

ADOPTION AND EFFECTIVENESS OF VIRTUAL-LEARNING ENVIRONMENTS IN CHILEAN TEACHERS

ADOPCIÓN Y EFECTIVIDAD DE UN ENTORNO VIRTUAL DE APRENDIZAJE EN PROFESORES CHILENOS

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ABSTRACT

Objective: To evaluate an integrated model of adoption and effectiveness of virtual learning environments, which includes attitudinal and behavioral variables. **Method:** Quantitative cross-sectional study of two stages. The information was collected through a series of scales and questionnaires applied online to the 168 participants, all of them professing professors, from different cities of Chile, who participated in a 5-week e-learning course. **Results:** Although it is feasible to integrate the processes of adoption and effectiveness of the use of technologies in a learning context, it was found that the variables that explain the intention to adopt learning environments are not related to the actual use of such environments or to the effectiveness of these. On the other hand, behavioral programming related to the use of the environment does relate to its actual use and indirectly measures its effectiveness. A simpler comprehensive model is proposed. **Conclusion:** Although it is possible to integrate attitudinal and behavioral variables to understand the process of adoption and effectiveness of virtual learning environments in adults, it is necessary to broaden their theoretical conceptualization, so the inclusion of motivational variables in this model should be considered.

KEY WORDS: Virtual-learning environments, technology adoption, learning technology, learning effectiveness, e-learning.

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Virtual learning environments (VLE) have frequently been used as a complement to or a substitute for traditional face-to-face lessons, mainly due to advantages such as easier and flexible access (Lee, Cheung, & Chen, 2005), reduced delivery cycle and lower costs (Saade & Bahli, 2005; Welsh, Wanberg, Brown, & Simmering, 2003), and better self-perception of learning (Alavi, Yoo, & Vogel, 1997). VLE can support a wide range of settings and stimuli presentations, having the potential to satisfy multiple requirements related to the goals and conditions of learning. However, the usage of learning technology in the middle and long-term has been accompanied by low levels of user satisfaction (Levy, 2007; Roca, Chiu, & Martínez, 2006), and low acceptance of the design (Reiser, 1994; Sitzmann, Kraiger, Stewart, & Wisher, 2006), producing a low effectiveness due to drop-out and/or underuse of the learning settings. On this scenario, with an increasing demand for developing and implementing learning technology on all levels of the educational system, the main challenges seem to be: 1) the understanding of variables involved in the adoption of and the engagement with learning technologies, and 2) how they are related to the effectiveness on the learning process.

The present study takes a novel perspective in exploring the integration between the adoption of learning technology and the effectiveness of the learning process. The approach explores new variables - and relationships between them - to more traditional approaches that seem to be struggling to explain and prevent dropouts and the low learning outcomes that faces a great number of virtual learning environments. It is expected to find - as is suggested by the literature - support for a link between the variables related to adoption of technology and those linked to learning effectiveness in virtual environments, as a single process that starts with the introduction of an individual to a VLE, and finalizes with the achievement of a learning output.

Adoption of technology

A wealth of the literature on technology adoption is based on individual attitudes and perceptions that shape people's approach towards technology, resulting on higher or lower chances of using it. One perspective that has been much developed and utilised over the last two decades is known as "Technology Acceptance Model" [TAM] (Davis, 1989). This model states that the perceived usefulness and the perceived ease of use of a given technology can predict an individual's intention of using it. Davis' TAM is derived from two broader theoretical frameworks. The first one is Bandura's theory of social learning (1977), which states that motivation and action are affected by personal attributions about self-efficacy, by self-regulation processes, and by behavioural and environmental factors. Bandura set the main frame to attempting understand what drives people's behaviour. The second framework comprises Ajzen's Theory of Reasoned Action (TRA) (1977) and Ajzen's Theory of Planned Behaviour (TPB) (1985). TRA states that individual's behavioural intention rests on an individual's attitude about the behaviour and the subjective norms - or social environment. Ajzen (1985) developed his idea further, proposing that people's behaviour is guided by their attitudes and belief towards the behaviour, and by their expectancies - positive or negative - about the consequences of the behaviour. Despite initial behavioural intentions, many users might fail to translate these intentions into actions, resulting in a mismatch between what is declared and what is done. While research (King & He, 2006; Sumak et al., 2011; Turner, Kitchenham, Brereton, Charters & Budgen, 2010) has found that intention of use is a good predictor of actual use, most of that literature might be considered as "short term adoption": the evaluation of usage of technology a few days or weeks after the assessment of behavioural intentions.

In terms of adoption of new technology, TAM identifies people's expectations about its usefulness and ease of use as predictors of their intention to use it and their actual use. A large amount of research has tested and/or modified Davis' model. Meta-analyses are broadly supportive of the original model (King & He, 2006; Schepers & Wetzels, 2007; Sumak, Hericko & Pusnik, 2011), while other studies include variables that might extend the left-hand side of the model – called “antecedent variables” – such as attitudes (Chang & Tung, 2008; Drennan, Kennedy, & Pisarski, 2005), cognitions (Lau & Woods, 2009; Saade & Bahli, 2005), or emotional states (Rezaei, Mohammadi, Asadi & Kalantary, 2008; Saade & Kira, 2007). Nonetheless, the core of the model, comprising perceived usefulness, perceived ease of use, and intention of/actual use as outcome variables remains strongly supported by the data. However, TAM is not enough to explain the high rates of dropouts observed on e-learning programs (Levy, 2007) or - more recently - on massive open online courses (MOOC), up to 90% (Rivard, 2013; Yang, Sinha, Adamson, & Rosé, 2013).

Since this study focuses on teachers use of learning technology for their own learning, it was assessed the influence of subjects previous experience with computers, which has been linked with demographic characteristics such age, gender, and educational level, but also with individual behaviours such as frequency of use, information processing, and performance (OECD, 2011; Pedersen, 2005; Zayim, Yildirim & Saka, 2006). The individual's previous experience with computers might influence their attitudes and cognitive skills, both of them core pieces of the learning process supported by computer-technology. The attitudes of a learner can be shaped by their positive or negative evaluations of previous interactions with learning technology - or technology in general - making them more or less keen to use a given virtual learning environment. On the other hand, cognitive skills or strategies can

be related to certain ways of using technology or behavioural regulation, making users more or less effective in achieving learning goals. Overall, previous experience with technology might explain how an individual's history of interactions with the technology influences his or her attitudes and behaviour.

Other variables could influence technology adoption at the medium and long term, such as the selected instructional design of the VLE (Penny, 2011), or the satisfaction with it Lee (2010). The present study focuses on the overall satisfaction with the course and the perceived instrumentality of the course as determinants of continued use of learning technology, together with its relationship with achievement of the learning goals.

Effectiveness of computer-based instruction

The complexity of assessing learning effectiveness starts with the very definition of the concept, which may include a large number of pedagogical, economic, and social factors (Halachev, 2009). Because a shared theoretical framework is lacking, researchers tend to use a diverse range of effectiveness measurements. Some commonly utilised assessments of effectiveness include objective measures of student performance (Kekkonen-Moneta & Moneta, 2002; Lim, Lee & Nam, 2007; Stonebraker & Hazeltine, 2004); the student's self-perception of learning (Buzetto-More & Mitchell, 2009), or a combination of multiple subjective and objective factors (Bhuasiri, Xaymoungkhoun, Zo, Rho & Ciganek, 2012; Johnson, Hornik & Salas, 2008). Such divergence makes it difficult to directly compare studies, or obtaining strong evidence of the effectiveness of a particular virtual learning environment (OECD, 2011; Sitzmann et al., 2006). Nevertheless, a group of four variables has been identified through the literature, and will be utilised by this study. The first of them is “satisfaction with the course”, a measure of how positive or negative is the overall perception about the content and format of the course (Johnson et

al., 2008); “actual use” will indicate the time and frequency which learners were dedicated to the contents and activities of the course; “final mark” will refer to the score obtained by the student in the course, according to standard, accepting the frequently discussed perspective that the mark corresponds to a determined level of knowledge, or at least, to the achievement of predefined observable learning outputs ; finally, “self-perceived learning” is the evaluation from the learner’s perspective of the extent to which they achieved their learning goals through the course.

The proposed model to assess effectiveness takes the final mark obtained by the student as the output (dependent) variable. Actual use is taken a basic condition of success on the context of computer-based instruction and will be considered as a predictor of effectiveness. In the same way, satisfaction with the course and self-perceived learning are included as predictors, given their effect in behavioural regulation.

Research questions and hypotheses

The main objective of the present research is to assess the relationship among the variables involved in the adoption of a VLE and those related to the effectiveness of it. Specifically, three issues will be explored. First, we examine the best predictors of intention of use and actual use within the VLE, in order to improve the way VLEs are designed or adapted for distinct audiences, so as to enhance engagement and reduce dropout. Second, we investigate the interactions between behavioural and attitudinal variables in the achievement of learning goals. Third we examine the linkage between the technology adoption process and the learning process, in order to advance towards an integrated framework that might be useful for practitioners from different disciplines entailed on the design and/or implementation of computer-supported learning programs.

To address these goals, I selected a set of variables that might predict the adoption of an e-learning environment, the engagement with it, and the final marks of the student (as an indicator of learning effectiveness). Mediations and moderations were explored to better understand the interaction among them. Hypothesis are the follow: 1) the scores on perceived usefulness, perceived ease of use, and previous computer usage will be directly related to intention of using the e-learning platform; 2) the scores on perceived usefulness, perceived ease of use, previous computer usage, and intention of use will be positively related to behavioural planning; 3) intention of use and behavioural planning will be directly related to scores on satisfaction with the course, actual use, and self-perception of learning; 4) actual use, satisfaction with the course, and self-perception of learning will be directly related to students final mark; and 5) satisfaction with the course learning will have a positive effect on actual use.

METHOD

Participants

Participants were 168 volunteers, all of them teachers from primary- and secondary-level schools in Chile which were enrolled in a five-weeks e-learning course on teaching methods suitable for practitioners of all backgrounds. 37 of them (22%) were male and their ages ranged from 24 to 62 ($M=39.4$; $SD=10$).

Instruments

Data was collected through two online questionnaires. A set of instruments utilized and validated in previous studies was adapted to suit this specific e-learning environment and the cultural uses of the sample. The first questionnaire was designed to assess the background variables, and delivered the first week of the course. It comprised questions about demographics, previous experience with computer devices, attitudes towards learning technology and

towards the expected use rates. The second questionnaire was delivered the last week of the course, and comprised scales on course satisfaction, on self-perception of learning, and a self-report on the time dedicated to the learning activities. The final marks of all participants were collected. Details of the instruments utilized in the present study are given below.

Questionnaire 1

Perceived ease of use and perceived usefulness. Perceived ease of use and perceived usefulness were assessed by adapting items developed by Davis (1989), which records respondents' perceptions regarding how straightforward the e-learning environment would be for them to use (example item: "Learning to operate the e-learning platform would be easy for me"), and about how convenient they thought it would be (example item: "Using the e-learning platform would enable me to accomplish tasks more quickly"), respectively. Respondents rated the items on a seven-point Likert scale (1= "Strongly disagree", 7= "Strongly agree").

Intention of use. To assess respondents' intention to use the e-learning environment, we used an adaptation of the statement used by Davis in his original study (1989). Items tap the extent to which the respondent intends to use the resource (item: 'I will try to use the e-learning platform on as many occasions as possible').

Behavioural planning. To complement the measurement of behavioural intention, three questions related to planned engagement with the e-learning course were included. These questions refer to a projection of the student's frequency of participation: "On average, how many days a week do you plan to use the platform?", "On average, how many hours a week do you plan to use the platform?", and "Considering the next seven days, how much time do you think you will dedicate to the platform activities?".

Computer use. The frequency which respondents utilize computer devices for a range of activities was measured with a 8-item questionnaire used by Tan & Teo (2000) (example item: "Please indicate the extent to which you use a computer to perform the following tasks: 1) Gather information, 2) Communicate (e.g., email, chat), 3) Download free software, etc.").

Questionnaire 2

Satisfaction with the course. Was measured by the Course Satisfaction Scale (Johnson et al., 2008), a 6-items instrument - example item: "I am satisfied with the clarity with which the class assignments were communicated" - which uses a 7 point Likert scale (1= "Strongly-agree"; 7:="Strongly-disagree").

Self-perception of learning. The students' perception about how much they had learned through the course was assessed with the adaptation of Alavi's Self-Reported Learning Scale (1997). Example item: "I learned to interrelate the important issues in the course material". Items are rated on a 1 ("Strongly disagree") to 7 ("Strongly agree") Likert scale.

Actual use. The time students dedicated to the course activities was measured using five items asking about the number of hours per day, and days per week, that participants spent engaging in learning activities related to the course (example item: "On average, how many days a week did you access to the e-learning platform?"). This measure asked about both the time spent online and offline, in order to tap total time spent working on course materials and activities.

Final Mark. As regular part of the course, participants were required to complete a formal assessment task which involved to apply and discuss the course contents. The tutors of the e-learning course assessed students' work using a scale with scores from a minimum of 1.0 to a maximum of 7.0 (standard range of marks used in Chile), according to how well students reflected the

course contents, discussions, and goals. These scores were given to the research team by the tutors - with the consent of the participants - as a measurement of learning achievement.

Procedure

Participants were enrolled in a five-weeks e-learning course on teaching methods about sexuality and affectivity. The course consisted on five modules which explained the instructional design, presented and discussed relevant topics on the matter, and proposed practical exercises to integrate the contents, readings and group discussions onto real teaching materials developed by the students. The first stage of the study was in week one of the course, and the second stage in the last week of the course. Participants' data was matched by an identification code assigned to each of them. In the case that a participant answered only one questionnaire, the unaccounted information was treated as missing data.

Statistical Analyses

Sample statistics and correlations among variables were processed using SPSS Statistics. To test the hypotheses a path analysis was performed using SPSS Amos v22, through Maximum Likelihood technique. It was decided to manage the variables using parcelling technique. As described by Little, Cunningham, Shahar and Widaman (2002), the parcelling technique consists on aggregating the scores of individual items

which belong to the same theoretical construct. As a result, the structural model is centred on a factor-solution with less parameters to be estimated, and avoids potential item-level issues such as lower reliability, or greater likelihood of distributional infringements. In order to utilize this technique, it is required that each variable is a) unidimensional, and b) explicit and clearly defined. The variables included in our model fulfilled these conditions. Total scores were obtained for each variable, and then centred in order to avoid biases due to difference in the range of scores.

RESULTS

Scales reliability and correlations

Internal consistency reliability (ICR) as Cronbach's alpha scores for all measures ranged from 0.73 to 0.95, which is consistent with previous literature. ICR was not calculated for intention of use, behavioural planning since there were three or less items for these variables. The correlations between variables were coherent with the relationships proposed based on theory, where variables related to technology adoption correlate between them, and the variables related to learning effectiveness do the same between them. Control variables such as age, gender, teaching expertise area, previous knowledge about the topic, and whether or not the participants had previous experience with e-learning were also explored and no significant effect nor interactions were found.

TABLE 1.

Mean, standard deviation, and internal consistency reliability of the variables included in the model.

Variable	Mean	SD	ICR
Perceived usefulness	5.735	.311	.905
Perceived ease of use	5.878	.077	.922
Computer experience	4.199	1.496	.791
Intention of use	5.927	.798	-
Behavioral planning	6.509	2.067	-
Satisfaction with the course	5.577	.126	.901
Self-perceived learning	5.876	.077	.952
Actual use	3.544	1.078	.822
Final Mark	5.896	1.121	-

TABLE 2.
Correlation coefficients of the variables included in the model.

	1	2	3	4	5	6	7	8	9
1. Perceived usefulness	1.00								
2. Perceived ease of use	.54**	1.00							
3. computer experience	-.04	.176	1.00						
4. Intention of use	.67**	.47**	.07	1.00					
5. Behavioral planning	.26**	.25**	.22*	.17	1.00				
6. Satisfaction with the course	.21	.07	-.07	.10	.24	1.00			
7. Self-perceived learning	.39**	-.07	-.09	.13	.27**	.66**	1.00		
8. Actual use	.19	.09	.10	.26	.38**	.26**	.42**	1.00	
9. Marking	.00	.06	.01	-.01	.20*	.18	.20*	.22*	1.00

Note: *p < .05; ** p < .001

Regarding the path analysis, four parameters were considered to assess the model quality: a) the chi-square statistics, whereby a non-significant result indicates good fit; b) the relative chi-square ratio [CMIN/DF], which is expected to be 3 or less in cases of good fit; c) the comparative fit index, where model fit is considered good when CFI ≥ .95; and d) the root mean square error approximation, which is considered acceptable when RMSEA ≤ .06.

All the variables composing the research model were included in the analysis. The results indicated a poor fit of the model in general, with χ^2 (16) =96.165, p<.000, CMIN/DF=6.010, CFI=.652, and RMSEA=.173. As can be observed on Figure 1, the variable Perceived Usefulness was a strong predictor of Intention of Use with a good R² associated, but neither perceived ease of use nor previous experience with

computers were significantly related to intention of use. It is interesting to observe the null relationship between previous experience with computers and perceived usefulness of the learning environment. Both, perceived usefulness and previous experience with computers were significantly related to behavioural planning, although the amount of explained variance was low. The almost null relationship between intention of use and behavioural planning is particularly interesting. On the right hand of the model, the major finding is the lack of relationship between intention of use and all the variables composing the engagement cluster, whereas behavioural planning has a positive and significant relationship with satisfaction, self-perceived learning, and actual use. Finally, satisfaction with the course and actual use were directly related to final mark, with a small effect of satisfaction on actual use.

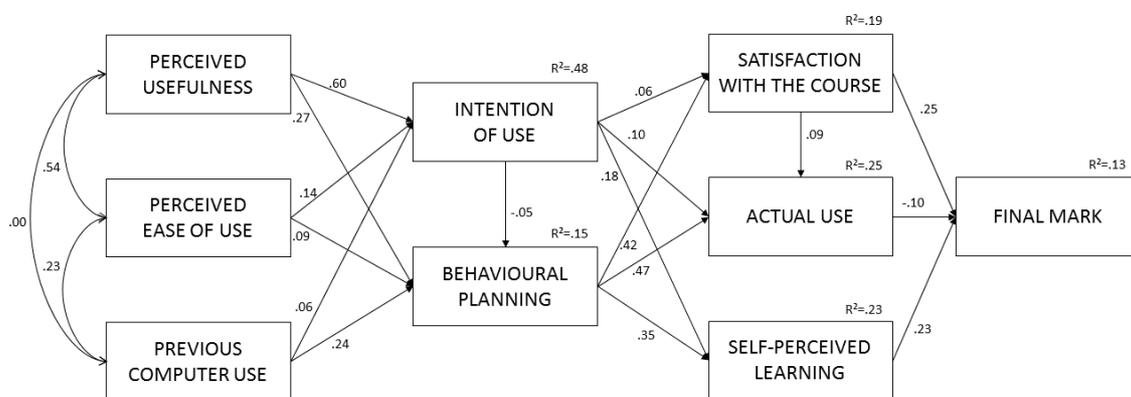


FIGURE 1.
Standardized beta values of the research model.

Based on these results the testing model was modified, excluding the variables perceived ease of use, intention of use, and self-perceived learning, which have been found to be non-significant components of the model. The fit of the revised model was significantly improved, with $\chi^2(8) = 6.850$, $p = .553$, $CMIN/DF = .856$, $CFI = 1.000$, and $RMSEA = .000$. The new model is much simpler, with less crossed paths mainly due to the exclusion of intention of use, with perceived usefulness and computer experience as direct predictors of behavioural planning, and with behavioural

planning directly related to satisfaction with the course and actual use, so actual use is directly related to final mark. Satisfaction with the course is also directly related to actual use and final mark, although its p value is slightly over .05. Despite the positive and significant relationships between the variables comprising the model, overall percentages of variance accounted were disappointingly low, with $R^2 = .12$ for behavioural planning, $R^2 = .07$ for satisfaction with the course, $R^2 = .22$ for actual use, and $R^2 = .11$ for final mark.

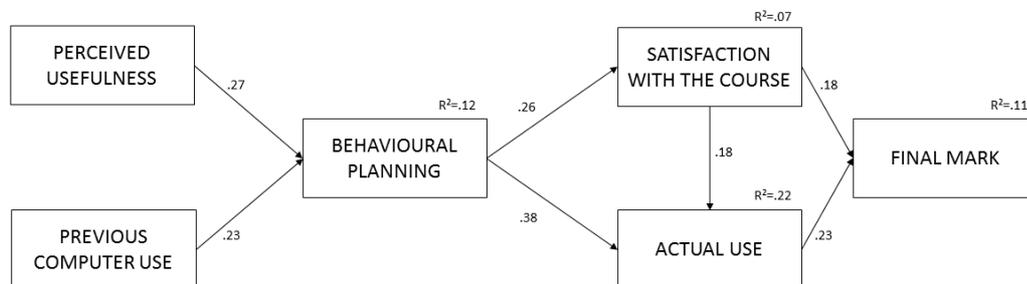


FIGURE 2.
Standardized beta values of the corrected research model.

With these results, Hypothesis 1 (perceived usefulness, perceived ease of use, and computer experience would be directly related to intention of use) is partially supported, due to the weak relationship between computer experience and intention of use. The second hypothesis (perceived usefulness, perceived ease of use, computer experience would be directly related to behavioural planning) is also partially supported, because of the non-significant relationship between ease of use and behavioural planning. The third hypothesis (intention of use and behavioural planning would be directly related to satisfaction with the course, actual use, and self-perceived learning) is also partially supported, due to the non-significant effect of intention of use on the other variables. The fourth hypothesis (satisfaction with the course, self-perceived learning, and actual use would be predictors of learners' final mark) finds support on the

effect of actual use, while the p-value of satisfaction with the course is slightly over .05, and the effect of self-perceived learning is non-significant. The fifth and last hypothesis (satisfaction with the course would have a positive effect on actual use) was not supported due to p value was slightly over .05.

DISCUSSION

In this study on variables related to adoption and effectiveness of an e-learning environment, we found that 1) behavioural planning was a better predictor of actual use of the learning platform than it was intention of use; 2) there seems to be a mismatch between the self-perception of learning and actual learning, suggesting that usage rate of the platform is a better predictor of performance than the learner's perceptions; and 3) that both, adoption and effectiveness

of learning technology, can be seen as parts of an integrated technology-enhanced learning model in which personal attitudes are related to behaviour, and behaviour is related to learning achievement. These findings are important both theoretically and practically, as we will discuss in turn.

Adoption of learning technology

These findings do support the established Davis's technology acceptance model for predicting intention of using technology (in this case, an e-learning environment). Nonetheless, the poor relationship between intention of use and actual use suggests that other variables may be involved on learning technology adoption and use. It was found that behavioural planning was a better predictor of actual use than intention of use, suggesting that variables other than attitudes, such as those tapping motivation and intention, might play a central role on adoption of learning technology. At the same time, actual use was significantly related to students' final mark (a common way of measuring learning achievement), reinforcing the idea that the first step towards improving the effectiveness of computer-enhanced learning is to achieve higher rates of adoption and engaged use.

Besides, it is important to consider that the correlation between learners' declared intention to use the e-learning environment assessed at the beginning of the course, and their declared time dedicated to the course reported five weeks later, was relatively low ($r = .38$). Thus, what participants thought they would do was not a good predictor of what they actually did. The effect of satisfaction on actual use ($\beta = .18$, $p = .058$) combined with the fact that the high initial expectations of use were not reflected in the actual use of the platform, suggest that the adoption of learning technology varies through time and that other variables are involved on it, which are likely explaining an important amount of the remaining variance. Therefore, the adoption of learning technology should not be seen as a passive, static response of the user

that begins with an intention and ends with the execution of a planned action, but as a dynamic and iterative process that may evolve over time, through changing circumstances. In future research, a design including repeated measures should help to clarify whether or not these ideas are correct.

Learning achievement

The results revealed only a small effect of the attitudinal variables - satisfaction with the course and self-perceived learning - on the learning outcome. There seems to be a mismatch between the self-perception of learning and the measurement of learning achievement, in other words, learners' views about their own learning was not accurate when compared with the marks obtained. This might be related to a self-discrepancy between people's representation of their self and their actual self (Higgins, 1987; Stanley & Burrow, 2015), meaning self-perceptions are not a reliable indicator of actual learning.

Satisfaction with the course was slightly related to actual use ($\beta = .18$, $p = .058$) and to final mark ($\beta = .18$, $p = .053$), which suggest that satisfied learners spend more time doing the course activities, and hence they achieve better results. However, from the current study, we cannot determine how these results were achieved. It might be due to differences on the individual attributes and the social capital of the learners - such as learning orientation and shared understanding, respectively (Kankanhalli, Pee, Tan, & Chhatwal, 2012), or to the role of motivation as an enhancer of self-directed learning (Shinkareva & Benson, 2007) and self-perceived learning (Chang, Chen, Huang, Huang, & Lee, 2011).

Time spent using the platform and developing the learning activities was the most relevant variable explaining students' mark. Nonetheless, the explained variance was low ($R^2 = .11$), which suggests that other factors not included in the model must be considered. For instance, variables related to the way that people learn might influence the

learning outcome, such as their learning approach (Biggs, Kember, & Leung, 2001; Kember, Biggs, & Leung, 2004) and learning styles (Dağ & Geçer, 2009; Felder & Spurlin, 2005; Tulbure, 2011). Additionally, the marking criteria, while known beforehand, might have been inconsistently applied. In future, an objective baseline of the knowledge on the topic must be included in order to compare the results and get more reliable conclusions.

Integrated model of computer-based learning

One of the main objectives of the present study was to develop a theoretical and empirical bridge between the learning technology adoption process and the effective use of learning technology for the achievement of learning goals. From the perspective of technology usage, it must enhance the way people develop their activities, hence a well-integrated model would be useful for a better design and improved adaptability of the VLEs to specific learner characteristics, goals, and conditions. The proposed model was based on individual attitudes and evaluations widely considered in the literature to explain this phenomenon, but nonetheless resulted in a low overall power ($R^2 = .11$).

From this, two ideas emerge for discussion. The first idea – relating to one of our main hypotheses – is that it is possible, in a logical and empirical way, to relate the variables involved in the adoption of learning technology with those explaining its effectiveness. The path from individual attitudes towards learning achievement, through behavioural planning and actual behaviour, indicates that the set and implementation of a plan is related to a better outcome. Future research must focus on understanding which aspects of the interaction between learners and virtual learning environments are most important for enhancing the engagement and effectiveness of learning technology, and whether they are related to the learner (user) or to the learning environment (design).

The second idea – which is a consequence of the first – is that the model must be augmented, probably through the inclusion of two kinds of variables: i) individual variables related to cognition and motivation, and ii) variables able capture the dynamic aspects of the adoption-learning process. Regarding the individual variables, locus of control has been observed as directly related to attitudes towards the use of virtual environments and to continued use (Broos & Roe, 2006; Coovert & Goldstein, 1980; Eom & Reiser, 2000; Joo, Joung, & Sim, 2011). In the same line, internal dispositions such as learning approach (Biggs et al., 2001; Kember et al., 2004) and learning styles (Dağ & Geçer, 2009; Tulbure, 2012) have been related to instructional designs and learning achievement. Maybe the inclusion of these variables will give some insight about individual attitudes towards learning technology, the rate of use that learners are willing to accomplish, and how learners deploy their cognitive resources to achieve the proposed learning goals. Finally, to understand the time-dependent aspects of the model (e.g. actual use among different weeks or key events of the course, or satisfaction with the course regarding specific activities) it is important to utilise a design with repeated measures to capture the role and behave of variables such as actual use and satisfaction with the course over the time (Nezlek, 2012).

Concluding remarks and future perspectives

Learning software and massive learning platforms are struggling to engage users from different backgrounds onto continued and significant learning experiences. In order to address these problems, this study attempted to assess and to integrate the main perspectives on the understanding of adoption and the effectiveness of learning technology. The model proposed was based on widely accepted literature on attitudinal variables on the topic.

Of particular interest, we established that although the Technology Adoption Model provided a good fit for the intention to use the technology, intention to use actually had no significant bearing on any of the subsequent variables relating to engagement with the course, or with the final mark. By contrast, behavioural planning did have significant predictive power in these engagement variables. These findings indicate that it is possible to chain the technology adoption and engagement within an integrated framework, but also that behavioural planning measures (rather than intention of use) provide the linkage between antecedent attitudes and engagement. Nonetheless, the percentage of variance captured in the data was modest. In order to increase explanatory power, variables in addition to individual attitudes should be included, for instance learning strategies, behavioural drivers, and repeated measures over time to capture the dynamic of the learning process. Overall, the study provides a call to update and enhance our understanding of the use and relevance of technology in learning contexts, in order to overcome the current and forthcoming challenges of education.

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RESUMO

Objetivo: Avaliar um modelo integrado de adoção e eficácia de ambientes virtuais de aprendizagem, que inclui variáveis atitudinais e comportamentais. **Método:** Estudo quantitativo transversal de duas etapas. As informações foram coletadas por meio de uma série de escalas e questionários aplicados on-line aos 168 participantes, todos professores de diferentes cidades do Chile, que participaram de um curso de e-learning de cinco semanas. **Resultados:** Embora seja viável integrar os processos de adoção e efetividade do uso de tecnologias em um contexto de aprendizagem, verificou-se que as variáveis que explicam a intenção de adotar ambientes de aprendizagem não estão relacionadas ao uso real desses ambientes ou à a eficácia destes. Por outro lado, a programação comportamental relacionada ao uso do ambiente se relaciona ao seu uso real e indiretamente mede sua eficácia. Um modelo abrangente mais simples é proposto. **Conclusão:** Embora seja possível integrar variáveis atitudinais e comportamentais para entender o processo de adoção e efetividade dos ambientes virtuais de aprendizagem em adultos, é necessário ampliar sua conceitualização teórica, portanto, a inclusão de variáveis motivacionais nesse modelo deve ser considerada.

PALAVRAS-CHAVE: Ambientes virtuais de aprendizagem, adoção de tecnologias, tecnologias de aprendizagem, eficácia da aprendizagem, e-learning.

RESUMEN

Objetivo: Evaluar un modelo integrado de adopción y efectividad de entornos virtuales de aprendizaje, el que comprende variables actitudinales y conductuales. **Método:** Estudio cuantitativo de carácter transversal de dos etapas. La información se recolectó mediante una serie de escalas y cuestionarios aplicados en línea a los 168 participantes, todos ellos profesores, de diferentes ciudades de Chile, quienes participaron de un curso e-learning de cinco semanas. **Resultados:** Si bien es factible integrar los procesos de adopción y efectividad del uso de tecnologías en contexto de aprendizaje, se encontró que las variables que explican la intención de adopción de los entornos de aprendizaje no tienen relación con el uso real de dichos entornos ni con la efectividad de éstos. Por otro lado, la programación conductual relacionada con el uso del entorno sí se relaciona con su uso real y de medida indirecta con su efectividad. Se propone un modelo comprensivo más simple. **Conclusión:** Si bien es posible integrar variables actitudinales y conductuales para entender el proceso de adopción y efectividad de entornos virtuales de aprendizaje en adultos, es necesario ampliar su conceptualización teórica, por lo que debería considerarse la inclusión de variables de tipo motivacional en este modelo.

PALABRAS CLAVE: Entornos virtuales de aprendizaje, adopción de tecnologías, tecnologías de aprendizaje, efectividad del aprendizaje, e-learning.