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# How to Measure Teachers' Acceptance of AI-driven Assessment in eLearning: A TAM-based Proposal

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## ABSTRACT

The use of AI is becoming a growing reality the educational field. One of the activities in which it is beginning to be implemented is the assessment of student achievement. This way, we can find in the literature an increasing number of investigations focused on the possibilities offered by the adoption of AI-driven assessment. However, the use of AI is also a source of concern that raises suspicions in some sectors of our society. In this context, knowing the position of the teachers towards this topic is critical to guarantee the successful development of the field.

This paper intends to fill a research gap in the literature by offering a technology adoption model based on TAM to study the factors that condition the use of AI-driven assessment among teachers. To present this model we offer a background on the use of AI in education and the technology acceptance among teachers, as well as the definition of the eight constructs and the relational hypotheses included. Finally, the possibilities of the model and future lines of research are discussed.

## KEYWORDS

Artificial intelligence, Technology acceptance model, Education, eLearning, Teachers.

## 1 Introduction

The use of Artificial Intelligence as a tool to facilitate or even replace human labors is becoming an increasing practice and nowadays we can find examples of its application in a wide variety of contexts from healthcare to computer sciences or education [1-8].

Inside the educational field AI is already present combined with other research tendencies such as Smart Classrooms, Personal Learning Environments or Learning Analytics supporting the adoption of data-driven approaches for the assessment and prediction of the success of the new methodologies and support the decision-making process [9-15].

At the same time, we can also find examples of the use of AI as didactic tool in the teaching of knowledge areas as music [16] or mathematics [17], or in the development of tutoring [18,19] or adaptive systems [20,21].

However, despite the evident advantages entailed in the use of AI in the teaching-learning process there is also a growing concern among the society with the implications and risks of the use of this technology [15, 22-25].

In this context it is of key importance to know the position of the teachers regarding the use of AI in education given that their

acceptance or rejection will condition the integration of these technologies in the teaching-learning process as it happens with any given ICTs [26,27].

This proposal intends to contribute to the analysis of the factors that condition the acceptance of AI-driven assessment tools in eLearning settings among teachers. In order to do so, we have developed an adoption model based on the Technology Acceptance Model (TAM) [28], expanded with constructs of relevance from other theories, specifically designed to measure the adoption of these technologies among teachers.

To present this proposal, the paper is organized as follows. Section two presents a literature review on the application of AI in educational settings and the use of TAM-based models to measure teachers' adoption of ICTs.

Subsequently, section number three describes the theoretical model, including the definitions of the constructs included in the model and the relational hypothesis outlined for them.

Finally, the fourth section include a brief series of conclusions and the future lines derived from this contribution.

## 2 Literature Review

Although the use of AI in educational settings is a phenomenon which has gained popularity in recent years [13, 14, 29, 30] it already has an incipient body of research susceptible of being explored. This section includes a literature review of these experiences as well as background on the use of TAM-based models to study ICT acceptance among teachers.

### 2.1 AI in Formal Education Settings

The use of AI in education constitutes a relatively young area of research which is evolving at a fast pace due to the recent popularity experienced by this innovation. This way, researchers have explored the use of IA to support the teaching learning process in a wide variety of contexts from virtual learning [31] to traditional education settings both with children [32] and adults [33] or incorporated to new learning objects such as robots [34] or smart learning environments [35].

In general, the use of AI in education can be classified in three groups:

1. Use of AI to analyze the human behavior in teaching learning contexts.
2. Use of AI as didactic tools.
3. Use of AI as assessment tool.

In the first group of investigations AI is used as analysis methodology in data-driven approaches to perform complex statistical analysis with large groups of data to analyze the behavior of both students and teachers to detect patterns useful to develop new successful didactic strategies and improve the educational process [36-38].

On the other hand, the second group of initiatives is focused in the use of IA to improve the teaching-learning activity integrated inside the process as didactic resources. This group includes trends like the creation of virtual personas, the development of personal learning environments or the use of intelligent learning objects.

The creation of virtual personas to help students during their learning constitutes one of the most common applications of AI found in the literature. This way, we can find papers that propose AIs that adopt the role of the teachers either in their tutoring activity [39] or as guide of the student during specific activities to improve their learning [32, 33, 40]. Additionally, there are other investigations that propose the use of AIs that play the role of virtual classmates that accompany the students during their learning process [41].

Secondly, we can also find applications of AI in the creation of learning resources like personal learning environments, that allow the development of immersive learning experiences trough the interaction with virtual 3D spaces [31,42], or the design of intelligent learning objects able to adapt to the characteristics of the students [43].

Finally, the last area of application of the AI in the educational context is their use to evaluate, assess or predict the performance of the students. In this line we can find examples of researches that analyze the predictive power of the performance of the students in certain activities on the students' grades [10].

In addition, we can also find researches focused on the use of AIs to perform or support the assessment of the students. There is a series of initiatives exploring the potential of the use of AI to assess the performance of students in specific tasks performed in real contexts [44, 45] or virtual worlds [31] as well as other investigations that propose the use of "intelligent assessment as a service" supported through cloud computing resources to evaluate students' knowledge [46].

Given that the assessment of the students' performance is one of the key competences of the teachers this proposal intends to contribute to this line of research by proposing a model able to study the factors that condition their adoption of AI-driven assessment tools in eLearning activities.

### 2.2 Teachers' ICT Acceptance

The analysis of the technology adoption of teachers constitutes a study object that has attracted the attention of the research community since the explosion of popularity of ICTs in the educational field. Nowadays, this issue constitutes a consolidated line of research of growing interest [47] motivated by the more and more pivotal role of technologies in educational contexts and the constant incorporation and fast development of ICTs [e.g.48, 49].

To study this process researchers have commonly recurred to the design and development of adoption models that explain the decision of the teachers of using or not a given technology through the relationships stablished among a series of external and internal motivational factors.

This way, since the inception of the Innovation Diffusion Theory (IDT) [50] in the 60s we can find a varied number of theories and models that has been applied to study the technology adoption among teachers e.g. [51-54].

The Technology Acceptance Model (TAM) [28] stands out as the main theory to study teachers' technology adoption [47, 48, 55]. This theory was formulated by Davis in the 80s inside the field of the behavioural psychology based on the assumptions of the Theory of Planned Behaviour (TPB) [56] and the Theory of Reasoned Action [TRA] with the intention of explaining the use of a given technology through a five-factor model (Figure 1).

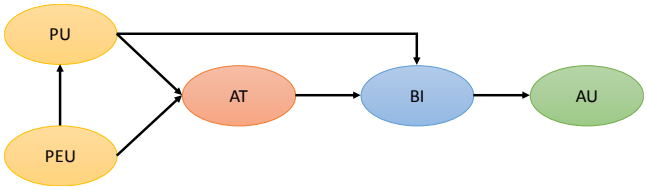


**Figure 1: Technology Acceptance Model (TAM) [28]**

Two constructs are situated on the basis of the model, namely perceived usefulness (PU) and perceived ease of use (PEU). Perceive usefulness is defined as the consideration "that using a specific application system will increase his or her job performance within an organizational context" [28, p.985] and perceived ease of use measures the "the degree to which the prospective user expects the target system to be free of effort" [28, p.985].

These two fundamental constructs in TAM condition the attitude (AT) of the person towards the use of the technology which in turn affects the behavioural intention of using it (BI). This last construct is the direct antecedent of the actual use of the system (AU). To measure the constructs, Davis designed an instrument composed by a series of Likert-Type items and proposed the following relational hypotheses:

- PU is positively related to attitude towards use.
- PEU is positively related to perceived usefulness.
- PEU is positively related to attitude towards use.
- AT is positively related to behavioral intention.
- PU is positively related to behavioral intention.
- BI is positively related to the actual use of the system.

TAM has evolved during the following years incorporating new constructs from other theories to overcome some of its limitations related with the lack of consideration of external variables. As a consequence, two versions of TAM have arisen in under the names of TAM2 [57] and TAM3 [58]. These new versions incorporate constructs such as subjective norm (SN) from the TPB [56] or perceived enjoyment (PE) from the Motivational Model (MM) [59]. However, TAM2 and TAM3 have been subject to criticism among the researcher community because of the loss of the parsimony and adaptability that characterizes the original proposal [60].

As a result, investigators have opted in many occasions for the development of acceptance models based on TAM expanded with selected constructs from other theories designed *ad hoc* and adapted to the object of study e.g. [61-63].

In the educational field, there is a growing number of investigations that apply TAM or TAM-based models to measure the technology acceptance of in-service teachers [48]. This way we can find initiatives that apply models adapted to measure teachers' adoption of ICTs such as mobile devices [63], LMSs [64] or augmented reality [65]. However, due to the novelty of the use of AI in education there is a lack of models designed to study the disposition of the teachers towards these tools which constitutes a research gap that this proposal intends to amend.

## 3 Model Proposal

In this section we will present the expanded TAM-based model designed to measure the acceptance of AI-driven assessment in eLearning among teachers. To do so, we will begin presenting the constructs and hypotheses adapted from TAM and, secondly, we will define the four new constructs incorporated from other theories, namely subjective norm, trust (TR), relative advantage (RA) and AI anxiety (AN).

### 3.1 Constructs from TAM

Although TAM was used as the basis to develop the model, there were some modifications performed on the original constructs proposed by Davis.

Firstly, the construct AU was excluded from the model due to its limited explanatory power and with the intention to obtain a higher simplicity. The decision to eliminate this construct is relatively common in the development of TAM-based models and is present both in TAM2 [57] and TAM3 [58].

Additionally, we also modify the relational hypotheses to adapt them both to the object of study and the exclusion of AU. Consequently, four hypotheses are proposed for these constructs based on TAM2 and TAM3:

- H1: PU is positively related to the teachers' intention to use AI-driven assessment in eLearning.
- H2: PEU is positively related to the teachers' intention to use AI-driven assessment in eLearning.
- H3: PEU is positively related to the usefulness perceived by the teachers in the employment of AI-driven assessment in eLearning.
- H4: BI is positively related to the use of AI-driven assessment resources of the students.

### 3.2 Constructs from other theories

After performing a literature review the four constructs maintained from the TAM model were expanded with four additional factors with the intention to increase the variance explained and to offer a deeper analysis of the variables that may affect teachers' decision to use AI-driven assessment tools. Following we provide de definitions and relational hypotheses of these constructs.

*3.2.1 AI Anxiety.* This construct was adapted from computer anxiety which is included in TAM3· as an antecedent of PEU and measures the stress or even fear experimented by the person when facing the use of a technology [66], in this case, AI-driven assessment. The controversy that surrounds the use AI in our society and the novelty of these resources may generate a feeling of apprehension on teachers that conditions their perceptions of the complexity associated to its use. Therefore, we propose the following hypotheses for this construct based on TAM3:

- H5: AN is negatively related with teachers' perceived ease of using AI-driven assessment.

*3.2.2 Relative Advantage.* Relative advantage is a construct formulated in IDT [50] that refers to the perception of the individual of the benefits entailed by the use of a given tool in comparison with the already existing alternatives. The inclusion of AI in the development of assessment activities entails a potential series of advantages both in terms of quality and potential reduction of workload in comparison with the current assessment practices in eLearning. Teachers' awareness of this situation may affect their perception of the usefulness of these tools, as is the case in other contexts [67]. In consequence, the following hypotheses is proposed for this construct:

- H6: RA is positively related to the usefulness perceived by the teachers in the employment of AI-driven assessment in eLearning.

*3.2.3 Subjective Norm.* As we have mentioned this construct was formulated as part of the TPB and it measures the perception of the individual of the social pressure towards the performance of a behavior. SN is a widely used construct in investigations on the technology acceptance process of teachers with good results [68-70] and it is included on both TAM2 and TAM3 as antecedent of PU and BI. Considering the current social debate on the use of AI, this construct will play an important role on the acceptance of these resources by the teachers. Consequently, we propose the following hypotheses based on TAM3:

- H7: SN is positively related to the teachers' intention to use AI-driven assessment in eLearning.
- H8: SN is positively related to the usefulness perceived by the teachers in the employment of AI-driven assessment in eLearning.

*3.2.4 Trust.* This construct makes reference to the confidence put by the individual on the other part [71] and plays an essential part in the disposition towards the use of AI-assisted technologies [72]. The use of this construct in TAM-based models designed for teaches is still limited but we can find examples of its use on other fields like banking [73] or organizational sciences [74] stablishing its effect on both PU and BI. Distrust is a major issue when it comes to AI adoption, therefore we propose the inclusion of this construct completing the model (Figure 2) with the following relational hypotheses:

- H9: TR is positively related to the teachers' intention to use AI-driven assessment in eLearning.
- H10: TR is positively related to the usefulness perceived by the teachers in the employment of AI-driven assessment in eLearning.

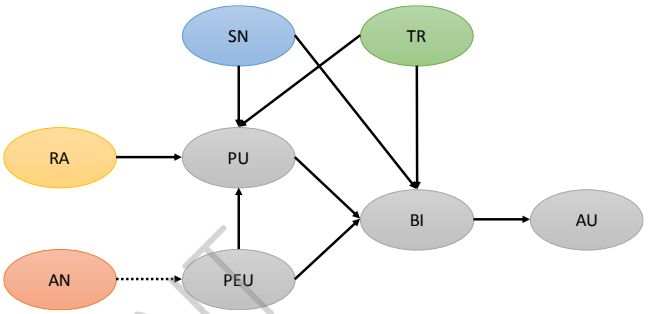


**Figure 2: Research Model**

## 4 Conclusions

The use of AI resources in the educational settings constitutes a growing interest in the research community. However, this field is still in a very early stage of development with a lo of grey areas pending to be explored which includes the adoption of these technologies among the educational agents.

The good disposition of the teachers is an essential requirement for the success of any technology innovation in education, therefore it is key to achieve a deep knowledge of the factors that will help to ensure it.

This paper intends to contribute to the development of the field offering a TAM-based model composed by 8 constructs and 10 relational hypotheses that can help to analyze the disposition of the teachers towards the use of these technologies providing information on the factors that condition the adoption of this technologies. This data can be used in the design of AI-driven assessment integration programs.

The model proposed intends to extend the TAM model covering some factors that were not included on the Davis proposal and are of relevance for the study of the adoption of AI-driven assessment among teachers.

As a future line of research, we are in the validation process of an instrument designed to measure the constructs of the model. This process will include the content validation of the items to measure the constructs and the performance of a pilot study to stablish the validity of the model.

Once the instrument is validated, it will be used to carry out a study on the acceptance of AI-driven assessment among eLearning teachers.

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