 75 items to assess the innovation attributes for their context, and in a series of tests reduced this to 28. Whilst just
two of the nine attributes used in this study were from those identified by Rogers (1995), the principle of how each is assessed, noted by Moore and Benbasat, is relevant and suggests that further reflection on how each of the current attributes should be assessed is appropriate, and can be guided by previous research.

As noted in the introduction, it is important to recognise that nowadays that the use of computers for learning is unlikely to be an absolute novelty, and that students such as those involved in this study are likely to have some experience of the use of computer to support their learning. In this case, as first year students (although in various different programs of study) they could be considered to still be in an initial adoption phase in relation to the use of a computer in this particular setting.

A final point to note is that the CALS focuses on adopters’ perceptions of the use of computers for learning, i.e. the innovation attributes, and not the practical, or other external factors noted earlier (e.g. Mumtaz, 2000; Tearle, 2003), which many studies have shown to be influential with regard to the adoption of technology. In this research, there is recognition that factors which may traditionally be termed as ‘external’ play a part in influencing the adoption of technology, but it is felt many of these can also be described as contextual factors. As the context for this research was a single site (one university), contextual factors were the same (or very similar) for all participants, so it was people’s perceptions which were important to understand. Some of these perceptions however will be influenced by the individual’s own construction of the context or the contextual factors, so it could be argued that contextual factors are socially constructed and hence are taken into consideration, being integral to the proposed instrument. It is recognised that consideration of ‘external factors’ remains important when considering adoption of computer use, and warrant further research.

This study adds to the literature in two respects. Firstly through the development of the CALS, an instrument to describe the perception of students towards the characteristics of computer use for learning, and secondly through its examination of the predictive value of the new instrument. The CALS is therefore offered as an instrument to play the important role of assessing perceptions towards computer use for learning which takes into account individual constructions of the contextual factors through its focus on assessing perceptions of innovation attributes. It is anticipated that further development of the instrument as well as field testing it in different contexts will contribute to our understanding of technology adoption in education, and perhaps in wider settings.

References


Tearle, P., & Davis, N. (1999). *Core curriculum: Telematics for teacher training (T3)*. EC T3 project deliverable no.15.2.2. Exeter: T3 and University of Exeter (62pp.).