Measuring Students' Acceptance to AI-Driven Assessment in eLearning: Proposing a First TAM-Based Research Model

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Abstract. Artificial Intelligence is one of the trend areas in research. It is applied in many different contexts successfully. One of the contexts where Artificial Intelligence is applied is in Education. In the literature, we find several works in the last years that explore the application of Artificial Intelligence-related techniques to analyze students' behavior, to enable virtual tutors or to assess the learning. However, what are the students' perceptions on this subject of Artificial Intelligence and Education? Do they accept the use of Artificial Intelligence techniques to assess their learning? Are they reluctant to be influenced by non-human agents in such a human process like education? To try to respond to these questions, this paper presents a novel proposal of a research model based on the Technology Acceptance Model. To describe the model, we present its different main constructs and variables, as well as the hypotheses to analyze, adapted to the object of study. Finally, we discuss the main implications of this research model, the opportunities that could come based on this proposal and the future of this research.

Keywords: Artificial intelligence · Technology acceptance model · Education · eLearning · Students

1 Introduction

Artificial Intelligence (AI) is used nowadays in a lot of different contexts [1–8]. It affects millions of humans every day and drives many outstanding innovations around the world. There is no doubt that AI is enabling individuals and companies to accomplish tasks that usually were impossible, even with a large number of people involved in. However, in parallel to the bright side of the advance, we observe that

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some part of the society is concerned with the (uncontrollable) advance of AI and its future implications [9–11].

Among the different application areas of the AI, we find the knowledge field of Education. With the appearance of new research tendencies like Learning Analytics, the Smart Classrooms, the Virtual Environments, or the Personal Learning Environments, we are experiencing the mixture of data-driven approaches which include the use of personal data to evaluate the learning process, guide the learning path, etc. [12–15].

Since many years ago, AI has been envisioned as a core part and booster agent of the future in education and human intelligence augmentation [16–20]. However, what are the students' perceptions on this subject of AI and Education? Do they accept the use of Artificial Intelligence techniques to assess their learning? Are they reluctant to be influenced by non-human agents in such a human process like education?

To dig into these questions, it is needed to have the proper tools and methods. This paper deals with these aspects, it is devoted to introducing WIP research which tries to figure out how users perceive the interaction with artificial intelligence in a significant field like the education one. To do so, we use the Technology Acceptance Model (TAM) [21, 22] as the primary basis on where to build our research. Using TAM, we have designed a set of elements composing a survey. This survey will let us know the current status of users' perceptions about AI & Education, their reluctance to be under the scrutiny of intelligent software pieces or their acceptance of this kind of advances.

To present this work, section two introduces background in mixing Artificial Intelligence and in applying TAM models in Education. The third section presents our approach, describing our first proposal of a survey to measure the users' acceptance of this kind of technology. The fourth section depicts the future work to be done and a brief conclusion on our proposal.

2 Background

This section depicts the current state of the art in the fields of AI applied to Education (first subsection) and Technology Acceptance in Education (second subsection).

2.1 AI & Education

As outlined in the introduction, the AI-related algorithms and tools applied to Education are gaining interest in the scientific community [23, 24]. This is not only a perception based on the current general attention and hype around AI. According to the Web of Science, the number of papers published related to the topics "Artificial Intelligence" and "Education" in its core collection is rising since 2008 (Fig. 1). In the last ten years (2010–2019) have been published the 65,56% of all the papers indexed in this database and related to both topics. Even more, during the years 2016–2018, were issued the 34,63% of all the articles published in this context.

The applications of AI in Education, despite the area, is evolving, are varied. Since many years ago, researchers tried to employ artificial intelligence techniques to deal with complex issues like those present in education: analyze students' behavior,

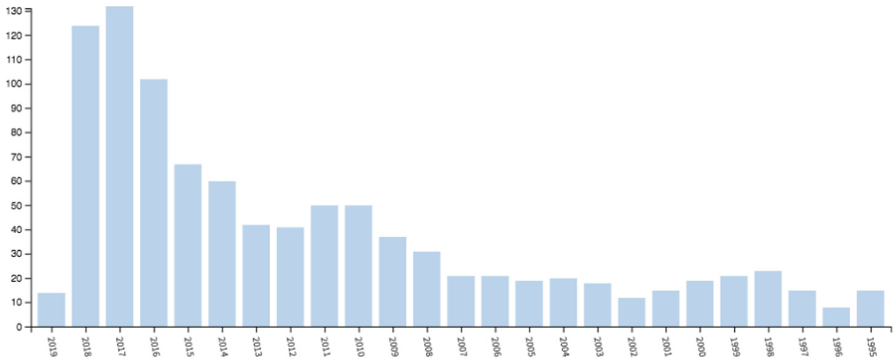

Fig. 1. Papers indexed in the Web of Science in the last 25 years (1995–2019) that contains the topics "Artificial Intelligence" and "Education". Source: Web of Science webofknowledge.com

develop strategies to personalize the learning, detect learning styles, help students during the learning tasks, assess their performance and learning results, etc.

The literature covers a wide range of approaches, solutions, and contexts. We can observe the application of AI in tasks performed in the real world [25], in the virtual one [26], in learning processes that involve K-12 students [27], in other processes with adult learners [28], in smart environments [25], in contexts which include interaction with social robots [29], etc.

To illustrate the impact of AI and related approaches in the field of Education, and according to the literature, we can distinguish different kinds of actuation. One is the application of AI to analyze the humans involved in learning (mainly students), other is the application of AI to improve the learning process, and finally, the use of AI to assess the learning and the results achieved.

In the case of analyzing students' behavior and mental strategies, we find interesting papers about evaluating students' problem-solving strategies [30], about assessing the learning styles of students [31, 32] or predicting the students' mood during online tests and its impact on their results [33].

In the context of improving the learning process can be observed different trends, for example: establish virtual tutors, virtual partners, or the personalization of the learning environments. One of the most common applications of the AI found in the literature is the creation of virtual tutors to guide students during their learning [28]. There are some exciting works related to enable those virtual tutors: from those papers that propose which learn from real teachers and tutors to imitate their behavior when interacting with students to help them [34], to others that try to guide students during specific learning-related tasks to improve their performance [27, 28, 35]. Other papers, rather than create virtual tutors, implement virtual partners for students who advance through the learning process with the students in every moment [36]. Finally, there are some excellent articles on the personalization of the learning environments and students' learning paths. For example, some authors dealt with the personalization of virtual 3D immersive environments [26] or another kind of virtual facilities for learning [37].

The last area of application to comment is the use of AI techniques to evaluate, assess or predict the learning and students' performance. Related to the prediction of results, some papers try to predict the student performance on certain tasks [38] or directly to predict their GPA in different courses [13]. In the case of assessing the learning (instead of predicting the results), we observe that it is a very active sub-area under the area of applying AI into the Education processes. For example, there are research papers and projects related to assessing the students in specific tasks [39], others related to evaluate the students' knowledge through cloud computing services (*a.k.a.* "intelligent assessment as a service") [40], others related to assess learning activities in different environments like 3D immersive scenarios [26], as well as other papers that try to asses activities in real-world facilities like laboratories [41].

This third area of application is the most relevant for the proposal presented in this paper. In the following sections, we will present how to analyze the students' acceptance of being subject of study by artificial intelligence.

2.2 Technology Acceptance in Education

The study of the factors that condition the acceptance of technology among educational users constitutes a large body of research [42] that continues to grow motivated by the fast technological development and the constant incorporation of new devices and information systems e.g. [43, 44] that may offer innovative solutions and contribute to the transformation of the teaching-learning process [45].

One of the primary resources for the study of these factors is the development of technology adoption models. This way we can find a wide variety of researches conducted in the educational field that applies different models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) [46] e.g. [47], the Task-Technology Fit Theory (TTF) [48] e.g. [49] or the Theory of Planned Behavior (TPB) [50] e.g. [51] for the study of the factors that affect the intention of using a given technology of the students.

However, despite this variety of theories TAM rises as the dominant model in the educational context [42, 52]. This theory explains the technology acceptance process through a model (Fig. 2) composed by five factors namely perceived usefulness (PU), perceived ease of use (PEU), attitude towards the use (AU), behavioral intention of use (BI) and actual use (U).

The success of this model is mainly due to its parsimony, given that it can explain a large percentage of the variance of BI and U with a relatively small number of constructs [52] and an instrument composed by 18 Likert-Type items to measure them. This combined with its transferability to different contexts and samples makes TAM the most suitable tool for the development of technology adoption studies in the educational field [42, 52].

However, TAM also has its limitations such as the lack of consideration of the effect of external variables, although their influence is recognized in the model, or its limited explanatory power when is applied in exploratory studies [53, 54].

In order to overcome these limitations, researchers frequently modify the model and expand it to adapt TAM to new contexts and technologies [52]. Some of the findings of

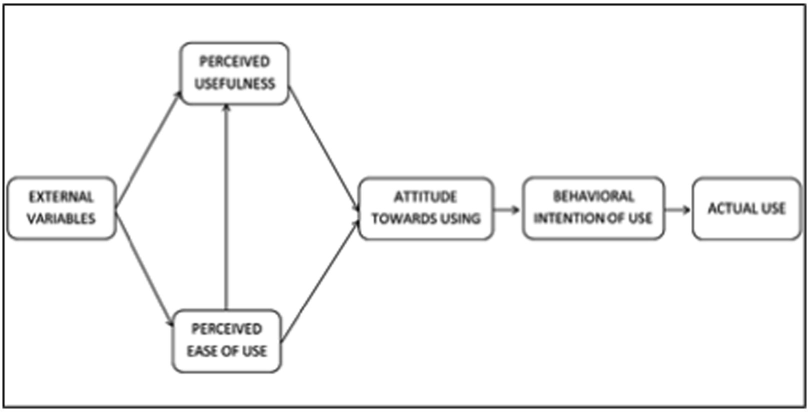

Fig. 2. TAM model [22]

these investigations have been integrated into two subsequent versions of TAM: TAM2 [55] and TAM3 [56].

This way in the educational field we can find examples of the design and application of TAM based models expanded with constructs from other adoption theories such as subjective norm [57], self-efficacy [58] or facilitating conditions [59] to analyze the students' acceptance of technologies including LMSs [57], mobile devices [60] or QR codes [59]. However, to the extent of our knowledge, there is a lack of models specifically designed to examine the acceptance of AI-driven assessment among eLearning students.

3 Proposal

As it has been established, the model presented in this proposal is based on TAM, from this theory we have kept its five main components [43] defined in the model as follows:

- PU: A dimension that measures the perception of the individuals of the degree in which the use of AI-driven assessment would enhance their learning.
- PEU: Defined as the users' perception of the degree of effort necessary to use the new resource.
- AU: A construct that refers to the students' evaluative affect (positive or negative feelings) towards using AI-driven assessment.
- BI: A factor in assessing the students' intention to partake in AI-driven assessment activities.
- U: The endogenous variable of the model, which measures the level of use of AI-driven assessment resources.

Additionally, we also kept the six main hypotheses of TAM [43] adapted to the object of study:

- H1. Perceived usefulness is positively related to the intention to participate in the AI-driven assessment activities of the students.
- H2. Perceived usefulness is positively related to the attitude towards the participation in AI-driven assessment activities of the students.
- H3. Perceived ease of use is positively related to the attitude towards the participation in AI-driven assessment activities of the students.
- H4. Perceived ease of use is positively related to the usefulness perceived by the students in the implementation of AI-driven assessment in eLearning.
- H5. Attitude towards use is positively related to the intention to participate in the AI-driven assessment activities of the students.
- H6. Behavioral intention is positively related to the use of AI-driven assessment resources of the students.

After performing a literature review, the adapted TAM was expanded with three additional variables from other theories with the intention increase the variance explained of the model, namely, subjective norm (SN), resistance to change (RC) and trust (TR).

SN is a variable formulated within the TPB that measures the effect of the social and organizational pressure perceived by the individual towards the performance of a given behavior. This variable is frequently used in investigations focused on the technology adoption of the students [57, 60] with good results and it is included in TAM2 [55] and TAM3 [56]. This way, the existence of an open debate on the convenience of using of AI [9–11] may exert a pressure on the individual that condition both their perception of the advantages of using AI-driven assessment and their intention to use this technology [56], therefore we propose the following hypotheses:

- H7. Subjective norm is positively related to the usefulness perceived by the students in the implementation of AI-driven assessment in eLearning.
- H8. Subjective norm is positively related to the intention to participate in AI-driven assessment activities of the students.

On the other hand, RC refers to the feeling of stress or discomfort experienced by the individuals when they have to face changes [61] and is deemed to have an adverse effect on their technology adoption [62].

The incorporation of AI-driven assessment on eLearning courses entails profound changes in the teaching-learning process including the increase of the human-computer interaction and the decrease of involvement of teachers in assessment activities. These changes may face resistance from the student that may affect their perception of the usefulness of the technology, their feelings towards its use and their subjective probability of participation in AI-driven assessment activities [63]. Thus, we propose the following three hypotheses for this construct:

- H9. Resistance to change is negatively related to the usefulness perceived by the students in the implementation of AI-driven assessment in eLearning.
- H10. Perceived usefulness is negatively related to the attitude towards the participation in AI-driven assessment activities of the students.
- H11. Resistance to change is negatively related to the intention to participate in the AI-driven assessment activities of the students.

- Finally, TR is a construct originated in the field of social psychology [64] nd defined as the willingness of the individual to rely on the other party [65]. This variable has been recognized as a critical element that determines human-automation interaction having a persuasive or dissuasive effect on the use of AI-assisted technologies such as automated vehicles [66].

Although the incorporation of this construct in TAM based models is still in an initial stage of development in the educational field, it is commonly used in other areas such as e-commerce [64], online banking [67] or electronic voting systems [68], showing its effect on the variables from TAM. The model proposal is completed (Fig. 3) with the following hypotheses for this construct:

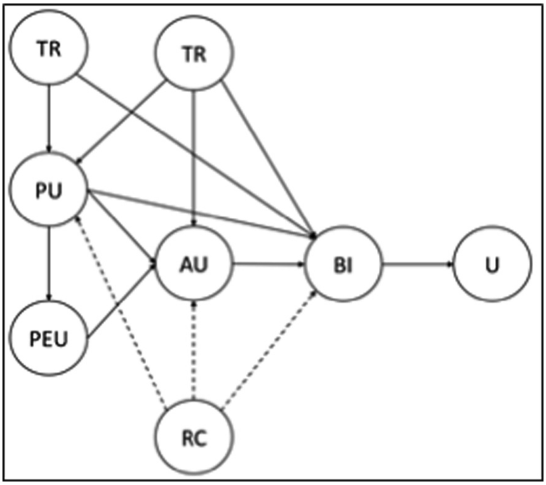

Fig. 3. Research model

- H12. Trust is positively related to the usefulness perceived by the students in the implementation of AI-driven assessment in eLearning.
- H13. Trust is positively related to the attitude towards the participation in AI-driven assessment activities of the students.
- H14. Trust is positively related to the intention to participate in the AI-driven assessment activities of the students.

4 Discussion and Conclusions

As seen in the literature, there is a rising interest in the scientific community about the use of AI-related techniques in education, but there is a lack of studies on what are the effects of the inclusion of these tools among the students. This paper presents a novel research model based on TAM elaborated after an extensive literature review. The purpose of the research model is to study how students accept the use of AI techniques and tools by educators when assessing the learning. The model is composed by 8 constructs that serve to examine the effect of utilitarian motivations, social pressure, dispositional resistance to change and personal conceptions of AI in the disposition of the students to participate in AI-assessed educational activities.

Based on this research model, we have developed an instrument to gather data about students' perceptions of the subject presented. This instrument is currently in the validation stage. Using the validated version of the instrument, we will carry out an empirical study on the acceptance of AI-driven assessment among students. This study aims to provide a solid foundation about subjects' perception on which other researchers could base their future works.

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