TAM and stages of adoption of blended learning in higher education by application of data mining techniques

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Abstract:
The purpose of the study was to analyze and identify the stages of the adoption of the blended learning methodology in higher education contexts, as well as assessing the relationship of these phases with a series of personal variables of perception of the innovation and contextual factors. 980 active academic staff participated from 43 Spanish public universities. TAM models for the operational definition of the variables were used as a theoretical framework. Through the use of data mining techniques (clustering and decision trees), groupings were made based on the B-Learning adoption stage and a subsequent predictive model of these stages. The results show that the intention to use blearning is the most important variable predictor in all models applied. In addition, the relationship between higher frequency of use and experience in digital educational environments with higher stages of implementation of the B-Learning methodology was verified. Regarding the sociodemographic variables included in the study, it was observed that they exert effects that are marginal in all cases.

Key words: Pedagogical issues; Blended learning; Stages of Adoption Technology; Higher education; Data mining techniques

Introduction

Most research based on Technology Acceptance Model (TAM) has focused on the adoption of specific and easily identifiable technologies, for example the adoption of the digital whiteboard in the classroom (Al-quirim, 2016), use iPads into university classrooms (Wardley &. Mang, 2016), etc. However, there is less research on the adoption of complex instructional systems. In this paper we are interested in analyzing a complex instructional system such as that represented by the Blended Learning methodology. The concept of adoption of Blended learning involves a series of activities, decisions and evaluations related to the effort to successfully integrate an innovation into the functional structures of a formal educational organization (Hall, 2013). The complexity of BL system appears because it includes not only technological factors but also instructive and didactic elements. But in addition to this, this complexity is also due to the fact that many teachers are not really aware of the use of this teaching method, know it but do not use it fully or simply transfer part of their classroom-based teaching routine to the e-learning format, without the necessary balanced integration of both modalities. Thus, we consider that the use of a blended learning environment is part of a continuum of actions (adoption phases) that are conditioned by a series of variables related to the subject (teachers), contextual factors and the techno-didactic innovation itself (Abdullah y Ward, 2016 ; Schepers & Wetzels, 2007; Scherer, Siddiq, & Tondeur, 2019; Marangunić & Granić,2015).

On the other hand, and from a methodological perspective, in most of the studies carried out using TAM models, Intention of Use or Actual Use itself of the given technological innovation is considered as a criterion variable and the other variables of the model as predictors. Many of these studies use statistical analysis based on models of structural or regression equations (Lin & Wang, 2012; Teo, 2009). Faced with this approach, in our work, after the initial definition of the different profiles of academic staff from the "adoption phase" of b-learning system in which they find themselves, we seek to obtain a grouping that allows us to differentiate groups of homogeneous elements from the values adopted in the dependent variable (Adoption Stages) in the different categories of independent or predictive variables, applying a type of analysis based on hierarchical segmentation (decision trees) on the basis that each subject is assigned to a single subset.

From this idea, and the approach of the theory based on TAM we set, as a general objective, the performance of an exploratory/correlational analysis to find out the levels or stages of BL adoption of a group of professors at Spanish public universities, studying their relationship with personal, professional and contextual factors. Indirectly, this knowledge about the stages of adoption can

provide information on the stage of the institutional diffusion of the B-Learning methodology in Spanish universities as a whole. Thus, we seek to identify profiles or traits that characterize each of the identified subgroups according to a series of variables that represent the three main areas: personal and professional characteristics, attributes perceived on BL and climate or organizational context and contextual variables. We assume that this strategy of analysis consisting of identifying the variables with the greatest effect or relationship in each of the BL adoption phases not only broadens the range of behaviors and contexts of application of TAM but it can also help managers and higher education decision-makers when designing teacher training programs and technicians interested in implementing blended learning methodology.

In this context, many universities and institutions of higher education are designing strategic plans and diverse actions to implement and propagate the use of BL methodologies in their training centres. (Lim & Wang, 2017). In this vein, some of these institutions are already beginning to train and initiate small groups of teachers (early adopters) in the process of implementing BL, going little by little, orienting their efforts with larger groups of teachers (Porter, Graham, Spring, & Welch, 2014).

In short, we assume in our work that if a higher education institution has the strategic objective of extending the use of blended learning-based teaching methodology within its organization, it will be essential to identify the phases or levels of use of BL by its teachers. In this way, groups of adopting teachers can be analyzed using the technological acceptance (TAM) according to the phase of use of this innovation.

The *Conceptual framework*

The theoretical basis for a large part of the institutional strategies aimed at disseminating innovations is the Innovation Diffusion Theory (IDT) proposed by Rogers in the 1960s. This theory describes four elements that make up the diffusion process: innovation, communication channels, the time that passes from the beginning of the dissemination process and the social system where the innovation is disseminated (Rogers, 2003). IDT points out, for example, that the first groups of adopters spread innovation through informal strategies, based on word of mouth, or through the leadership exercised by professors or outstanding researchers. However, most adopters (early majority, late majority or laggard) require specific institutional support depending on the level of use or adoption phase of the innovation in which they are located. In general, this support consists of technical support, training on the characteristics of the innovation and pedagogical orientation (Porter, Graham, Bodily, & Sandberg, 2016).

So, from a macro perspective, the dissemination process analyzes how innovation spreads over time, in a specific context, with the ultimate goal of being adopted by particular individuals based on a series of choices and decision-making of an individual nature (micro process of adoption). These choices may be associated with certain variables or personal factors (sociodemographic, professional, etc.) and also contextual factors, as well as conditioned by the perception of the characteristics or attributes of the innovation itself. Both from the macro and micro perspectives, the adoption of an innovation includes several stages through which an adopting organization or subject goes from levels of non-use to higher levels of innovation dominance (Author, 2009; Straub, 2009). In general, these levels can be condensed into three different types: pre-adoption, adoption and post-adoption (Kim & Crowston, 2011), each of which contain different stages that suggest progression based on knowledge and understanding of the given technology and group a series of factors and variables that have been identified from different theoretical approaches.

Most of these theoretical approaches analyze the individual acceptance based on assumptions of behavioural decision centered on cognitive aspects such as the beliefs that a subject has on a specific technology or innovation, the intention or not to use it, the pressure of the social environment, etc. The most widely used explanatory models to describe or explain the individual adoption of technological innovations are the Technology Acceptance Models (TAM), which have undergone various modifications and extensions over the last few years (TAM1, TAM2, TAM3) (Davis, 1989; Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Venkatesh, Morris & Davis,2003; Teo, 2011; Teo, Fan & Du, 2015, etc.). In fact, approximations have been undertaken between the TAM models and the IDT model (for example, the Unified Theory of Acceptance and Use of Technology ,UTAUT, proposed by Venkatesh et al., 2003; Venkatesh, Brown, Maruping & Bala, 2008). In general, the modifications to the initial models try to overcome some of the main criticisms received by the TAM models related to their predictive validity and the insufficient psychometric consistency of the variables that are a normal part of these models (Al-

Busaidi, 2013; Khechine, Lakhal, Pascot, & Bytha, 2014; Author, 2014a). From the framework offered by these models of adoption of technological innovations it is assumed that the adoption of innovation implies a change in at least three dimensions: at an individual level that addresses the subject that adopts, the level of the innovation in itself and the contextual characteristics (Straub, 2009).

The dimension relative to the adopter involves considering the internal characteristics of people, such as their belief systems, behavioural aspects, feelings, etc., which would affect the decision or intention to use technology (Eickelmann & Vennemann, 2017; Author, 2016). For example, in an international study on ICT and change in schools conducted by the OECD, in which 94 good practices from 23 countries around the world were analyzed, it was found that the rate of adoption of ICT in schools followed the traditional rhythms of diffusion of innovation, affected mainly by the personal characteristics of the individuals (Venezky & Davis,2002). These personal characteristics are those that mark individual differences with respect to the adoption of
technology. For Zmud & Cox (1979), they can be classified into three types: firstly, individual cognitive variables, which relate to perception and mental constructs that influence behaviour. Secondly, individual personality variables (locus of control, anxiety, self-efficacy, introversion/extroversion, dogmatism, etc.). Lastly, individual demographic and situational variables, referring to a broad set of personal characteristics (age, sex,) or related to organization in work environments (guidance and training received, experience and academic rank, etc.).

The second dimension refers to the perception of the attributes of the innovation and, in this case, the adoption process is considered to be qualitatively different depending on the type of technology and innovation analysed .According to the model of adoption based on interests (CBAM, Concerns-Based Adoption Model), while the individual dimension deals with attitudes and feelings, the dimension relative to the innovation addresses the set of practices and actions related to the innovation (Hall, 2013, 2014). Thus, the adoption of the innovation is related to factors such as relative advantage, compatibility, visibility, complexity, etc., (variables that are usually included in TAM models). As an example, it is assumed that an individual is more likely to abandon the adoption process when he perceives that the innovation is more complex than when he considers it easier to use, or when he perceives that it offers few advantages over other options available to him (Aldunate & Nussbaum, 2013).

Finally, the context dimension involves assessing where the individual's decisions regarding innovation take place. The social system in which adoption takes place connects the individual with a set of rules, general guidelines or simply behavioural regularities. Much of the research on diffusion has taken place in informal contexts, while research on adoption focuses on general formal contexts (Straub, 2009) in which adoption is interpreted as a voluntary process and, therefore, the perception of social pressure or subjective normality (Fishbein & Ajzen, 1975) may have less effect. In this type of context, another series of external or determining factors explain the adoption of innovation (Tearle, 2003); Hennessy, Ruthven and Brindley, 2005; Porter and Graham, 2016; Salinas, Nussbaum, Herrera, Solarte and Aldunate, 2016;), related to institutional support or the existence of the necessary infrastructures to ensure the adequate implementation of innovation.

In our work we take as explanatory variables some of the main personal, professional and contextual variables identified in the literature on TAM to analyze their relationship with the "phases of adoption" criterion variable, which we analyze below.

The Stages of Adoption of innovations in academic contexts

Focusing in particular on educational settings, the study of the phases, stages or levels that academic staff follow when adopting an innovative practice associated with technological elements has been a recurring topic of interest for researchers. In general, the conceptual structures of adoption of educational innovation based on models of stages of development assume that the purpose of adoption is the integration of innovation in training processes. In the literature we can find several proposals that understand innovation as a process of change in stages (Hall & Hord, 1987; Christensen, 1997; Russell, 1996; Sánchez, 2003), where there is an initial stage in which the teacher knows or becomes aware of the existence of innovation and, after one or more stages, the teacher is involved in a practical way with the same, building new practices through reflection and experimentation (Zhao, Frank, & Ellefson, 2006). After this, in a final stage, the teacher would be able to effectively integrate innovation into their training processes.

A general review of these studies refers, in the first place, to classic works such as the adoption model based on teachers' concerns (CBAM, Concerns Based Adoption Model) based on the studies of Fuller (1969) and above all of Hall and collaborators (Hall, Wallace, & Dossett, 1973; Loucks & Hall, 1979) who propose a model of technological adoption in which three diagnostic dimensions are distinguished (Stages of Concern, SoC) that address the personal side of change (individual); Levels of Use, LoU), which describe the different behaviours of users and non-users with respect to innovation and Innovations Configuration, which are the possible ways of functioning of change (Hall, 2013, 2014) and two prescriptive dimensions related to actions necessary to manage the change derived from educational innovation (Anatomy of interventions and Taxonomy of interventions). The CBAM-LoU has been used in numerous studies to determine the levels of use of technology (Christensen, 1997; Christensen, Griffin and Knezek, 2001a; Christensen and Knezek, 2001b; Christensen and Knezek, 2006; Swain, 2006) and is the base of The Stages of Adoption of Technology used in current research.

The CBAM hypothesis states that when an individual is faced with a new educational innovation, his behaviour is initially governed by concerns about himself and the demands that the new situation imposes on him. After overcoming these concerns with himself (self-concern), the individual comes to have concerns about the nature of the task and the quality of its performance. Finally, the individual begins to worry about the impact of the teaching effort.
In this line, another classic studies such as those by Loucks and Hall (1979) have described seven levels or stages:

- Awareness (academic staff have little interest or relationship with the innovation);
- Informational (the educator shows a general interest in the innovation and would like to know more about it);
- Personal (there is a higher level of interest about the personal consequences of the innovation and the possible results of implementing it);
- Management (this is a level of greater involvement in which academic staff learn about the processes and tasks associated with the management of information and resources associated with the innovation);
- Consequence (academic staff focus on the impact of the innovation);
- Collaboration (at this level, the educator seeks technical and profesional interaction with colleagues to improve the implementation of the innovation);
- Refocusing (academic staff who reach this last level consider the benefits of the innovation and seek the necessary feedback to find improvements or even alternatives to the innovation).

For its part, the work of Hord, Rutherford, Huling-Austin and Hall (1987) describes the following levels of use of the innovation: *Non-use* (no interest in the innovation):

- Orientation (the user is beginning to take the initiative to learn more about the innovation);
- Preparation (the educator has organized and defined plans to start using the innovation); Mechanical (the user is making changes to better organize the use of the innovation);
- Routine (the educator has an established pattern of use and hardly makes changes to the behaviour of implementation of the innovation);
- Refinement (the educator makes changes to improve the results of the innovation); Integration (the user makes deliberate efforts to coordinate with others in the use of the innovation);
- Renewal (the educator in this phase looks for more effective alternatives for the use of the innovation).

These pioneering attempts to describe the sequence of stages through which a individual becomes aware of a new technology until the decision to adopt it, are inspired by E. Rogers' Theory of Diffusion of Innovation proposed in the 1960s. Rogers' theory puts the emphasis on the rate of adoption in order to determine the type and profile of adopters; that is, it states that, from a time horizon, it is possible to infer the characteristics of the adopters of an innovation. For Rogers (2003), there are five stages in this model: knowledge, persuasion, decision, implementation and confirmation. In the first stage –knowledge– the individual is exposed to a new innovation and tries to learn something about its purpose and function. In this case, knowledge can involve simple contact (when dealing with available and general information about that innovation), the search for

more specific information about the use of the innovation or deeper examination of its functioning principles. In the second stage –persuasion– the individual gathers enough information to form a positive or negative attitude towards the object of innovation. This attitude is generally the sum of a series of beliefs that are formed from consulting various sources, but, in particular, the influence of colleagues and significant people for the individual during this phase plays a special role. Once these beliefs have been assessed, the individual seeks additional information and a decision is made as to whether or not the innovation is adopted. The last two stages involve active use of the innovation. In the implementation stage, the educator makes direct, regular use of the innovation, going from being a passive to active adopter, and engages with the innovation to the point where he can reinvent it. In the final confirmation stage, the innovation is checked and tested in a specific context to enable its advantages and disadvantages to be assessed after continued use (Autor, 2009).

Moreover, other approaches have also analyzed the adoption of technological innovations from the perspective of institutions. For example, Saga and Zmud's metamodel (1994) provides a systemic overview to understand the elements involved, from technological acceptance to infusión (appropriation) of the technologies. It describes three main stages: Acceptance (involving use of the technology voluntarily. In this stage, what is important are beliefs, attitudes and the intention by academic staff to use the innovation); Routinization (the technology is considered as a standard element of the normal routine of an organization. That is, the innovation is institutionalized); and Infusion or Appropriation (the process of deeply and comprehensively embedding a technological application into the work systems of an organization, which affects the use towards, frequency of use, standardized use, administrative intervention, process reengineering, communication and user knowledge, etc.). For Saga and Zmud, this is the moment from which the organization begins to reconceptualise certain processes through the technology that has been incorporated.

In sum, the study on the stages or phases of technology adoption have served as a conceptual and methodological framework to study a good part of the teaching/ICT relationship in the training processes, either to predict the integration of technoloy (Agyei & Voogt, 2011), to explore the way in which technology is adopted or not by teachers (Aldunate & Nussbaum, 2013) and for comparative studies among teachers from different nations (Salinas, Nussbaum, Herrera, Solarte, & Aldunate, 2016) among others.

TAM and (Stages of) Adoption of Blended learning in higher education

The most relevant and recent works in this line of study are those of Graham and collaborators (Graham, Woodfield, & Harrison, 2013; Porter, Graham, Spring, & Welch, 2014) who, based on the classic work of Rogers, (1962/2003) propose stages or phases through which the teachers and institutions will pass in the BL adoption process, each of which requires a specific strategy, structures and supports. These authors distinguish several levels: Stage 1 (Awareness / Exploration): the institution lacks a strategy with respect to BL, it offers very limited support to its teachers in its use); Stage 2 (Early Adoption): the institution defines policies to support the implementation of BL, adopting institutional strategies) and Stage 3 (mature implementation). The structure proposed by Graham et al., (2013) has been used in several investigations. For example, Porter & Graham, 2016, in a study carried out with 214 university professors to know the degree to which the key factors (Strategy, Structure, Support) facilitate or prevent the adoption of BL, as well as the decision making necessary for the adoption phases or adopters' profiles, finds as more significant in the decision to adopt BL the influence of availability of sufficient resources, technological support, pedagogical support, and an alignment in the aims of professors and administrators for BL adoption.

On the other hand, in a recent review of the literature, Brown (2016) categorized, according to their internal or external nature, the factors that influence the decision making process of adopting the B-Learning methodology in university contexts. Thus, external factors include interaction with the technology, academic workload, the institutional environment and interaction with students, while internal factors are the beliefs and attitudes of the academic staff and the learning that they manage to develop. For him, internal influence begins from the cognitive processes of the educator, for example, the pedagogical or instructional philosophy corresponds to a mental model that is generated from experience and through reflective processes. In contrast, external influences can be

referred to as structural, institutional or cultural factors depending on the observer's analytical perspective. Within the external influences, factors relating to BL methodology have been identified (factors relating to the level of digital competence, ease of use or perceived utility, difficulties in accessing technology or lack of infrastructure could negatively explain the decision to implement the B-Learning methodology). Other types of variables are also highlighted by academic staff when accepting or rejecting the use of teaching methodologies based on B-Learning. Among them, the additional effort required of academic staff for planning and preparing classes and teaching materials (academic workload), the level of institutional support available, structural technological aspects that are the responsibility of the institution, or even, student resistance to changing their university work habits, etc., can discourage academic staff from using BL (Tearle, 2003; Hennessy et al., 2005).

Based on all of the above, we propose an analysis strategy consisting of identifying the variables with the greatest effect or relationship in each of the BL adoption phases. The ultimate goal of the work should contribute to generate knowledge that helps favour strategic actions to optimize the institutional diffusion of the BL training modality in higher education contexts.

Method

The methodological process is developed with the general objective of identifying the phases of technological adoption in which the faculty of Spanish public universities are found, analyzing the relationship between these phases of adoption and personal, professional and contextual variables from the technological acceptance approach (TAM).

The research questions are the following:

- Is it possible to establish an empirical classification of the level of adoption of blended learning with university professors based on the idea of stages of technological adoption?
- Do the sociodemographic variables and contextual and variable factors associated with he perception of the BL innovation attributes have a significant relationship with the different levels of B-Learning adoption?
- Can the levels of B-Learning adoption by university professors be predicted adequately based on their socio-demographic characteristics and their score on the main factor taken from TAM models (contextual factors and attributes of B-Learning innovation)?

Participants

Data collection was carried out through an online survey of active professors from Spanish public universities, resulting in a valid sample of 980 university teachers. In this way, an incidental and voluntary non-probabilistic sampling was applied. The sample error fixed for the calculation of proportions with a confidence level of 95%, and maximum heterogeneity (p=q=.05), was ± 3.13%. The field work was carried out from March to June 2017.

Variables and instruments

Most of the studies based on TAM, the Intention of Use or Use itself of the given technological innovation is considered as a criterion variable and the other variables and measurement scales (Perceived Utility (PU), Perceived Ease of Use (PEOU), etc.) as predictor variables. In contrast to this approach, in our work and after initial definition of the different profiles of academic staff based on the b-learning "adoption stage" at which they are, and using clustering techniques, we obtained a grouping that was considered as the criterion variable of the study. The rest of the TAM and others variables are considered as predictors.For the measurement of the criterion variable, the Spanish version (Morales, 1999) of the Stages of Adoption of Technology Scale (Christensen, 1999; Christenden and Knezek, 2001b) was used. This scale has been used in several studies with a Spanish-speaking school population (Lignan Camarena, 1999, Mengual & Blasco, 2006).

Under the consideration that the university teaching staff can be found in intermediate positions between the adoption phases of the technology, the Guttman scale originally presented by Christensen (1999) is substituted by a Likert-type response scale with 5 response levels. On that scale, level 1 is presented as Not in agreement and level 5 as Strongly agree. In total, the Stages of Adoption of Technology instrument consists of 6 items, based on the phases proposed by Christensen (1999): (1) Awareness; (2) Knowledge / Understanding or Learning; (3) Basic Use / Appropriation; (4) Familiarity and Confidence; (5) Application; and (6) Integration. Stages 5 (Application) and 6 (Integration) were integrated into a single stage called "Expansion."

For the measurement of TAM variables: Perceived Utility (PU), Perceived Ease of Use (PEOU), Facilitating Conditions (FC), Self-efficacy (SE), Anxiety (Anx) and Social Image (SI), reactives adapted from the specialized literature on the subject (Fishbein & Ajzen, 1975; Davis, 1989; Venkatesh et al., 2008; Brown, Dennis, & Venkatesh, 2010; Teo, et al., 2015) were taken. For the measurement of the Attitude towards BL (ATT_BL), a 6-point semantic differential scale (pleasant-unpleasant, cumbersome- simple, bad-good, useful-useless, beneficial-harmful, indispensable secondary) was produced, and, lastly, for the measurement of the "Decision-Intention" variable, a 7-point Likert scale from "extremely probable" to "extremely improbable" was used.

Procedure

Given the objectives set, both clustering and decision trees are considered as the most appropiate techniques for achieving them. Thus, an analytical procedure is carried out consisting essentially of applying data mining techniques in two well differentiated phases:

- In the first place, to establish a formal grouping of the subjects according to the adoption phase of the B-Learning in which they are found, clustering techniques are applied. These techniques allow one to obtain a grouping of subjects according to their level of affinity or closeness in their responses to the scale used.
- Secondly, in order to know the extent to which socio-demographic variables and dimensions of the TAM models are capable of predicting the B-Learning adoption phase, both inferential techniques and decision trees are applied.

In relation to other traditional multivariate techniques, data mining techniques optimize the process of obtaining non trivial information regardless of the volume of data available (Martínez-Abad & Chaparro-Caso-López, 2017; Castro & Lizasoain, 2012). In this regard, by not basing the statistical analysis on theoretical distributions or the calculation of typical errors, biases related to the fulfilment of prior assumptions or the availability of sample sizes and number of broad variables are avoided.

Analysis

Before proceeding with the data analysis, the statistical package SPSS-AMOS (V.25) was used to perform an initial exploratory analysis of the reliability and dimensionality of the scales (criteria: Cronbach's Alpha values higher than .7 and item-total correlation greater than .3) and a confirmatory factorial analysis under the Maximum Likelihood estimation (criteria: standardized loads greater than 0.7 and Average Variance Extracted greater than 0.5 and higher to the correlations between dimensions). The results obtained from the application of the complete model had an acceptable adjustment ($\chi 2/d.f=3,26$ (933,51/286); CFI=0,953 ;TLI=0,943; IFI=0,954; PCFI=0,777; NFI=0,934; RMSEA=0,048).

For the establishment of the classification of the subjects in the first phase, based on the first research question raised in the study, models based on the k-means clustering technique were tested from the SPSS software. In the validation of the results obtained in the clustering techniques used, only models in which all the variables were highly significant (p.<.001) in the explanation of the groupings were accepted. Once this criterion was met, the model with a greater number of clusters that converged in the smallest number of iterations was selected.

The last phase, implemented to respond to research questions 2 and 3, involved the use of decision trees with the open source software Weka. Prior, an initial inferential study was carried out in order to know which predictive variables were significantly related to any of the groups identified in the criterion variable (alpha=.05). The J48 algorithm is selected. The indicators Precision, True Positive, area under the ROC curve and Kappa coefficient were used to analyze the goodness of fit of the trees obtained.

Results

4.1. Grouping of the subjects into the stages of adoption: clustering

The selected optimal model generated 7 clusters, as can be seen in Table 1

Table 1. Grouping of subjects according to their score in the b-learning stages

	Clúster						
	1	**2**	**3**	**4**	**5**	**6**	**7**
12.2.fase1_AWARENESS	4	3	3	1	1	4	4

12.3.fase2_KNOWLEDGE	2	4	3	1	1	4	1
12.4.fase3_APPROPRIATION	2	4	4	1	1	2	1
12.5.fase4_USE-FAMILIARIZATION	3	3	5	5	2	3	2
12.6.fase5_EXPANSION USE	3	3	4	4	2	2	2

Thus, the following groups can be defined:

- **Cluster 5 (n=141)**. Without acceptance due to ignorance, discomfort and demotivation.
- **Cluster 7 (n=129)**. Knowledge but without acceptance due to discomfort and demotivation.
- **Cluster 1 (n=127)**. Knowledge and comfort but without acceptance due to demotivation.
- **Cluster 6 (n=58)**. Without acceptance, in the process of learning, with moderate comfort and motivation.
- **Cluster 2 (n=176)**. In the process of learning and acceptance, with moderate comfort and motivation.
- **Cluster 3 (n=172).** In the process of acceptance, with high comfort and motivation.
- **Cluster 4 (n=177)**. Full acceptance, with high comfort and motivation.

The clusters provide a fairly balance distribution, except in the case of Cluster 6. Thus, the data confirms the existence of a set of clusters in ascending order according to the levels of acceptance and motivation/comfort towards the use of b-learning. The empirical data seem to fit reasonably, therefore, to the theoretical model proposed by Christensen (1997) regarding the phases of adoption of b-learning

4.2 Initial characterization of the groups

As indicated in Table 2, a significant relationship is observed between the classification of the subjects based on clustering and a significant number of the sociodemographic variables and TAM scales employed.

Table 2. Significance of the relationship between the predictor variables and the criterion variable

Variable	Test	Test score	p-value
Age	Chi-square	50.126	**.012**
Branch of knowledge	Chi-square	28.429	.242
Academic rank	Chi-square	44.185	**.046**
Teaching experience (Years)	Chi-square	50.640	**.011**
Management position	Chi-square	14.316	**.026**
Perceived utility	ANOVA	47.384	**<.001**
Social image	ANOVA	5.614	**<.001**
Perceived ease of use	ANOVA	55.663	**<.001**
Facilitating conditions	ANOVA	29.052	**<.001**
Self-efficacy	ANOVA	48.835	**<.001**
Anxiety	ANOVA	22.118	**<.001**
Attitudes towards b-learning	ANOVA	38.140	**<.001**
B-learning intention of use	ANOVA	103.614	**<.001**
B-learning use	ANOVA	100.451	**<.001**

The following tendencies are observed:

- Age and professional experience: A significant relationship is observed, which shows how the most motivated teachers are those who are in an intermediate period of their professional career (35-55 years). Both the younger teachers (under 25) with less teaching experience and the teachers who have a longer professional career (over 65) are more unmotivated towards the adoption of b-learning. On the other hand, while teachers with moderate levels of experience (less than 10 years old) and a medium-low age (less than 35 years old) are beginning to integrate b-learning as a teaching methodology and show moderate general motivation, it is the teachers between the ages of 35 and 60 and with levels of experience of between 11 and 20 years, which present both greater motivation and higher levels of b-learning adoption.
- Professional category and management positions: In this case, significant results may be affected by a spurious relationship between this variable and others such as age and

professional experience. It seems that people who are in intermediate education categories and who have held important management positions are shown in higher stages for the adoption of b-learning.

In the other TAM variables related to attitudes and perceptions towards b-learning, the tendencies are similar: While academic staff with more experience and motivation towards the integration of b-learning have lower rates of anxiety and higher levels in terms of Perceived usefulness, Social image, Perceived ease of use, Facilitating Conditions, Self-efficacy, Attitudes and Intention of use, these tendencies are reversed and intensified when we analyze the groups of academic staff with lower motivation and lower integration rates.

Decision trees

It was decided to apply decision trees to different groupings under the following criteria: each leaf of the generated tree must have at least 20 subjects with a confidence level for pruning of .25. The groupings of subjects were the following: Initial grouping of 7 clusters, as indicated above. Grouping derived from this initial grouping, in which we have 4 groups depending on integration levels of integration of b-learning methodologies:

- Group 1, null acceptance: Academic staff who do not use b-learning, nor do they have any intention to do so (Group 5 of the initial grouping)
- Group 2, embryonic acceptance: Academic staff who do not use b-learning, but have some intention to do so (Groups 1 and 7)
- Group 3, emerging acceptance: Academic staff who are starting to use b-learning and are committed to learning and integrating it (Groups 2 and 6)
- Group 4, broad acceptance: Academic staff with experience/commitment to its integration (Groups 3 and 4)

Classification with 3 groups, depending on the levels of motivation:

- Group 1, limited motivation: Teachers with little motivation and reluctance towards the idea of integrating b-learning (Groups 5 and 7)
- Group 2, moderate motivation: Moderately motivated academic staff willing to integrate b-learning (Groups 1, 2 and 6)
- Group 3, high motivation: Highly motivated academic staff who favour the integration of b-learning (Groups 3 and 4)

Classification tree 7 groups: Initial clustering

A tree with 39 branches and 22 leaves was obtained and correctly classified more than 44% of the subjects, with a low kappa statistic value (.35). Group with better precision is 4 (full acceptance, with high comfort and motivation), and group 6 (Without acceptance, in the process of learning, with moderate comfort and motivation) does not receive any classification.

Table 3. Classification tree adjustment and classifications (7-group model)

GROUP	CLASIFICATION TREE (J48)							Total	TP	ROC Area
	a	b	c	d	e	f	g			
1	41	31	20	7	3	0	15	118	34,75%	.751
2	6	121	23	4	6	0	12	174	69,54%	.808
3	3	43	88	35	0	0	1	173	50,87%	.827
4	7	24	44	87	2	0	10	178	48,88%	.836
5	13	29	6	3	29	0	36	121	23,97%	.799
6	13	19	3	0	3	0	14	58	0.00%	.827
7	20	16	1	0	24	0	51	119	42,86%	.858
Total	103	283	185	136	67	0	139	941	44.31%	.816
Precision	39,81%	42,76%	47,57%	63,97%	43,28%	0.00%	36.69%	44.31%		

The tree obtained is shown in Figure 2.We observe that the most discriminating variable is intention of use. Academic staff with intentions of use lower than -0.91 points are only classified in

Groups 5, 1 and 7, clusters that indicate lower levels of motivation and use. At lower levels of the tree, we find, for example, that all individuals with very low intention and ease of use are classified in Cluster 5, and that low utility levels, together with high ages, signify belonging to Cluster 7, despite considering relatively simple use. For the subjects with moderate intention of use, the variable that best discriminates is current use, with low use related to less motivation and comfort, and this fact worsening in cases of less perceived ease of use. For its part, the most widespread use, together with high ease-of-use levels (>0.721), signifies belonging to Cluster 3, while, at low ease-of-use levels, we only find classifications in Cluster 2 (moderate motivation and comfort) or 7, depending on the levels of anxiety, current use and attitudes. At high levels of intention of use, we only find classifications in Clusters 2, 3 and 4, reaching 3 and 4 in cases of high self-efficacy, and in cases of low self-efficacy but medium or high perceived ease of use.

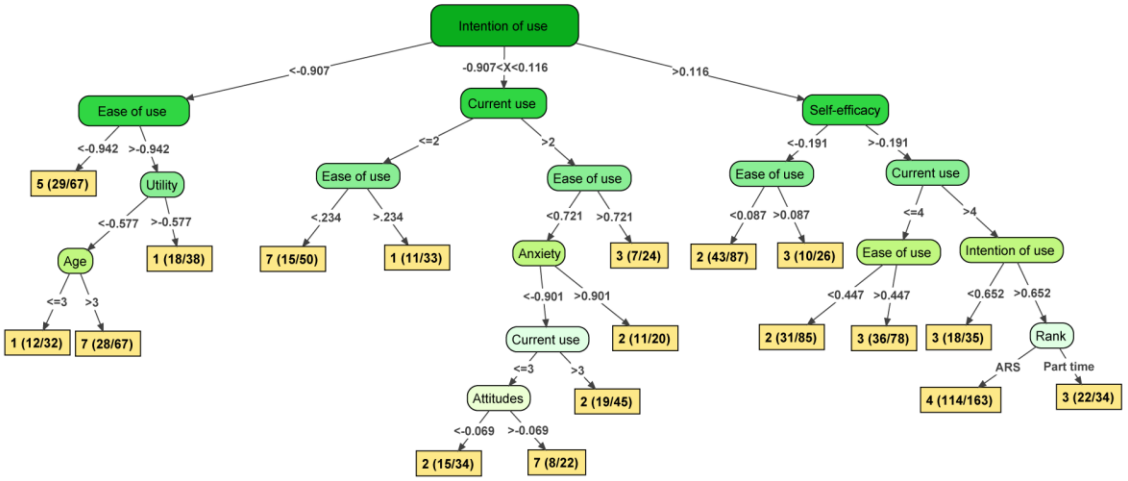

Figure 2. Classification tree 7-group model (algorithm J48)

Applying the cross-validation, we obtain 37.02% of well-classified instances, a fairly limited value with a very low kappa indicator (.244). Since this model is not particularly satisfactory, new groupings are made from the 7 initial groups according to level of b_learning acceptance (4 groups) and motivation and comfort towards its integration (3 groups).

Classification tree 4 groups: Levels of b-learning integration

The decision tree correctly classifies in this case 62.76% of the subjects, with a medium kappa statistic value (.471). Table 4 shows that the model is more accurate in identifying subjects with high-use levels than with more limited use levels (especially to the first group of subjects).

Table 4. Classification tree adjustment and classifications (4-group model)

GROUP	CLASIFICATION TREE (J48)				Total	Correct	ROC Area
	a	b	c	d			
1	32	38	30	16	117	27,35%	.790
2	16	128	43	42	231	55,41%	.788
3	5	37	122	60	227	53,74%	.776
4	6	20	24	294	348	84,48%	.880
Total	59	223	219	412	923	62,41%	.820
Precision	54.24%	57.40%	55.71%	71.36%	62.41%		

The intention of use is still the variable that discriminates best, showing that subjects with an intention to use less than -0.907 are never classified in Groups 3 or 4 (of emergent and wide acceptance). In these cases, teachers with lower ease-of-use levels are classified in Group 1. In most of the other cases subjects are classified in Group 2, of embryonic acceptance. In terms of intermediate and high intention of use, current use of b-learning acquires renewed importance. In the first case, moderate or low use, together with high or medium-high anxiety levels, signifies being classified in the group of academic staff who claim not to use b-learning but have some

intention of integrating it in the future. The other academic staff in this group, except for those with high current use and self-efficacy, are classified in the group who are committed to the acceptance of b-learning, having begun to integrate it into their current practices. Subjects with a high or medium-high intention (>0.168) are largely academic staff from the group with the most experience and commitment to the acceptance of b-learning. In this case, teachers with low self-efficacy stand out among the group of academic staff who are beginning to integrate b-learning.

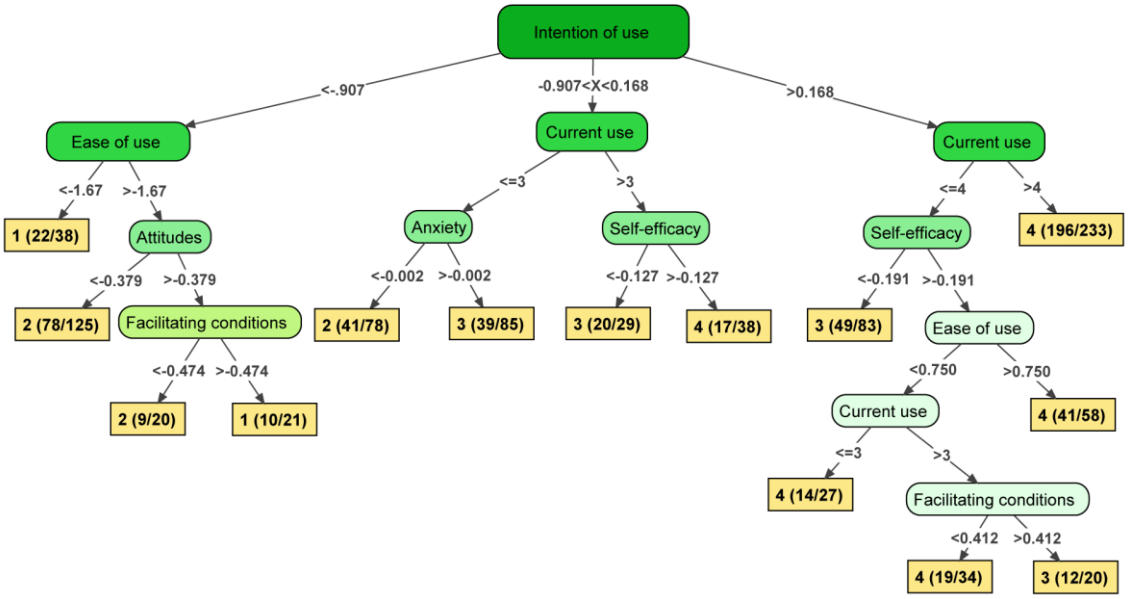

Figure 3 Classification tree 4-group model (algorithm J48)

Applying the cross-validation, we obtain 55.75% of well classified academic staff, a moderate value with a low kappa indicator (.371).

Classification tree 3 groups: Levels of motivation and comfort towards b- learning

The decision tree correctly classifies 66.81% of the subjects, with a medium kappa statistic value (.493). The model is more accurate in identifying subjects with extreme motivation levels (highly motivated or unmotivated).

Table 5 Adjustment and classification classification tree (model 3 groups)

GRUPO	CLASSIFICATION TREE (J48)			Total	Correct	ROC Área
	a	b	c			
1	113	103	12	229	49.34%	.846
2	32	241	68	343	70.26%	.747
3	8	76	260	347	74.93%	.859
TOTAL	153	420	340	919	66.81%	.814
Precision	73.86%	57.38%	76.47%	66.81%		

The tree generated (Figure 4) shows information similar to the two previous models. Intention of use continues to be the variable that discriminates best, followed by ease of use and current use, and variables such as self-efficacy and teaching experience continue to appear as variables that are slightly less discriminating. Most of the academic staff who declare a low intention of use are classified in the first group, referring to academic staff who are not very motivated and reluctant to integrate b-learning. Only academic staff who do not consider the use of these technologies excessively difficult, with low or medium-low teaching experience, and who understand that low facilitating conditions do not exist are classified in the following group, referring to moderately motivated academic staff willing to integrate b-learning into teaching. Teachers with moderate intention of use are classified in the Group 2, although the accuracy of the prediction is low. Lastly,

academic staff with a high intention of use are classified in Group 3 in a generalized manner, and with very high accuracy.

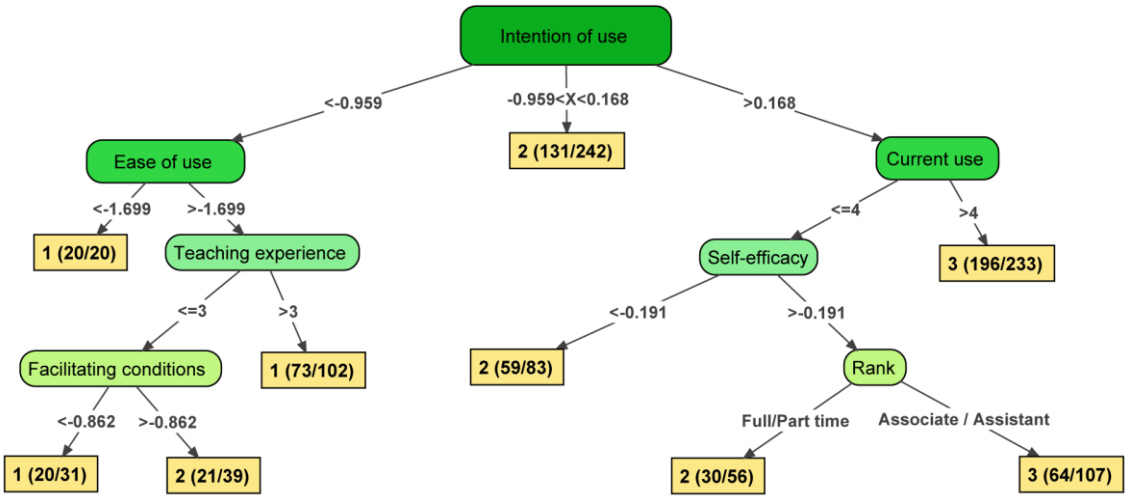

Figure 4 Classification tree 3-group model (algorithm J48)

The cross-validation obtain a 63.42% of well-qualified academic staff (only 3.39% lower than the training sample), a medium-high value with a moderate kappa indicator (.439).

Discussion and Conclusion

In the specialized literature there are meta-analyses that reveal that in most studies conducted with TAM models, behavioral intention of use, effective use or even continuity of use of the given technology (in our case, the b- learning system) act as criterion variables and other variables and their hypothesized relationships as predictors. In fact, it has been shown that when intention of use is appropriately measured, it accounts for an appreciable proportion of variance over actual behavior (Armitage & Conner, 2001; Fishbein & Ajzen, 2011). But there is also 30 to 40% of the research done on BL that tends to use intention as a predictor variable (Halverson, Graham, Spring, Drysdale, & Henrie, 2014; Rad, Nilashi, & Dahlan, 2017; Spring & Graham, 2017) as we have done in our study. In actuality, it would be logical to define operationally and subsequently assess real or effective behavior ("Actual use of BL") as a criterion variable. In fact, some studies suggest using Actual use as a criterion variable (Rad et al., 2017). However, in our specific case, and although it can be assumed that in the community of researchers and experts there is a certain degree of agreement on the concept of Blended Learning (Spring & Graham, 2017), the truth is that among the users (teachers and teaching technicians) there are great differences on how to understand BL and above all to understand coherently what "using or adopting BL" implies.

Therefore, a fundamental question is to clarify what b-learning adoption behavior means. To what extent is the "learning" factor of subjects and not only the technological factor assessed? (beliefs, attitudes towards the technological aspects of BL). The literatura reveals abundant research on the adoption of both e-Learning and b-Learning that has focused on the "e" (technology, electronics, virtual platforms, etc.), or on the "b" (blended, integration of face-to-face and online modalities), while research focused on "learning" is relatively small and receives little attention. This and other questions represent some of the challenges of research in this field, and although they do not necessarily pose a limitation to our study, it is clear that more effort is needed to deepen understanding and offer new data on this and other questions in order to obtain a more comprehensive and accurate view of the process of adoption of BL methodologies in academic settings.

A first approach could involve defining a certain graduation in actual use of BL, by means of stages or levels. In this research, we adopt precisely this perspective using the Stages of Adoption of Technology scale (Christensen & Knezek, 2001), thus relativizing the effect or conceptual distance between the Intention and the effective use of innovation. In this way, the behavioral intention, as a predictor variable, discriminates the groups or levels of the academic staff more effectively and thus finds certain relationships associated with variables of interest. In fact, the results obtained through the data mining techniques applied have facilitated a more refined analysis of the factors associated with the BL adoption stage and Discovery of certain relationships and interactions between predictor variables which have enabled identification of the main risk and protection factors that, under certain circumstances (mainly the different degrees of current use and future intention of use of BL), can have a negative or positive influence on the BL adoption stage of the academic staff.

Analysis of the different stages that we have identified in our study makes it possible to indicate that there is a high level of uncertainty among academic staff, largely due to the high level of ignorance about what effective use of the B-Learning methodology involves; in general, there are negative beliefs about the extra effort that it involves, but beyond this generalized belief, a large number of academic staff ignore its actual effects and end up not using technology, as several recent studies indicate (Arancibia Muñoz, Valdivia Zamorano, Araneda Riveros, & Cabero-Almenara, 2017). This uncertainty or lack of effective knowledge about BL systems is revealed to a greater extent in the stages prior to effective use of the innovation (Stages I, II and III). This makes it difficult to clearly establish predictability factors in the actual or potential use of the b-learning methodology at those stages of the innovation adoption process and also makes it necessary for university institutions to implement prior-training strategies for academic staff (Author, 2014a).

On the other hand, in our study, we have found notable consistency and acceptable adjustment of the results obtained, focusing on certain main variables that may explain why academic staff are in one stage or another of adopting, integrating and trusting the BL system. Initially, through a purely empirical method under systematic criteria, clustering provided a classification of academic staff clearly adjusted to the theoretical models presented in the literature based on TAM studies in which it has been proven that when the Intention of use is properly measured it accounts for an appreciable proportion of variance over real behavior (Armitage & Conner, 2001; Fishbein & Ajzen, 2011). Subsequently, through analysis of the decision trees obtained, we found that the intention of use stands out as the most important variable in all the models applied. This means that greater intention of use indicates better values both in motivation and willingness to implement, and in the effective use of b-learning in teaching. In cases in which the intention of use is medium or low, variables such as ease of use, facilitating conditions, levels of anxiety and self-efficacy exert a protective effect, enabling the academic staff to have both better willingness and motivation towards use, and effective use of these methodologies. For their part, in higher levels of intention of use, perceived ease of use and self-efficacy are the factors that, if found at low levels, can have a negative effect on levels of motivation and willingness to use these methodologies.

Regarding the sociodemographic and contextual variables included in the study, we observed that they exert effects that are marginal in all cases. In this regard, while the values in ages and extensive teaching experience exert a protective effect in cases in which the intention of use is low, promoting greater motivation and willingness to integrate b-learning, academic rank seems to have significant influence in cases of high intention of use: in these cases, albeit only slightly, it seems that academic staff with a more stable teaching profile in the university tend to belong to groups with greater experience, motivation and willingness to integrate b-learning. Lastly, as expected, the b-learning educator's current frequency of use is an important factor when explaining why academic staff are more motivated and willing to use b-learning, but only in cases where the intention of use is medium or medium-high. In line with previous studies (Morales, 1999), our results support the relationship between greater frequency and experience of use in educational settings and digital competence with stages of greater implementation or acceptation of the B-Learning methodology according to the stages characterized in our work.

Conclusion

The use of approaches based on technological acceptance models (TAM) is useful for the study of BL. In our study we have proposed an original and innovative design in which the main variables of TAM (PU, PEOU, BI, etc.) are associated with phases of adoption of the BL innovation. In our view, this allows a broader view of the process of acceptance/adoption of complex instructional systems such as the blended learnig methodology. In any case, we consider that the interest in focusing attention on a complex system such as the one represented by BL methodology from the perspective of models of technological acceptance, reinforces an interesting line of research that can enrich the approach and scope of the theory TAM and generates knowledge that helps favour strategic actions to optimize the institutional diffusion of the BL training modality in higher education contexts.

Limitations

As we have indicated, an aspect that is worth pointing out when limiting the results of this work concerns the evident conceptual confusion that exists regarding the b-learning metodology. Among the various authors who have addressed the concept of b-learning in the last ten years (Bartolomé Pina, 2004; Chikhani & Briceño, 2012; Graham, 2005), there are different positions both on the lack of theoretical foundations that define and clarify it, and on the assessment of the results obtained in the empirical works carried out on the application of this methodology in different teaching/learning contexts.It is clear that this is an important limitation from the moment that it is essential to specify what is meant by b-learning and, from there, to assess to what extent the combined methodology is perceived as an educational innovation. Quite often, using a virtual platform (such as Moodle) to support face-to-face classes or carry out distance courses in which some face-to-face interaction occurs with the learning group is considered as a combined methodology. Both cases could be considered BL, but in a very incipient and pedagogically rudimentary form. Strictly speaking, the b-learning methodology involves combining different training strategies by optimizing the resources available both in the classroom and in virtual environments and all according to an integrated sequencing of the two types of environments (Bersin, 2004; Bielawski & Metcalf, 2003; Bonk & Graham, 2005; Graham, 2005).

With regard to the methodological procedure implemented in the study, it should be noted that, although decision trees, in contrast to traditional inferential techniques, have facilitated a more refined analysis of the relationship and interactions between the set of predictor variables and the criterion variable, satisfactory adjustment indices have not been obtained in the cross validations applied. This question signifies that, although the relationships found between the variables have been systematic and consistent with the previous state of affairs, it is necessary to delve deeper into the study of the protection and risk factors associated with the current stage of adoption of BL, in order to achieve a wider and clearer variable map that results in better adjusted decision trees. The obtaining of more complete and adjusted trees will lead to better prediction and identification of the concrete actions that could be implemented by higher education institutions as protective or motivating factors depending on the profile of the academic staff to whom they are aimed.

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Statements on open data, ethics and conflict of interest

This work protects the privacy of our respondents and the data collected is for this reason not available to others. This study was conducted and approved under the ethical guidelines in place at each of the schools that participated in the study. The present work does not present any conflict of interest.

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