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Intention to use AI in accounting education: an analysis from the TAM and TPB perspectives

Diana Yanet Gaviria Rodríguez [1], Alejandro Valencia-Arias [2*], Juan Guillermo Arango Arango [3], Juan Manuel Raunelli Sander [4], Lilian Verde Flores [2] and Jackeline Valencia [5]

[1]Facultad de Ciencias Económicas y Administrativas, Instituto Tecnológico Metropolitano, Medellín, Colombia, [2]Escuela de Ingeniería Industrial, Universidad Señor de Sipán, Chiclayo, Peru, [3]Ciencias Básicas, Instituto Tecnológico Metropolitano, Medellín, Colombia, [4]Facultad de Ingeniería Arquitectura y Urbanismo, Universidad Señor de Sipán, Chiclayo, Peru, [5]Vicerrectoría de Investigación y postgrado, Universidad de Los Lagos, Osorno, Chile

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EDITED BY
Chayanika Uniyal,
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REVIEWED BY
Rajat Sant,
University of Delhi, India
Rasha Nouraldeen,
Beirut Arab University, Lebanon

*CORRESPONDENCE
Alejandro Valencia-Arias
valenciajho@uss.edu.pe

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Introduction: This study examines the integration of Artificial Intelligence (AI)-based tools into university-level accounting education in Medellín, Colombia. The objective was to identify the factors that influence students' intention to adopt these technologies, using theoretical frameworks such as the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM).
Methods: An experimental methodology was applied, which included the development of an educational video incorporating AI and an accounting simulator. A total of 105 students participated in the study and completed a Likert-type questionnaire designed to evaluate constructs including attitude, perceived usefulness, ease of use, subjective norm, and behavioral control.
Results: The analysis revealed that perceived ease of use significantly influenced both perceived usefulness and behavioral control. Additionally, subjective norm had an impact on attitude and intention to use. However, perceived usefulness did not translate into favorable attitudes toward AI adoption, indicating a gap between the functionalities students recognized and their expectations of the technology.
Discussion: The findings highlight the importance of contextualizing AI functionalities within educational settings. They suggest the need for pedagogical strategies that align technological tools with students' expectations and foster a more receptive environment toward digital innovation in accounting education.

KEYWORDS

perceived usefulness, perceived ease of use, behavioral intention, higher education, subjective norm, perceived behavioral control

1 Introduction

Technological advances have profoundly transformed educational processes, enabling the integration of innovative tools into university curricula. Among these emerging technologies, Artificial Intelligence (AI) has proven to be one of the most promising, enhancing efficiency, personalizing learning experiences, and preparing students to meet the demands of the contemporary labor market (Gruenbichler et al., 2024). The advent of the digital revolution has prompted higher education institutions to adopt AI-based solutions, recognizing their potential to automate processes, deliver real-time analytics, and enrich the learning experience.

In the context of higher education, Artificial Intelligence (AI) has begun to play a pivotal role. This is evidenced by its enabling of personalized learning experiences, identification of knowledge gaps, and enhancement of interaction through virtual tutors and intelligent assessment systems (Norzelan et al., 2024). Its integration into academic programs addresses two crucial needs: the need for a more technologically proficient workforce and the development of digital and adaptive skills that are critical in today's era. This transformation has been particularly evident in various academic disciplines, including public accounting.

In this context, AI has proven to be a valuable tool in the training of future accountants, supporting the management of complex tasks such as analyzing large volumes of data, forecasting financial trends, and optimizing accounting processes (Al-Okaily et al., 2023). The integration of these technologies has been instrumental in enhancing the quality of accounting education and preparing students to thrive in a business environment that is increasingly characterized by automation and digital transformation.

However, the effective adoption of AI in university education is influenced by various factors, including the availability of technological infrastructure, the level of digital literacy among students and faculty, perceptions of AI's usefulness, and institutional policies that support its implementation (Algerafi et al., 2023). In the specific case of accounting students, it is essential to understand the factors that influence their intention to adopt such technologies. In contexts where traditional methods have historically prevailed, variables such as perceived usefulness, ease of use, trust in the technology, and willingness to learn new digital tools are particularly relevant (Bui et al., 2025).

In light of these considerations, this study aims to identify the factors that influence the intention to use artificial intelligence in the educational activities of accounting students in Medellín, Colombia. The objective is to contribute knowledge that can enhance the implementation of these technologies in academic programmes, promoting accounting education that is more aligned with the demands of the twenty-first century.

1.1 Theoretical framework

A number of studies have analyzed the adoption of AI in higher education, identifying key factors that influence its implementation. Specifically, Alhumaid et al. (2023) emphasize that perceived compatibility and ease of use are pivotal factors in determining the adoption of AI applications in educational institutions. In contrast, Pillai et al. (2024) emphasize the significance of variables such as personalization, interactivity, and trust in the utilization of AI-based teaching bots (T-bots) within higher education. In contrast, authors such as Alotaibi and Alshehri (2023) have emphasized that the integration of AI in higher education in Saudi Arabia presents opportunities for the transformation of teaching methodologies. However, challenges related to teacher training and technological infrastructure have also been identified.

In the specific context of accounting and finance programs, research conducted by Sudaryanto et al. (2023) examined the factors influencing the adoption of AI technology by accounting students. The study revealed that ease of use and perceived usefulness are significant factors in AI adoption, while digital competence and technological readiness did not demonstrate a direct impact. In a similar vein, Al-Okaily (2024) conducted a study that analyzed the impact of AI on data quality and financial reporting in the field of accounting and financial disclosure. The study underscored the significance of adopting digital disclosure practices in enhancing data quality.

In order to comprehend adoption factors from a behavioral perspective, one must first acquaint oneself with the theoretical underpinnings of the Planned Behavior Model (TPB). This seminal model, proposed by Ajzen (1991), posits that an individual's inclination to engage in a particular behavior is influenced by three pivotal factors: attitude toward the behavior, subjective norms, and perceived control over the behavior. In this context, attitude is defined as a person's positive or negative evaluation of an action. Subjective norms are defined as the influence of others on an individual's decision, while perceived control addresses the ease or difficulty an individual perceives in performing the behavior.

In contrast, the Technology Acceptance Model (TAM), proposed by Davis et al. (1989), expands this perspective by focusing on two key factors: perceived usefulness and perceived ease of use. The concept of perceived usefulness is delineated as the perception that a technology will enhance task performance, while perceived ease of use is defined as the perception that utilizing the technology will require minimal effort. These factors are considered fundamental, as they directly influence users' attitudes toward technology. The adoption of such technology is contingent upon its perceived usefulness and ease of use by the users, which in turn fosters a positive attitude toward toward its utilization. Consequently, this has been demonstrated to enhance their inclination to adopt it, underscoring the significance of these two factors in technology acceptance models.

Integrating the TPB and TAM facilitates a more comprehensive understanding of technology adoption by combining the factors of perceived usefulness and ease of use (TAM) with social norms and perceived control over behavior (TPB). Gaviria et al. (2022) employed this integration to examine university students' intention to utilize virtual learning objects. Their findings demonstrated that attitudes toward technology, social influences, and perceived control are pivotal determinants of technology adoption.

1.2 Perceived usefulness

Perceived usefulness is a pivotal factor in technology acceptance models, as it pertains to the extent to which a user perceives that utilizing a technology will enhance their performance in a particular task. This variable has been demonstrated to exert a direct influence on attitudes toward technology, with a concomitant positive impact on users' propensity to adopt it. As posited by Margraf et al. (2020), perceived usefulness is foundational for users to cultivate a favorable attitude toward technology. This phenomenon can be attributed to the principle that users are more likely to be motivated to utilize a tool if they believe it will be beneficial to their daily activities. Recent studies have corroborated this association: Wiprayoga et al. (2023) found that perceived usefulness significantly enhances attitude, which in turn mediates the adoption process. Denovan and Marsasi (2025) demonstrated that for Generation Y and Z consumers, perceived usefulness not only affects attitude directly but also indirectly through satisfaction and trust.

With regard to behavioral intention, perceived usefulness is also of crucial importance, in that users tend to exhibit a greater intention to adopt a technology if they believe its use will generate clear benefits. The relationship between perceived usefulness and behavioral intention has been extensively validated in prior studies, including that of Humida et al. (2022), who determined that perceived usefulness is a primary predictor of intention to use. Amoako-Gyampah's (2007) research yielded analogous results, emphasizing that perceived usefulness, particularly when coupled with user engagement, directly reinforces in ERP adoption. In recent educational contexts, Alshammari and Babu (2025) demonstrated that perceived usefulness positively influences students' intention to use AI-powered tools like ChatGPT, with satisfaction acting as a mediating factor. Consequently, it can be posited that perceived usefulness exerts a positive influence on both attitude toward behavior and behavioral intention, although its impact may be modulated by contextual and psychological variables such as satisfaction, trust, and user expectations.

H1: Perceived usefulness has a positive influence on attitude toward behavior.
H2: Perceived usefulness has a positive influence on behavioral intention.

1.3 Perceived ease of use

The notion of perceived ease of use is a widely acknowledged critical factor in the adoption of novel technologies. This is because it refers to the extent to which users believe that using a given system will require minimal effort. According to Tahar et al. (2020), when users perceive a technology as easy to use, this perception tends to enhance their evaluation of its usefulness, as they associate ease with a more efficient and less demanding experience. Alshammari and Babu's (2025) study demonstrated that the ease of use of Chat GPT significantly influences students' behavioral intention to adopt it, with satisfaction acting as a mediating factor. Kim et al. (2025) similarly found that ease of use enhances both perceived usefulness and adoption, especially when paired with enjoyment. Cao et al. (2025) demonstrated that in rural contexts, ease of use becomes paramount when coupled with adequate training and digital literacy. As posited by Oematan et al. (2024), user satisfaction exerts a mediating role between ease of use and behavioral intention in e-commerce settings. The findings, when considered collectively, suggest that ease of use not only enhances users' perception of utility but also plays a pivotal role in the emotional and motivational dimensions that facilitate adoption.

Furthermore, perceived ease of use has been demonstrated to exert a positive influence on perceived behavioral control. When users interact with technologies that are intuitive and straightforward, they report greater confidence in their ability to use them effectively. Valencia-Arias et al. (2023) posit that this perceived autonomy is fundamental to promoting self-efficacy in technology adoption. Hoque et al. (2024) further corroborate this finding, demonstrating that perceived behavioral control serves as a mediator between innovativeness and the continued usage of e-money platforms. In the context of AI-assisted language learning, Wu et al. (2024) found that ease of use directly enhanced students' sense of control and willingness to engage with digital tools. Finally, Warsono et al. (2023) assert that perceived ease of use exerts a consistent and positive influence on perceived usefulness, perceived behavioral control, and behavioral intention. A synthesis of extant studies indicates that perceived ease of use not only serves as a predictor of user intention but also constitutes a foundational component of perceived capability in digital environments.

H3: Perceived ease of use has a positive influence on perceived usefulness.
H4: Perceived ease of use has a positive influence on perceived behavioral control.
H5: Perceived ease of use has a positive influence on behavioral intention.

1.4 Attitude toward behavior

Attitude toward behavior is defined as an individual's positive or negative evaluation of performing a specific action, such as the adoption of a new technology. Research has demonstrated that an individual's propensity to engage with a given technology is contingent upon their disposition toward it. In essence, a positive attitude toward a technology is associated with increased inclination to engage with it. This heightened level of engagement has been shown to foster an increased likelihood of adoption. This assertion is corroborated by the findings of Ho et al. (2020), who determined that positive attitudes toward a given behavior are a significant predictor of the intention to engage in that behavior. In a similar vein, Bai et al. (2024) discovered that teachers' attitudes toward technology significantly mediate the relationship between their technology self-efficacy and behavioral intention, underscoring the pivotal role of attitude in determining actual adoption. Furthermore, Zhao et al. (2025) demonstrated in the context of tourism behavior that attitude influences intention directly and also moderates the strength of other psychological factors, such as motivation and perceived value. Consequently, if users find a technology beneficial and feel at ease with its use, their propensity to adopt it is notably heightened, thereby streamlining the decision-making process toward its effective implementation.

H6: Attitude toward behavior has a positive influence on behavioral intention.

1.5 Subjective norm

The subjective norm, defined as an individual's perception of social expectations and the influence of others on their decisions, plays a crucial role in shaping attitudes and behaviors. As La Barbera and Ajzen (2020) demonstrate, when individuals perceive that their acquaintances hold a belief in the adoption of a given technology, they are more inclined to adopt a favorable attitude toward its utilization. This social pressure functions as a motivating factor, as individuals often align themselves with the expectations of their social environment, thereby reinforcing their propensity to adopt new technologies. Baba et al. (2025) corroborate the notion that subjective norms serve as a substantial predictor of behavioral intention, a phenomenon that is particularly pronounced when these norms are firmly entrenched within a robust community ethos.

In a similar vein, Baba et al. (2025) study found that perceived social expectations significantly influence individuals' attitudes and willingness to engage in health-related behaviors, such as vaccination. This highlights the broader role of subjective norms in behavior regulation. In the context of AI adoption, Wang et al. (2024) demonstrated that social influence, as operationalized through subjective norm, significantly affects university students' intentions to use generative artificial intelligence tools.

Furthermore, subjective norms have been demonstrated to influence an individual's perception of their ability to control their behavior, particularly in the context of technology use. As posited by Aschwanden et al. (2021), individuals experience an increase in confidence in their ability to adopt a specific technology when they perceive societal approval of its utilization. This phenomenon is further exacerbated by the perceived support derived from one's immediate social circle. Essam et al. (2025) discovered that subjective norms, in conjunction with perceived behavioral control, serve a dual moderating function in shaping behavioral intentions, particularly in consumption contexts.

Similar vein, Kaba et al. (2025) identified that social influence interacts with demographic factors to shape knowledge-sharing intentions through both attitudinal and normative mechanisms. This social effect engenders a heightened sense of control, prompting individuals to align their actions with the expectations of their peers. Wismantoro and Susilowati (2025) also emphasize that subjective norms, when reinforced by positive attitudes and control beliefs, enhance pro-environmental behavioral intentions. Finally, given the potential of subjective norm to influence both attitude and perceived behavioral control, it is conceivable that it could exert a direct effect on the intention to adopt the technology, particularly in contexts where individuals not only perceive themselves as capable and hold favorable attitudes, but also feel socially encouraged to act accordingly (La Barbera and Ajzen, 2020).

H7: The subjective norm has a positive influence on attitude toward behavior.
H8: The subjective norm has a positive influence on perceived behavioral control.
H9: The subjective norm has a positive influence on behavioral intention.

1.6 Control of perceived behavior

The perception of control over behavior plays a fundamental role in decision-making, as it directly influences a person's ability to act in accordance with their intentions. The propensity for individuals to adopt new technologies is positively correlated with their perceived access to the requisite resources, skills, and support systems. This sense of self-efficacy reinforces their confidence that they can overcome any obstacles that arise, which in turn motivates them to take the desired action (Vamvaka et al., 2020). Consequently, an augmented perception of autonomy in behavior engenders a heightened probability of individuals actualizing their intentions to adopt the technology or behavior in question.

H10: Perceived behavioral control has a positive influence on behavioral intention.

As illustrated in Figure 1, the proposed theoretical model integrates 10 hypotheses derived from the integration of TPB and TAM theories. The model offers a clear illustration of the relationships between key variables, including perceived usefulness, perceived ease of use, subjective norm, attitude toward the behavior, perceived behavioral control, and behavioral intention. It provides a coherent representation of the mutual influences that shape the technology adoption process.

2 Methodology

An experimental case study was conducted, applying a pedagogical strategy to a classroom training activity. The objective of this study was to ascertain the factors that influence the intention to utilize the "AI VIDEO COMBINED WITH THE SIMULATOR." The present study concentrated on the evaluation of the relationship between constructs such as attitude toward the behavior, behavioral intention, perceived behavioral control, perceived ease of use, perceived usefulness, and subjective norms.

The present study was conducted in two parts. The initial phase entailed the development of an AI-generated video to illustrate the unit-based depreciation method. The script generated by Chat GPT was subjected to a process of review and modification, and was subsequently recorded using the "Fliki.ai" program. The simulator was then designed using Geo Gebra software, incorporating all the concepts of depreciation and impairment. These concepts and definitions were applied in accordance with the regulatory framework of Decree 2420 of 2015. It is evident that Annexes 2 and 3 of the International Financial Reporting Standards illustrate the recognition, initial and subsequent measurement of property, plant and equipment, and the standards that develop impairment. Subsequent to this, the relevant equations and algorithms were designed. Following the construction of the simulator, it was uploaded to the website in the form of a Descartes book (Gaviria et al., 2022). This website contains an open repository of works oriented to Interactive Learning Objects (ILOs). These simulators are designed with free software such as Geo Gebra and Descartes, along with video materials to guide learning for university students in various subjects, including Basic Mathematics, Differential Calculus, and Accounting Sciences.

In the second part of the study, a training activity was implemented in the classroom during the 2024–01 semester. The activity was entitled "VIDEO AI COMBINED WITH THE SIMULATOR". The study was administered to five groups of students who had previously studied the topic "Depreciation Methods." Of the five groups, three were taught by professors who were not involved in the study's research, while two groups

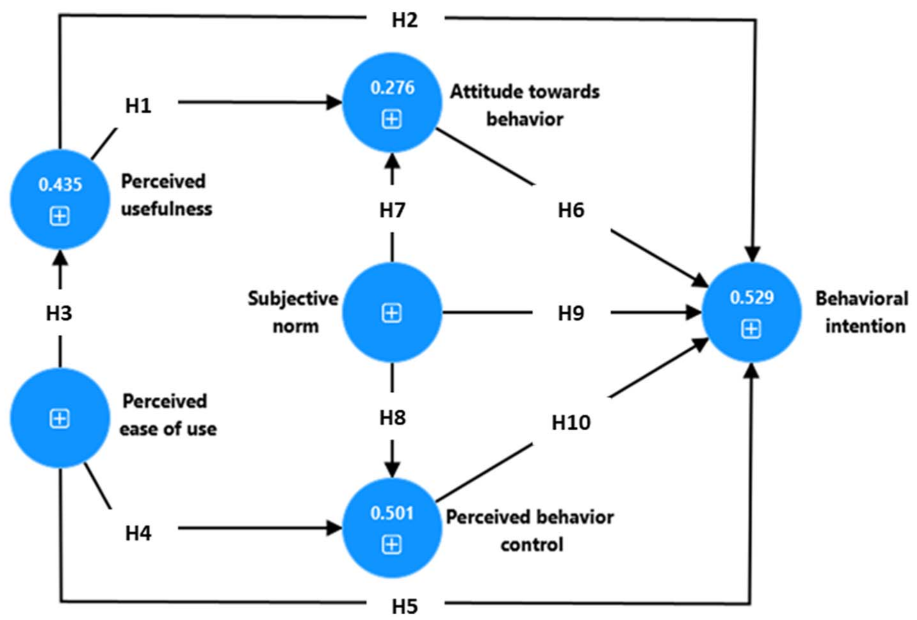

FIGURE 1
Proposed model. Prepared by the authors.

were taught by one of the study's researchers. All participating students were enrolled at the Metropolitan Technological Institute (ITM) in Medellín, Colombia, with the majority belonging to the Finance Department and representing the Public Accounting and Technology in Cost and Budget Analysis programmes.

Prior to the implementation of the activity in the classroom, a preparatory and verification process was conducted with three professors other than the study's researchers. At that juncture, the activity was disseminated to the teachers, in the form of the simulator with an established guide. This enabled the teachers to familiarize themselves and conduct a verification test using their own exercises and methodology. This preliminary stage enabled the validation of the simulator and the methods used to guide the process step by step, ensuring that the fieldwork was conducted with reliable data and was carried out efficiently and in a coordinated manner to obtain valid and accurate research results.

Following the implementation of the training activity, an instrument adapted to this study was developed and validated in Factors That Affect the Usage Intention of Virtual Learning Objects by College Students (Gaviria et al., 2022). The questionnaire comprised 20 questions, designed to assess constructs including attitude toward the behavior, behavioral intention, perceived behavioral control, perceived ease of use, perceived usefulness, and subjective norms.

As part of the methodological design, the educational materials were developed by researchers D.Y.G-R. and J.G.A.A., who created an artificial intelligence-based video for pedagogical purposes. The content was initially generated using the Chat GPT tool and subsequently reviewed, adapted, and validated by three professors with experience in accounting and technologies applied to education. The validation by expert judgment was focused on ensuring conceptual clarity, alignment with the learning objectives, and the pedagogical relevance of the resource. The final video was produced using the Fliki.ai platform, ensuring a comprehensible and engaging visual format for students.

Furthermore, the interactive simulator was developed by J.G.A.A. and L.V.F. in the Geo Gebra environment, incorporating the regulatory principles established in Decree 2420 of 2015 on depreciation and impairment of assets. The simulator was integrated into an interactive digital book and was pilot-tested by three teachers who were not members of the research team. This preliminary phase facilitated the validation of the simulator's usability, the clarity of its instructions, and its practical functionality within authentic classroom contexts. The feedback received was integrated to improve the tool before its formal implementation in the participating groups.

The questions were designed using a Likert-type scale, which allowed respondents to indicate their level of agreement or disagreement with various statements. The scale ranged from 5 (strongly agree) to 1 (strongly disagree), thereby capturing the intensity of participants' perceptions. This rating system is commonly used in behavioral and educational research to quantify attitudes and opinions. The specific structure of the scale is presented in Table 1.

However, subsequent to the validation of the model, it was determined that a mere 13 of these questions met the criteria for relevance for the analysis. This reduction ensured that the selected questions were the most effective for addressing the six constructs.

The completion of this instrument was achieved by 105 students under the following conditions: the students had studied the topic of Property, Plant, and Equipment —The Depreciation by Use Method and the Deterioration of Property, Plant, and Equipment. The students participated in a training activity with

TABLE 1 Measurement scale used for likert-type questions.

Theoretical model	Construct	Question
TPB	Attitude toward behavior	Do you think that “AI videos combined with simulators” are facilitators for learning?
		Do you think that “AI videos combined with simulators” motivate and stimulate your participation in class?
		Do you think that the “AI videos combined with simulators” respond to the activities proposed in the subjects (tasks, evaluations, among others)?
		Do you think that “AI videos combined with simulators” has a relationship between theory and its application in solving examples, exercises and problems?
		Do you think that using “AI videos combined with simulators” allows you to have more meaningful learning?
TPB	Behavioral intention	Do you intend to use “AI videos combined with simulators” to improve your learning processes?
		In the near future, would you be in favor of using “AI videos combined with simulators” to improve your training process?
TPB	Perceived behavioral control	Do you think you are capable of adopting “AI videos combined with simulators” in your study and training techniques?
		Do you think you would make better use of your independent work in the subject if you could access “AI videos combined with simulators”?
TAM	Perceived ease of use	Do you feel that the guidance for using the “AI videos combined with simulators” is clear and allows you to actively access this material?
		Do you find the process of learning how to incorporate “AI Videos combined with simulators” to address the topics of your subjects easy?
		Is it necessary to have some basic knowledge of ICT to interact with “AI Videos combined with Simulators”?
TAM	Perceived usefulness	Does the use of “AI Videos combined with simulators” make the content easier to understand?
		Would you like to be independent in your learning pace with the help of “AI videos combined with simulators” in accordance with your professional background?
E-TAM	Subjective norm	Do you think teachers are encouraging the use of “AI videos combined with simulators” in their subjects?
		If your classmates start using “AI videos combined with simulators”, would you also implement them in your activities?
		Do you feel that your peers value the applications they access through the “AI videos combined with simulators” as useful educational tools?
		Do you think teachers should make greater use of “AI videos combined with simulators” in their teaching processes?
		Do the media and the constant changes in the environment influence the use of “AI videos combined with simulators” in learning processes?

Prepared by the authors.

the instructor, during which they were explained using “VIDEO AI COMBINED WITH THE SIMULATOR.”

The data collected during this study will be treated with strict confidentiality and will not be shared with any external entity. The data will be utilized exclusively for research purposes, with analysis based on responses to the 20 Likert-type questions, age, gender, and semester completed. Confidentiality protection was ensured by the non-disclosure of the personal information of the students who participated in the study (Publication Manual of the American Psychological Association).

To complement the experimental implementation, it is imperative to clarify that the activity was structured in a controlled classroom environment, with a duration of ∼90 m per session. The experimental groups received the same pedagogical sequence. First, students viewed the AI-generated video, followed by hands-on interaction with the simulator under the guidance of the researcher. Prior to the initiation of the study, the teachers received orientation on the instructional strategy to ensure fidelity of implementation across groups. During the activity, students were encouraged to explore the simulator individually or in pairs and to reflect on how the video supported their understanding of the topic. The researchers observed the sessions without interfering, ensuring consistency in the execution while minimizing bias. This implementation design enabled the structured observation of students' engagement with AI-based educational tools within a natural academic context.

The questionnaire utilized in this study was adapted from the validated instrument developed by Gaviria et al. (2022), titled Factors That Affect the Usage Intention of Virtual Learning Objects by College Students. The original instrument was designed to assess factors related to technology acceptance in educational contexts and was grounded in the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). For the purposes of this study, the original items were reviewed and modified by the research team to ensure conceptual alignment with the specific constructs under investigation: attitude toward behavior, behavioral intention, perceived behavioral control, perceived ease of use, perceived usefulness, and subjective norms. In adapting

TABLE 2 Cross-loads of measurement items for each construct.

	Attitude toward behavior	Behavioral intention	Perceived behavior control	Perceived ease of use	Perceived usefulness	Subjective norm
ATB1	0.807	0.420	0.310	0.464	0.369	0.389
ATB2	0.727	0.396	0.234	0.345	0.268	0.312
ATB3	0.752	0.428	0.352	0.431	0.347	0.404
BI2	0.496	0.836	0.409	0.410	0.460	0.445
BI3	0.459	0.902	0.666	0.504	0.451	0.600
PBC3	0.352	0.368	0.710	0.430	0.482	0.419
PBC4	0.302	0.614	0.884	0.493	0.558	0.637
PEU1	0.467	0.351	0.296	0.718	0.370	0.379
PEU2	0.458	0.504	0.594	0.917	0.665	0.578
PU2	0.306	0.270	0.380	0.376	0.742	0.300
PU3	0.409	0.548	0.655	0.674	0.923	0.564
SN2	0.284	0.428	0.481	0.321	0.313	0.773
SN4	0.498	0.573	0.631	0.634	0.565	0.892

Highlighted external loadings represent the correlation with their respective constructs. Outer loading > 0.708. Source: Prepared by the authors using SmartPLS 4.

the instrument, additional input was obtained from three subject-matter experts in accounting and educational research, who contributed to the refinement of item wording, content validity, and contextual relevance.

The development process entailed the explicit mapping of each question to a theoretical construct. For instance, items pertaining to perceived usefulness included statements such as "I believe the AI-based simulator helps me better understand depreciation methods," while perceived behavioral control was assessed with items like "I feel confident in my ability to use AI-based tools for accounting tasks." The clarity and internal consistency of the questions were assessed in a pilot test conducted with 20 students from a different cohort. This pilot test led to the refinement of several items prior to final data collection. As illustrated in Table 1 The Likert-type structure was maintained from the original scale to preserve psychometric integrity and ensure comparability with prior research.

3 Statistical model results

The statistical analysis was conducted using Structural Equation Modeling (SEM), a multivariate analysis technique that, according to Zeng et al. (2021), is considered both routine and essential in the validation of theoretical models. Specifically, this study employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which focuses on maximizing the explained variance of the dependent latent constructs rather than reproducing a theoretical covariance matrix. The analysis was performed using Smart PLS 4 software (Ringle et al., 2022).

The analytical process comprised two main stages: the measurement model and the structural model. In the measurement model, the assessment included convergent validity (via factor loadings and Average Variance Extracted AVE), internal consistency reliability (using Cronbach's alpha and composite reliability), and discriminant validity. The latter was evaluated through the cross-loadings criterion, ensuring that each indicator loads more highly on its assigned construct than on any other, as recommended by Hair et al. (2019). In the structural model, the proposed hypotheses were tested, and the explanatory power of the model was examined using coefficients of determination (R^2) and path coefficients.

3.1 Analysis of the measurement model

The analysis initiates with the validation of the model's external loadings to ensure convergent validity. According to experts in the field, external loadings should exceed 0.708, thereby ensuring that the square of that number indicates that the construct score incorporates a minimum of 50% of the variable's variance (Hair et al., 2017). In this sense, the initial criterion is fulfilled, as demonstrated in Table 2 which shows that all indicators exhibit satisfactory external loadings. Additionally, it has been observed that the correlations of the indicators' external loadings with respect to their construct are greater than the correlations with other constructs (which they should not measure) (Rasoolimanesh, 2022). Moreover, indicators that do not meet the specified criterion are eliminated in order to avoid any detrimental impact on the model's quality. Consequently, the following constructs are eliminated: The following elements must be given full consideration: The following elements are listed herewith: BI1, PU1, PBC1, PBC2, SN1, SN3, and SN5.

The aforementioned validation encompasses a multicollinearity analysis, which is conducted utilizing the variance inflation factor (VIF). In the context of PLS-SEM, a tolerance value of less than 0.2 is recommended, as values greater than 5 indicate critical levels of collinearity between constructs. Consequently, a value of less

TABLE 3 Convergent validity of the model.

Construct	Indicator	Outer loadings	VIF	Composite reliability	Average variance extracted (AVE)
Attitude toward behavior	ATB1	0.807	1.364	0.807	0.582
	ATB2	0.727	1.268		
	ATB3	0.752	1.202		
Behavioral intention	BI2	0.836	1.366	0.861	0.756
	BI3	0.902	1.366		
Perceived behavior control	PBC3	0.710	1.098	0.781	0.643
	PBC4	0.884	1.098		
Perceived ease of use	PEU1	0.718	1.171	0.806	0.679
	PEU2	0.917	1.171		
Perceived usefulness	PU2	0.742	1.222	0.822	0.701
	PU3	0.923	1.222		
Subjective norm	SN2	0.773	1.193	0.820	0.696
	SN4	0.892	1.193		

Outer loadings > 0.7; VIF < 3.3; CR > 0.7; AVE > 0.5. Source: Prepared by the authors using SmartPLS 4.

than 3.3 is proposed (Martínez Ávila and Fierro Moreno, 2018). The results of this analysis, presented in Table 3 demonstrate that this criterion is met and, therefore, the model does not present collinearity issues.

Furthermore, the convergent validity analysis demonstrates that the Average Variance Extracted (AVE) criterion is met, which is regarded as the most significant test. According to experts in the field, the AVE value for each construct must be a minimum of 0.5 in order to be considered acceptable (Purwanto and Sudargini, 2021). The results presented in Table 3 further corroborate the validity of this criterion. Consequently, the model demonstrates convergent validity.

A reliability test is also conducted, utilizing composite reliability (CR) to ascertain the model's internal consistency. The findings of this study indicate that the model demonstrates sufficient internal consistency. Consequently, higher CR values are indicative of greater reliability and internal consistency. As posited by Hair et al. (2019), reliability values ranging from 0.6 to 0.7 are deemed to be "acceptable in exploratory research," whereas values between 0.70 and 0.90 are classified as "satisfactory to good."

In this study, CR was prioritized over Cronbach's alpha, another reliability measure, as CR has been demonstrated to produce higher values than Cronbach's alpha (Purwanto and Sudargini, 2021). This discrepancy can be attributed to the fact that CR, in contrast to Cronbach's alpha, does not presuppose that all indicators are equally reliable. Consequently, CR is more appropriate for PLS-SEM (Hair et al., 2011). Consequently, the outcomes presented in Table 3 substantiate that the model meets the established reliability criteria.

Furthermore, the instrument's psychometric properties were evaluated using reliability and validity indicators. The reliability of the data was assessed using Cronbach's alpha coefficient, a statistical measure of internal consistency. The coefficient values for all constructs exceeded the 0.70 threshold, indicating acceptable reliability. The Composite Reliability (CR) metric was also utilized, yielding values ranging from 0.78 to 0.86, which exceed the recommended minimum of 0.70. The external factor loadings of the items were found to be above 0.708, a criterion that ensures the convergent validity of the indicators. This validity is further substantiated by the Average Variance Extracted (AVE) values, which consistently exceeded 0.50 in all cases. Finally, the Variance Inflation Factor (VIF) values remained below 3.3, ruling out the presence of multicollinearity. These results confirm that the instrument applied possesses adequate psychometric properties for measuring the theoretical constructs of the proposed model.

The discriminant validity of the model was then assessed using the Fornell-Larcker criterion, which compares the square root of the AVE with the correlations between the latent variables. As posited by Afthanorhan et al. (2021), the square root of the AVE for each construct must exceed its highest correlation with any other construct in order to demonstrate the discriminant validity of the model. The results, presented in Table 4, confirm that this criterion is met.

3.2 Analysis of the structure model

The present analysis encompasses both hypothesis testing and the predictive capability of the model. The results of the hypothesis testing are presented in Table 5. In order to conduct this analysis, the path coefficient test was performed, examining each path separately. The findings indicate that all path coefficients are significant at the $p = 0.000$ level, with additional support from a significance level of $p < 0.05$ (Astrachan et al., 2014). The findings of the study indicate that seven hypotheses of the model are accepted, while three are rejected.

The validity of this analysis is contingent upon the model's capacity to provide a comprehensive explanation. The results of this study are presented in Figure 2. The coefficient of determination R^2 is utilized to evaluate this power, as it quantifies the predictive value

TABLE 4 Fornell-Larcker criterion.

	Attitude toward behavior	Behavioral intention	Perceived ease of use	Perceived usefulness	Perceived behavior control	Subjective norm
Attitude toward behavior	0.763					
Behavioral intention	0.544	0.870				
Perceived ease of use	0.545	0.530	0.824			
Perceived usefulness	0.433	0.521	0.660	0.837		
Perceived behavior control	0.395	0.634	0.574	0.648	0.802	
Subjective norm	0.486	0.609	0.598	0.546	0.675	0.835

Source: Prepared by the authors using SmartPLS 4.

TABLE 5 Contrast of structural hypotheses.

Hyphotesis	Original sample (O)	*T* statistics	*p* values
Attitude toward behavior → behavioral intention	0.272	2.307	0.021
Perceived ease of use → behavioral intention	0.033	0.303	0.762
Perceived ease of use → perceived usefulness	0.660	9.575	0.000
Perceived ease of use → perceived behavior control	0.265	2.665	0.008
Perceived usefulness → attitude toward behavior	0.239	1.949	0.051
Perceived usefulness → behavioral intention	0.054	0.392	0.695
Perceived behavior control → behavioral intention	0.337	2.581	0.010
Subjective norm → attitude toward behavior	0.355	3.727	0.000
Subjective norm → behavioral intention	0.199	2.014	0.044
Subjective norm → perceived behavior control	0.516	5.767	0.000

T statistics > 1.96; > p values < 0.05. Source: Prepared by the authors using SmartPLS 4.

within the sample. According to reference values, an explained variance of 0.72 is considered satisfactory, 0.56 is moderate, and 0.34 is weak (Hair et al., 2017). The findings suggest that behavioral intention and perceived behavioral control possess a moderate-to-high degree of predictive capability. Conversely, perceived usefulness exhibited moderate-low predictive capability, while attitude toward the behavior demonstrated low predictive capacity.

In addition, a non-parametric Stone-Geisser Q2 test was employed to evaluate the extent to which the model approximates expectations. This test establishes values greater than zero as the evaluation criterion (Ringle et al., 2014). However, it is important to note the existence of benchmark values: Predictive accuracy is categorized as low (greater than zero), medium (greater than 0.25), or high (greater than 0.5) (Ghasemy et al., 2020). The findings suggest that perceived behavioral control ($Q^2 = 0.467$) and perceived usefulness (0.412) emerge as the factors exhibiting the greatest predictive capacity.

With respect to demographic characteristics, the sample comprised 105 undergraduate students enrolled in the Public Accounting and Technology in Cost and Budget Analysis programs at the Instituto Tecnológico Metropolitano (ITM) in Medellín, Colombia. Of these, 58.1% were female and 41.9% male. Regarding age demographics, the data revealed that 67.6% of the subjects fell within the 18 to 24 age range, 25.7% were between 25 and 30 years of age, and 6.7% were above 30. With respect to academic progression, 34.3% of the sample were in the first three semesters, 48.6% were in semesters four to six, and 17.1% were in the seventh semester or higher.

TABLE 6 Demographic characteristics of the participants.

Variable	Category	Frequency	Percentage (%)
Gender	Female	61	58.10%
	Male	44	41.90%
Age	18–24 years	71	67.60%
	25–30 years	27	25.70%
	Over 30 years	7	6.70%
Current semester	1s—3rd	36	34.30%
	4th—6th	51	48.60%
	7th or above	18	17.10%

Source: Prepared by the authors based on questionnaire data.

While the findings yielded meaningful insights for the ITM student population, it is imperative to acknowledge the limitations of generalizability within the specific institutional and geographical context. The sampling method was based on accessible and voluntary participation, which may introduce a self-selection bias,

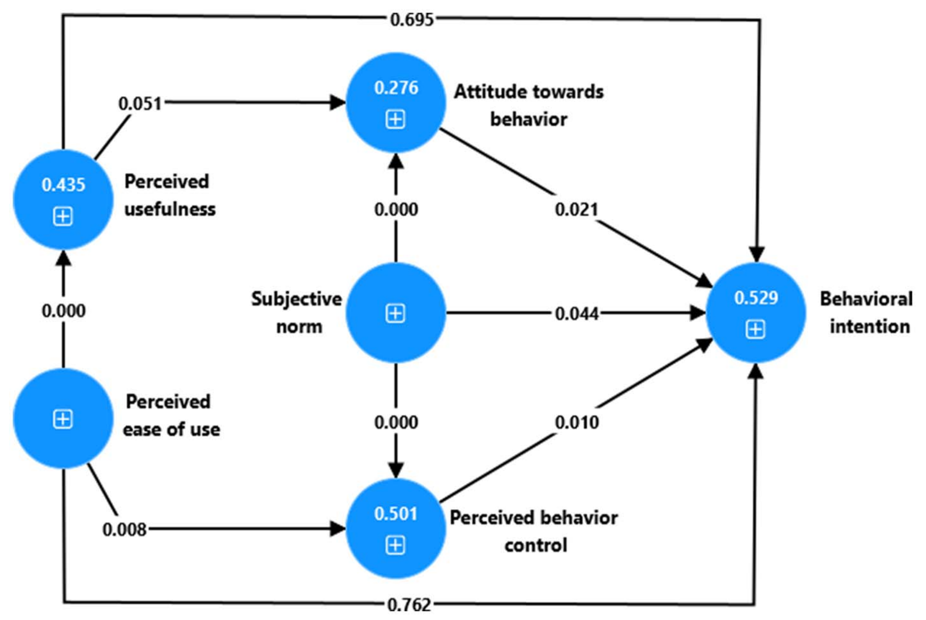

FIGURE 2
Hypothesis contrast and predictive capacity of the model.

as reflected in the demographic distribution presented in Table 6. Consequently, the results should be interpreted with caution when attempting to extrapolate them to other institutions, regions, or academic programs. Future research is encouraged to replicate this study using larger and more diverse samples, including both public and private institutions, as well as urban and rural contexts, to enhance the external validity of the findings.

4 Discussion

The study's findings indicate a robust correlation between perceived ease of use and perceived usefulness. Consequently, students who anticipate minimal technical challenges or complexity when utilizing these tools are more likely to recognize their practical benefits. A substantial body of prior research has identified a positive correlation between these two factors, thereby mediating the relationship between the level of technological readiness exhibited by accounting students and the adoption of artificial intelligence technology (Damerji and Salimi, 2021).

Another significant relationship that has been identified is that of subjective norm versus perceived behavioral control. The study revealed that students' perceptions of social expectations and the influence of prominent individuals served to bolster their confidence in their capacity to utilize AI tools effectively. The findings of this study are corroborated by research conducted by Hwang et al. (2024), which identified a positive correlation between subjective norm and perceived behavioral control in the adoption of artificial intelligence technology.

In a similar vein, subjective norms were also demonstrated to exert influence over students' attitudes. This finding suggests that when students perceive that their social environment values and supports the use of this technology, they are more likely to adopt a positive attitude toward its use in accounting education, considering it useful, beneficial, and desirable. The results of the present study underscore the pivotal role of subjective norms in students' technology adoption decisions, thereby facilitating the adoption and approval of specific behaviors (Wang et al., 2024).

The findings further demonstrated that perceived ease of use exerted an influence on perceived behavioral control. Consequently, students' confidence in their ability to use AI tools effectively is increased when they perceive them as easy to handle and understand. The findings of the study demonstrated that control had a significant impact on intention to use. Consequently, students who perceive themselves to possess the necessary skills, resources, and capacity to utilize AI tools are more inclined to express a greater willingness or intention to incorporate them into their learning processes. These results align with the findings of Roy et al. (2022), who determined that perceived behavioral control influences the intention to adopt AI-based robots in university education.

A further salient finding pertains to the influence that subjective norms exert on students' intention to utilize artificial intelligence. In this sense, students are more likely to develop a firm intention to adopt AI in their learning process if they perceive that their social environment values and supports its use. These findings are consistent with those of previous studies that have examined the efficacy of AI-based technologies in the education of university students (Li et al., 2022; Roy et al., 2022).

Conversely, certain hypothesized relationships within the model including those between perceived usefulness and attitude, as well as between perceived usefulness and behavioral intention were determined to be statistically insignificant, as evidenced by p-values that exceeded the 0.05 threshold. However, these results do not indicate a negative influence, since the relationships retain a positive sign. This distinction is of consequence because it suggests

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that while students may have perceived the tools as useful and easy to use, these perceptions did not have a significant impact on their attitudes or behavioral intentions in this particular context.

The absence of statistically significant relationships may be attributed to several factors. One potential explanation for this phenomenon lies in context-specific expectations or cultural and pedagogical influences that moderate how students translate their perceptions into attitudes or intentions. As Krishnanraw and Ismail (2025) have observed, technology readiness may moderate the relationship between perceived usefulness and attitude, particularly in environments where students have limited prior exposure to AI tools or are accustomed to traditional learning methods. In a similar vein, Bui et al. (2025) found that although Vietnamese accounting students recognized the practicality of AI technologies, their attitudes remained cautious or skeptical due to prevailing educational norms that emphasize conventional over technology-mediated instruction.

This discrepancy may also be indicative of a divergence between the theoretical appreciation and practical applicability of the concept. While students may acknowledge the conceptual benefits of AI tools, they may face challenges in recognizing how these benefits translate into tangible improvements in their own learning outcomes. Al-Okaily (2025) found that, in the context of Chat GPT utilization among accounting students, students' attitudes were more strongly shaped by factors such as trust in the technology, its relevance to the curriculum, and the role played by instructors, despite high levels of perceived usefulness.

In summary, the study revealed that perceived ease of use and perceived usefulness did not have a significant impact on behavioral intention. Additionally, the findings indicated that perceived usefulness did not significantly influence attitude. However, this absence of significance does not necessarily imply a negative influence. Instead, it suggests that other contextual or intervening variables may play a critical role in shaping students' acceptance of AI tools. These findings underscore the necessity for strategies that more closely align the perceived usefulness and ease of use of AI tools with students' actual learning experiences and expectations, as well as with institutional and pedagogical support mechanisms.

4.1 Limitations

The limitations of the study are finally highlighted. Firstly, the research was conducted with accounting students from the ITM, which restricts the sample to a single institution. Consequently, the generalizability of the findings may be constrained. It is recommended that subsequent studies encompass an examination of the phenomenon in a variety of higher education institutions, encompassing both urban and rural areas of the country. This approach will facilitate the acquisition of a more comprehensive set of insights and the incorporation of a diverse array of academic and cultural settings.

Secondly, although this study integrates two robust theoretical frameworks the TPB and the TAM the inclusion of other models, such as the UTAUT, may enrich the theoretical foundation. Such inclusion has the potential to provide a more multifactorial and comprehensive perspective on technology adoption, particularly in educational contexts involving emerging technologies such as artificial intelligence.

A notable constraint pertains to the experimental design, which lacked a control group. The absence of a comparative condition imposes limitations on the capacity to isolate the effects of the intervention, specifically the AI-generated video and simulator. In the absence of a baseline or an alternative instructional method, it is challenging to attribute the observed effects exclusively to the intervention. Consequently, this limits the internal validity of the study.

Additionally, the brief exposure to the intervention may have influenced the development of stable perceptions and attitudes. Given that students' interactions with the AI tools were limited to a single session, it is possible that their responses may reflect initial reactions rather than sustained or long-term behavioral intentions. This limited exposure may help explain why some expected relationships such as the influence of perceived usefulness on attitude or intention were found to be statistically insignificant, even though the direction of the associations was positive. The findings of this study underscore the importance of designing longitudinal studies that capture changes in technology acceptance over time and in response to extended engagement with educational technologies.

5 Conclusions

The objective of this study was to examine the behavioral factors that influence accounting students' intention to adopt AI-based educational tools, specifically through the use of AI-generated videos combined with interactive simulators. The present study was grounded in the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The objective of the present study was to explore the influence of constructs such as perceived usefulness, perceived ease of use, attitude, perceived behavioral control, and subjective norm on students' intention to utilize these tools.

The findings emphasize the pivotal role of perceived ease of use in shaping students' evaluations of the usefulness of AI-based tools in accounting education. When students perceive these tools as intuitive and easy to navigate, they are more likely to recognize their value and relevance to academic learning. This underscores the significance of user-friendly design and interface accessibility in promoting adoption within technology-enhanced learning environments.

Furthermore, the influence of the social environment, particularly the support from peers and instructors, was identified as an important element in enhancing students' confidence in adopting AI tools. However, the findings of this study suggest that such social influences did not demonstrate a statistically significant relationship with behavioral intention. This observation may indicate a need for further exploration of contextual or implementation-related factors.

While a non-significant relationship was identified between perceived usefulness and attitude, the direction of the relationship was not negative. This outcome deviates from conventional expectations within the TAM framework, suggesting that the technology may be in its nascent stages of adoption or that there is a discrepancy between students' expectations and their preliminary experience with the tools. It is evident that further research is necessary to achieve a more profound comprehension of the subtleties inherent to this association.

While the results provide insights into the behavioral mechanisms involved in AI adoption, the conclusions must be interpreted within the limitations of the study. These limitations include the absence of a control group, the short-term exposure to the intervention, and the focus on a single institutional context. Therefore, it is imperative to exercise caution when generalizing the findings.

Future research should replicate and expand these findings across diverse academic and cultural settings, using longitudinal approaches and more robust experimental designs. Furthermore, the integration of alternative or complementary theoretical frameworks has the potential to facilitate a more comprehensive understanding of the multifaceted factors that influence technology adoption in accounting education.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical approval was not required for the studies involving humans because the questionnaire was anonymous, with no personal information collected or included. This was previously indicated, and participants would participate in the questionnaire if they accepted the conditions. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and institutional requirements.

Author contributions

DG: Writing – review & editing, Writing – original draft. AV-A: Writing – original draft, Writing – review & editing. JA: Writing – original draft, Writing – review & editing. JR: Writing – review & editing, Writing – original draft. LV: Writing – review & editing, Writing – original draft. JV: Writing – review & editing, Writing – original draft.

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