Interdisciplinary Description of Complex Systems 24(4), 380-398, 2026

EXPLORING AI ACCEPTANCE IN HIGHER EDUCATION DATA ANALYTICS FOR ACCOUNTING AND AUDITING: A TAM-DRIVEN PLS-SEM ANALYSIS

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DOI: 10.7906/indecs.24.4.2
Regular article

Received: 23 February 2026.
Accepted: 9 April 2026.

ABSTRACT

The objective of this research is to identify and evaluate the determinants of AI technology acceptance and usage intention in higher education courses focused on data analytics in accounting and auditing. The research sample comprises 281 students from the Faculty of Economics & Business at the University of Zagreb in Croatia. To conduct the analysis, we employed the original Technology Acceptance Model and the Partial Least Square-Structural Equation Modelling analytical approach. A central finding of this study is the dominant role of Perceived Ease of Use. Perceived Ease of Use has a fundamental position in shaping students' perceptions. Although modifications of Technology Acceptance Model-based models do not include attitude towards use, in our research, this factor serves as an important channel from perceived usefulness and perceived ease of use to behavioral intention to use AI. Furthermore, in our study, behavioral intention to use has the strongest predictive power for actual use of AI. An important contribution of this article concerns the specifics of applying AI in teaching, namely data analytics, which is increasingly significant across various professions, especially in accounting and auditing. Data analytics is an area strongly affected by the development of AI, leading to many new and improved tools and methodologies that leverage generative AI. For university programs to adequately respond to market needs, it is important to understand how students perceive the application of artificial intelligence in learning data analytics, and to what extent they are ready to adopt new technologies that will shape their future professional development.

KEY WORDS

artificial intelligence, AI, data analytics, higher education, TAM, accounting

CLASSIFICATION

JEL: I21, I23, M41, M42

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INTRODUCTION

The accelerated development of information and communication technology over the last five years has led to radical changes in global perspectives, policies, the economy, the business environment, and the everyday lives of individuals. With the widespread application of modern technologies such as Blockchain, RPA, IPA, IoT, cloud computing, edge computing, computer vision and machine learning, it is specifically the development of deep learning and the application of generative artificial intelligence that has had the most significant impact and influence on almost all dimensions of the global environment. Besides optimizing teaching skills, AI reforms the evaluation mechanism of higher education and innovates the coordination of school-running resources. Business processes and activities are more effective and efficient, and individual productivity has significantly increased. Although individuals have certain fears about the disappearance of numerous jobs and professions, it is important to recognize that future employability depends on their ability to keep pace with technological development and to develop appropriate competencies. Acquiring the knowledge, skills, and experience to use advanced and emerging technologies actively is imperative for maintaining competitiveness in the labor market. The education system, from primary to higher education, plays a crucial role in acquiring the necessary knowledge and developing appropriate skills. Technological development has a fundamental effect on the transformation of educational processes, leading to the integration of innovative tools into study programs [1]. Modernization of higher education programs is a necessary condition for acquiring the competencies required to work in an environment characterized by digital transformation, intelligent process automation, the adoption of generative artificial intelligence, and the upcoming development of Industry 5.0. In such big-data environment, data analytics has gained significant momentum in recent years. Data analytics has been strongly affected by the development of artificial intelligence, leading to many new and improved tools and methodologies that leverage generative AI. AI enables the processing of large amounts of data, the automation of complex analytical procedures, and the generation of insights that were previously unavailable due to technical limitations. Data analytics enables the automation of routine manual tasks and boosts efficiency and effectiveness in data-rich fields, such as accounting and auditing [2]. The implementation of analytical methods that were impossible due to hardware and software limitations is becoming increasingly common today. Limitations basically come down to the analyst's creativity and competence. Thus, data analytics results supported by advanced technology and AI serve as the basis for business decision-making, the improvement of business processes and internal control systems, risk management, and overall corporate governance. Moreover, the importance of data analytics skills is proven by accounting professional bodies. Today, to comply with Technical Competency Areas, accounting organizations, such as the CPA, emphasize the need to include data analytics in the curricula of universities offering accounting and auditing degrees [2]. An important source of relevant, objective, transparent, and reliable data in any such business environment is the accounting system. Crucial roles in collecting, storing, and processing financial and accounting data are played by accounting information systems, which have a significant role in supporting decision-making by the company's management [3]. Traditionally, accounting and auditing are professions that rely on the collection, verification, processing, and analysis of data, and on the interpretation of the information obtained, i.e., the results of data analytics. Therefore, it is not unexpected that digital transformation has significantly accelerated the development of intelligent process automation, enabled the application of various techniques for detecting anomalies, outliers, and patterns, as well as advanced predictive, and prescriptive models. AI is changing and improving accounting and auditing processes, transforming the roles of accountants and auditors from technical to supervisory and analytical. Nowadays, professionals use AI technology to conduct more informative financial analysis and provide strategic advice to management, thereby changing their career development and specialization [4]. These transformations redefine the competencies needed for future professionals, with particular emphasis on digital skills and knowledge, analytical thinking, professional judgment, and professional skepticism. Market demands in the accounting field emphasize the need for accountants to adapt to AI technology and develop skills such as creativity, problem-solving, and communication [4]. Additionally, these contemporary technologies enhance the quality of accounting education and prepare students for current business conditions, as illustrated by digitalization processes [1]. Additionally, AI tools ease the implementation of continuous auditing in the business environment by leveraging automated software and advanced technologies to monitor, collect, and analyze audit evidence in real time [3]. Given that it significantly increases effectiveness and efficiency, the accounting and auditing professions depend heavily on AI technology) [5]. Nowadays, crucial skills for accounting and auditing graduates include SQL and database management, AI-based data analytics, and critical thinking [2]. For university programs to adequately respond to market needs, it is important to understand how students perceive the application of artificial intelligence in learning data analytics, and to what extent they are ready to adopt new technologies that will shape their future professional development. Thus, a holistic approach to planning future curriculum is crucial to ensure that students attain proficiency in AI and advanced technologies [3].

Thus, the main objective of this article is to identify and evaluate the determinants of acceptance and usage intention for AI technology in higher education courses focused on data analytics in accounting and auditing, employing the Technology Acceptance Model (TAM) and the Partial Least Square-Structural Equation Modelling (PLS-SEM) analytical approach.

LITERATURE REVIEW

To date, many authors have researched perceived usefulness and usage of AI in higher education [1-16]. Most of these studies focused on student perceptions and actual use of AI in education; however, several studies focused on teachers and educators, i.e. faculty members [6, 10, 13], or focused on students and faculty members [11]. More recent studies on the use of AI in accounting and auditing education are based on primary research conducted through questionnaires and TAM with most studies using the PLS-SEM approach to analyse the data [1, 3, 9]. In contrast, Abdullah and Almaqtari [4] used SEM. The following sections present the literature from the broad to the specific: first, covering AI adoption in higher education generally then narrowing to accounting and auditing education followed by a synthesis of key TAM variables across studies, and concluding with the research gap this article addresses.

AI ADOPTION IN HIGHER EDUCATION

Research on AI adoption in higher education spans diverse geographic and disciplinary contexts, with most studies employing the TAM or its extensions to examine students' and instructors' perceptions, adopting approaches that differ from the predominantly quantitative TAM literature. Billy and Anush [11] investigated students' and teachers' perceptions of AI use. Unlike other studies, which were mainly based on TAM, these authors had a different approach. Billy and Anush [11] conducted interviews to examine students' and instructors' perceptions of AI in education. They found that students with a better understanding of AI, particularly those in STEM courses, were more open to integrating it into classrooms. Additionally, the benefits of technology over traditional teaching methods influence students' attitudes. While AI systems can enhance communication and provide personalized support, concerns remain about responsibility, effectiveness, and surveillance [11].

Quantitative TAM-based studies generally confirm a positive relationship between perceived usefulness, ease of use, and AI adoption intention. Aldreabi et al. [7] studied the impact of Generative AI (GenAI) on higher education from 374 students using the UTAUT2 model and SEM approach. They found that ease of use and support resources are crucial for students' adoption of GenAI tools, suggesting that practical utility and accessibility are more important than enjoyment or accuracy [7]. Almusharraf and Bailey [8] also explored how integrating generative AI into higher education affected teaching and learning, specifically in the context of students' language learning. The authors used a cross-sectional design to explore direct and indirect relationships between perceptions and the actual use of GenAI. The sample included 407 Saudi Arabian and 274 South Korean students who rated their English proficiency. Perceived ease of use had the strongest impact on students' perceptions of GenAI, whereas actual use had the weakest. Based on these results, the authors concluded that there is a gap between students' ability to understand GenAI tools and their willingness or need to use them. Furthermore, they found a positive relationship between age and actual use, which indicates that "older students may be more adaptable or see greater value in these tools" [8].

Similar results obtained by Tbaishat et al. [16], who studied the factors affecting university students' adoption of generative artificial intelligence tools in higher education. Using the TAM and SEM, they analyzed a sample of 517 students from Jordanian universities. The findings revealed that, alongside perceived usefulness and ease of use, adoption was influenced by motivational needs, autonomy, competence, and relatedness, with social influences being less significant. Among students, authors found relatedness to be a predictor of actual use competence, underscoring the importance of psychological needs in sustaining meaningful engagement. Ultimately, the authors concluded that motivational dynamics might be more significant than social norms in collectivist cultures [16].

Ngomane [12] conducted a quantitative study on factors influencing the use of AI-powered tools in academic research among South African university students. Based on a sample of 271 final year undergraduate and postgraduate students from Wits University, the study used an extended TAM that included perceived information effectiveness, prior knowledge, awareness, and social influence. The findings reveal that perceived usefulness, ease of use, prior knowledge, and awareness are key drivers of tool utilization. Furthermore, this is moderated by trust and self-efficacy. The perceived usefulness and ease of use of AI tools influence students' decisions to utilise them, indicating that most students view them as relevant to their research and find them easy to use [12].

Al-Zahrani and Alasmari [10] conducted a TAM study with 509 participants from 259 institutions across 19 Middle East and North Africa (MENA) countries. They found that AI adoption is still in its early stages, showing significant differences between developed and underdeveloped nations. The TAM analysis revealed that a high adoption rate is closely tied to perceived usefulness, whereas average or below-average self-assessments are associated with perceived ease of use. Infrastructure limitations affect perceptions of implementation, and there are strong correlations between AI adoption and positive learning outcomes, highlighting its practical value. As a key barrier, the authors singled out faculty readiness and training to adopt AI in education. A significant barrier to AI adoption in curricula is the lack of needed expertise among teachers [10]. Additionally, they emphasized that the lack of technological infrastructure, data privacy and ethical concerns, and the lack of clear policy and strategic direction are challenges and barriers to AI adoption in higher education institutions in the MENA region.

Among faculty-focused studies, Robinson [13] applied the TAM to study the relationships among perceived ease of use (PEU), perceived usefulness (PU), attitude towards using (ATU), and intention to use (IU) among faculty at Seminole State College of Florida. Using a structured questionnaire administered to 64 faculty members, the study found that PEU significantly predicts PU; however, PU negatively affects ATU – a result that conflicts with the broader literature. The authors concluded that while educators recognise the potential benefits of AI tools, they remain concerned about issues such as academic integrity, job security, and ethical dilemmas [13]. Al Darayseh [6] studied 83 science teachers in Abu Dhabi to investigate their perceptions of AI applications in science education. The results indicated strong acceptance of AI among the teachers. Using the TAM, the study found a positive relationship between AI use and factors such as self-efficacy, PEU, expected benefits, attitudes, and behavioural intentions. The authors concluded that teachers perceived ease of use and necessary skills positively influenced their attitudes and intentions to adopt AI in the future [6].

Finally, several studies highlight the broader importance of attitude as a predictor of behavioural intention. Sharma et al. [14] used the TAM to investigate how perceived usefulness, PEU, attitude, prior experience, and awareness influence students' intentions to adopt AI tools such as ChatGPT for their studies. They gathered data from 205 students through an online survey, utilizing purposive and convenience sampling methods. The authors' concluded that PU significantly influences students' intentions to adopt ChatGPT.

AI IN ACCOUNTING AND AUDITING EDUCATION

Only a few studies have examined the perceived usefulness and actual use of AI in data analytics courses in accounting and auditing [1-5, 9, 15]. Ali et al. [5] and Tandiono [15] provided a literature review of the main developmental directions of AI use in accounting and auditing education. Significant conclusions from the literature review identify competencies as crucial factors for AI adoption. Thus, Ali et al. [5] concluded that education is insufficiently aligned with the application of AI, thereby hindering employees' ability to adapt to changes in accounting and auditing practices. They further concluded that accounting and auditors will not completely vanish, because, despite the implementation of AI technologies, human creativity and professional judgment are still required. Rather, accountants and auditors will take on another role – improving efficiency and adding value to the company – as traditional accounting processes are automated [5]. Their conclusion that AI should serve as a complement to human intelligence, enhancing the work processes of accountants and auditors while reducing the time and effort needed to complete tasks, is consistent with the Internet 5.0 postulate.

Tandiono [15] concluded that AI has a significant impact on the accounting profession as a whole, emphasizing that accounting educators must be prepared to adapt curricula and employ methods to ensure students acquire the competencies needed to succeed in this evolving industry. In a more concrete direction, Prokofieva [2] offered a concrete suggestion for using data analytics in teaching audit with AI. The author demonstrates how data analytics boosts productivity across different phases of financial statement audits, supported by the auditing management platform Mind-Bridge, which automates the auditing workflow and focuses on the audit cycle and tasks. Additionally, implementing AI and deep learning in accounting education could develop practical skills in applying sophisticated technologies, such as task automation and deep learning [4]. Thus, integrating automation, data analytics, and AI into accounting courses enables students to develop the skills needed to adapt to digitalization [4].

Empirical TAM-based studies in accounting and auditing education report consistent findings. Gaviria Rodríguez et al. [1], examining 105 university-level accounting students in Medellín, Colombia, found that perceived ease of use and perceived usefulness did not significantly affect behavioural intention to use – though they noted that when students find tools intuitive and easy to navigate, they are more likely to recognize their value in academic learning [1]. Using a sample of 228 respondents from various Saudi organizations, Abdullah and Almaqtari [4] recognised the usefullness and concluded that AI has beneficial effects on accounting and auditing methodologies. In the context of education, the authors found a significant positive relationship with readiness. Jyashree [3] found that several factors, including optimism, innovativeness, discomfort, job relevance, and superior functionality, influence students' intentions to engage with AI. The author concluded that universities are well-positioned to enhance their curricula and educational approaches to prepare students better for a professional landscape increasingly centred on AI. To achieve this goal, he recommends incorporating case studies and practical simulations into the learning experience. His research indicates that discomfort affects students' willingness to use AI and involved 136 third- and fourth-year accounting students from various institutions in Malaysia.

On the other hand, Al-Okaily [9] adopted a different approach by investigating factors relevant to the use and continued use of ChatGPT among 1025 accounting students at Jordanian higher education institutions for educational purposes. Unlike other studies, the author investigated various aspects that shape ChatGPT's continued use and extended the classical TAM factors to include COVID-19 concerns, protection motivation, and peer influence. Authors found that concerns about COVID-19 and protection motivation significantly affect usage, and that usage and peer influence impact continuance intention to use ChatGPT. By innovating study programs, professors offer opportunities to study contemporary accounting and auditing approaches and provide the necessary foundation for developing the competencies of future accountants and auditors.

KEY TAM VARIABLES AS PREDICTORS OF AI ACCEPTANCE

Across the literature reviewed, three TAM constructs consistently emerge as the primary predictors of AI acceptance in higher education: PU, PEU, and ATU. While individual studies report some divergent findings, the overall pattern is one of convergence.

Perceived Usefulness

Most studies confirm that perceived usefulness is a significant positive predictor of behavioural intention to use AI. Sharma et al. [14] PU significantly influences students' intentions to adopt ChatGPT. Al-Zahrani and Alasmari [10] found that a high adoption rate is closely tied to perceived usefulness. Abdullah and Almaqtari [4] confirmed a positive relationship between AI and perceived usefulness in accounting and auditing professions. Prędkiewicz and Biegun [17] agree that perceived usefulness and ease of use significantly influence attitudes toward AI adoption among accountants. Conflicting results were reported by Robinson [13], whose study found that perceived usefulness negatively affected ATU among faculty at Seminole State College of Florida, and by Gaviria Rodríguez et al. [1], who found that perceived usefulness did not significantly affect behavioural intention to use.

Perceived Ease of Use

Most research identifies out ease of use as a relevant and dominant factor influencing perceived usefulness and/or actual use of AI in education [1, 4, 6-8, 10, 12-14, 16]. Al Darayseh [6] found that teachers PEU and necessary skills positively influenced their attitudes and intentions to adopt AI in the future [6]. Aldreabi et al. [7] found that ease of use and support resources are crucial for students' adoption of GenAI tools. Almusharraf and Bailey [8] found that PEU showed the strongest impact on students' perception of GenAI. Ngomane [12] confirmed ease of use as a key driver of tool utilization, with trust and self-efficacy moderating its effect. Robinson [13] also emphasize ease of use as an important factor regarding AI in education. A notable exception is Sharma et al. [14], who found that ease of use is not a significant variable in their model, with Gaviria Rodríguez et al. [1] obtaining similar results. Al-Zahrani and Alasmari [10] emphasized the lack of necessary expertise among teachers and technological infrastructure as a key barriers to AI adoption.

In the context of this research's objective, the ease of use of AI in learning data analytics is a significant variable. The assumption is that ease of use for today's generation of economics students is a crucial characteristic for the application of a technology, including artificial intelligence. Previous research also confirms that the simpler the technology, the greater its perceived usefulness, and that students are more likely to use it.

Attitude Toward Using as a Predictor of Intention to Use

ATU AI consistently emerges as a significant predictor of behavioural intention across studies. Tbaishat et al. [16] confirmed that, among other variables, ATU AI is a significant predictor of behavioural intention to use AI. Furthermore, authors found that both perceived usefulness and ease of use shape attitude. Thus, they concluded that when students see tangible benefits combined with simplicity, their attitude becomes more positive and their intention to use increases. By investigating AI acceptance in managerial accounting, Vărzaru [18] also found a favourable attitude and a high intention to use AI. Prędkiewicz and Biegun [17] agree that perceived usefulness and ease of use significantly influence attitudes toward AI adoption among accountants. Al Darayseh [6] stressed that teachers need appropriate tools to integrate AI into their teaching processes, thereby improving their positive attitude towards technology.

Therefore, professors' attitudes and approaches towards emerging technologies, including AI, significantly shape students' attitudes and their intention to use technology. Although technology is omnipresent today – both among teachers and students - the question is to what extent teachers actually implement it in the teaching process and to what extent they remain inclined toward traditional teaching methods. Regardless of this, we assume that attitudes towards AI have a significant impact on the intention to use, and indirectly on the actual use of AI in the teaching process, especially in the area of learning data analytics techniques.

RESEARCH GAP AND POSITIONING OF THIS STUDY

The literature review reveals several important patterns. First, TAM remains the dominant theoretical framework for examining AI acceptance in higher education, with PLS-SEM as the prevailing analytical method. Second, while authors consistently identify PU, ease of use, and attitude as relevant predictors, findings are not uniform, particularly among faculty, where conflicting results suggest that contextual factors (institutional culture, disciplinary norms, concerns about academic integrity, ethical questions) moderate the relationship between TAM constructs and adoption intention. Third, and most importantly for the present study, there are very few empirical investigations that combine these conditions simultaneously: (1) a TAM-PLS-SEM approach, (2) a focus on using AI in data analytics education in fields of accounting and auditing.

The literature review confirms the importance of implementing AI across the educational process. Accounting and auditing-related curricula are not exempt. This study addresses the identified gap by examining AI acceptance specifically within the data analytics courses in higher education in accounting and auditing, using a TAM-driven PLS-SEM analysis. In doing so, it contributes to an insufficiently explored intersection of AI adoption research, accounting education, and data analytics pedagogy, while also offering practical implications for curriculum designers and faculty seeking to integrate AI tools into their teaching. Additionally, the research extends the existing body of knowledge by accounting for professors' attitudes and approaches towards emerging technologies as an indirect influence on students' intention to use AI. By innovating study programs, professors offer opportunities to study contemporary accounting and auditing approaches and provide the necessary foundation for developing the competencies of future accountants and auditors.

METHODOLOGY

RESEARCH MODEL DEVELOPMENT

In today's environment, where technology plays an indispensable role in almost all human activities and business processes, it is important to understand how future generations will adopt the latest technologies, such as artificial intelligence. These findings are especially important for shaping future educational programs. Considering that there are only a few studies that investigate using AI technology in accounting and auditing education from a student perspective, and even fewer studies that research the importance of AI-supported data analytics in accounting and auditing, this study focuses on identifying the determinants influencing the acceptance and intention to use AI technology in higher education courses focused on data analytics in accounting and auditing. To test the research hypotheses developed to address these issues, this research uses the TAM. It is an approach whose main goal is to examine users' perceptions of a particular technology acceptance and actual use. Theories and models of technology adoption create a suitable theoretical framework and experimental approach that support the effective use of technology and systems [19]. In the 1980s, Fred Davis aimed to develop and test a theoretical model regarding how system characteristics influence user acceptance of computer-based information systems during their early stages, when this information holds the most value [20]. His conceptual model focuses on stimulus (system features & capabilities), the organism (users' motivation to use the system), and the response (actual system use). Davis [20] based his model on the Fishbein's 1967 model. The author emphasizes that the results of the study based on this model provide useful information for system designers and implementers to make informed decisions among alternative approaches. Thus, in the context of this research, the results will provide valuable information for educational programs and curriculum development on the use of AI in data analytics courses in accounting and auditing.

The first factor included in the model is PEU. This factor is important because it evaluates users' subjective perceptions of technology's ease of use and intuitiveness. Davis [20] defines perceived ease of use as the extent to which a person believes that using a specific system requires little physical and mental effort. It indirectly affects the actual use of technology and directly affects users' perception of usefulness, i.e., perceived ease of use has a causal effect on perceived usefulness [21]. In the context of this research, simplicity is a crucial factor because it can increase students' motivation and reduce resistance to AI technology in learning data analytics in accounting and auditing. Perceived simplicity usually determines whether students will use technology. The complexity of technology may lead to anxiety and rejection of it.

PU is one of the most influential determinants of technology acceptance. The determinant represents the extent to which a person believes that technology will improve their performance at work or in tasks [20]. Perceived usefulness represents the strongest predictor of intention to use the technology [22]. If the user believes that technology is genuinely useful for increasing productivity and efficiency, he or she will use it, even if it is not the simplest option. This factor enables a rational assessment of improvements in work, time savings, quality, and similar outcomes. Additionally, if users perceive that technology is easy to use, they are more likely to consider it useful. AI-based data analytics tools may be complex; thus, students want to be sure of the technology's usefulness before investing time in learning it. For them, clear added value must be obvious to have a strong impact on motivation to learn new AI-based data analytics tools.

Unlike cognitive assessment, which assesses thinking, logic, and rational analysis, ATU is an affective assessment based on the user's emotions and feelings when using the technology. Although the modified models (TAM2, TAM3, UTAUT, UTAUT2) do not include this factor, it is an integral part of the TAM. Davis et al. [22] state that, according to the Theory of Reasoned Action, an individual's attitude toward a behaviour is shaped by their salient beliefs about the consequences of performing that behaviour, multiplied by the evaluation of those consequences. On the one hand, perceived usefulness and ease of use represent cognitive factors, and on the other, attitude represents emotional standing; together, they provide a more complete picture when new and unknown technology is the subject of the research. Considering that AI is a specific technology with a significant impact on human opinion, causing fear that 'AI-machines' will replace people's jobs, ATU represents a crucial factor for understanding the acceptance of AI in education among students as future professionals.

Behavioural intention (BI) is a user's intention to use certain technology. This factor indicates actual technology use and represents the degree to which the user is ready and intends to use technology. PU and PEU affect behavioural intention and link psychological assessments to actual behaviour [23]. Theease of use of technology increases its usefulness, and more useful technology increases intention to use it. BI is highly stable factor and the strongest predictor of actual technology use. BI is important because it predicts whether students intend to use an AI-supported tool for data analytics in accounting and auditing. If there is resilience towards AI technology, intention is a crucial factor in understanding the future digital transformation of the accounting and auditing profession. Thus, it helps predict whether students will continue to use AI technology in data analytics after graduation, i.e., in their professional careers.

The last factor, i.e., the model's outcome (actual use), represents the actual attitude of technology users. In relation to the previous factor, the stronger the behavioural intention to use, the greater the actual use of technology. Researchers can measure actual use in two ways: objectively (e.g., system logs, time spent in the application, number of completed tasks) or subjectively (e.g., user statements, as in TAM). This factor is a direct measure of technology acceptance.

Related to these conclusions and previously defined research objectives, the hypotheses of this research are:

H_1: PEU positively influences PU.

H_2: PEU positively influences ATU.

H_3: PU positively influences ATU.

H_4: PU positively influences Behavioral Intention to Use (BIU).

H_5: ATU positively influences BIU.

H_6: BIU positively influences ACU.

The factors used in the hypotheses and the conceptual model, Figure **1**, are fundamental constructs in the TAM. PEU refers to users' perceptions of the simplicity and effort required to use AI technology. The model assumes that greater ease of use of AI technology increases perceptions of PU and ATU, especially in the context of education. Students are more likely to use intuitive, logical technology. However, a key factor for ATU is PU, as students will have a positive attitude if they believe that AI technology will improve their performance and results.

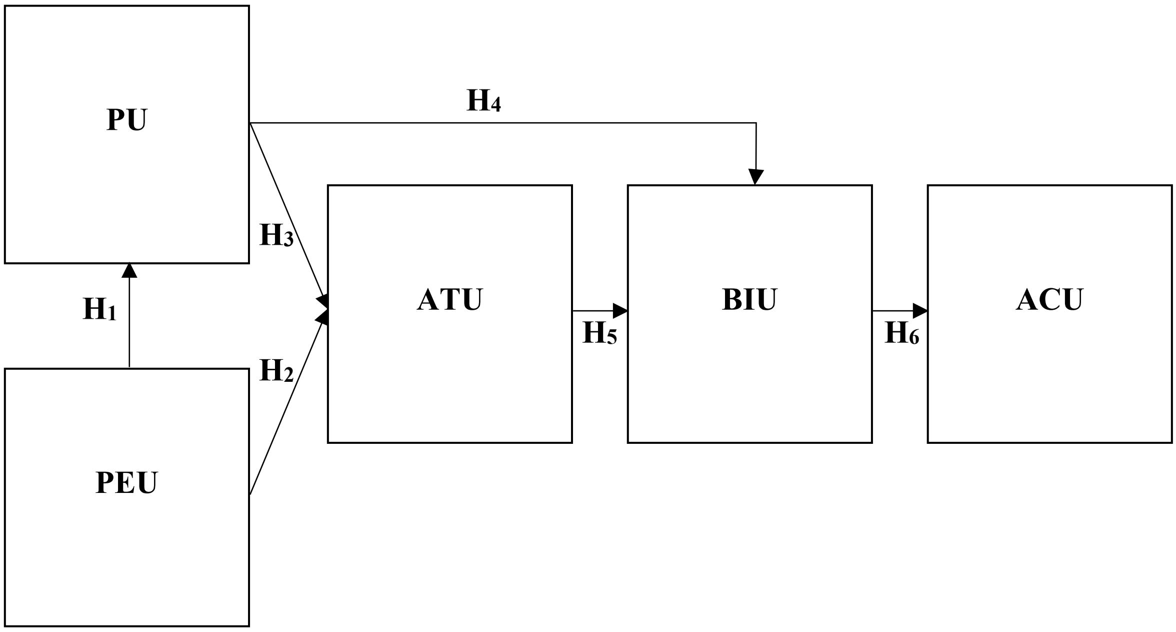

Figure 1. Conceptual model of research on AI technology in higher education courses related to data analytics in accounting and auditing

SAMPLE AND DATA COLLECTION

The targeted population for identifying and evaluating the determinants influencing the acceptance and usage intention of AI technology in higher education courses focused on data analytics in accounting and auditing was students of the Faculty of Economics & Business, University of Zagreb, Croatia. We distributed the questionnaire to students via the *LimeSurvey* platform. We collected data across several waves between January 2024 and January 2025, accounting for exam, lecture, and academic (semester) breaks. During the period, 559 students participated in the research; however, 281 of them answered all questions/statements in the questionnaire, which formed the final sample used in the research. The descriptive statistics show that 75% of students are female and 25% are male. Students in the sample are evenly distributed across the first five years of study. Regarding previous high school education, almost 60% of students (162) completed general secondary school (gymnasium), and over 30% (89) completed secondary school of economics. The rest of them graduated from other high schools.

RESEARCH INSTRUMENT

The questionnaire consisted of closed-ended questions divided into three parts: 1. General information on examinees, 2. Students' perceptions on using AI in studying, 3. Knowledge and usage of AI-based tools and applications.

In the introduction of the questionnaire, the following statement was provided to students: "The objective of the research is to examine students' perceptions of the use of artificial intelligence in the teaching process related to data analytics techniques in accounting and auditing.

Participation in the research and completion of the questionnaire does not require any prior knowledge of accounting or auditing, nor does it depend on your study major". The last question was open-ended and optional, allowing students to express their opinions on AI technology. This opportunity used 18 students (6,4%).

A major part of the questionnaire focused on statements regarding students' PEU, PU, ATU, BI, and actual usage of the AI technology. This part included 17 statements, randomly distributed in the questionnaire. Each statement students evaluated on a 7-point Likert scale, where grade 1 represented *Completely disagree* and grade 7 represented *Absolutely agree*. Used statements of each determinant (construct) are shown in Table 1.

Table 1. Constructs and statements used in the research.

Constructs	Statements	References
PEU	• PEU01: It is easy for me to learn to use AI-based systems. • PEU02: Learning by AI-based systems is easy for me. • PEU03: Overall, I think that AI-based systems are easy to master.	[20, 21, 24]
PU	• PU01: Using AI-based systems helps me to learn more efficiently. • PU02: Studying with AI-based systems would improve my study results. • PU03: AI-based systems make my study easier.	[20, 21, 24]
ATU	• ATU01: I like using AI-based systems for my study. • ATU02: I feel good about using AI-based systems. • ATU03: Using AI-based systems is an attractive way for me to study.	[24]
BIU	• BIU01: I intended to adopt AI-based systems from my study. • BIU02: I will use AI-based systems for studying as soon as I have the opportunity. • BIU03: The likelihood that I would recommend AI-based learning systems to my friends is high. • BIU04: I believe that using AI-based systems for studying is useful, and I plan to use them regularly.	[23-25]
Actual Use (ACU)	• ACU01: AI-based systems help me improve my study performance. • ACU02: I often use AI-based systems to help in studying. • ACU03: AI-based systems help me enhance my learning efficiency. • ACU04: I am using AI-based systems to understand study materials.	[7, 12, 24, 26, 27]

DATA ANALYSIS

To analyze the gathered data, we used SPSS for descriptive statistics and to obtain results from the measurement model. To evaluate structural models, we used the R package *seminr*. Regarding structural modelling, we focused on more robust prediction models better suited to smaller samples and non-normally distributed data. Although we based the constructs on the well-established TAM framework, given the research objective of predicting actual usage of AI-based tools in learning data analytics for accounting and auditing, PLS-SEM is more appropriate than CB-SEM. Additionally, we tested data for normality using the Kolmogorov-Smirnov and Shapiro-Wilk tests, which indicated non-normality for all variables (p-values = 0,000), confirming that PLS-SEM is a better fit than CB-SEM.

RESULTS

The first criterion for assessing measurement models is Cronbach’s alpha, Table **2**. The indicator provides a reliability estimate based on the intercorrelations among the observed composite variables. The composite reliability ranges from 0 to 1, with higher values signifying greater reliability [28]. Although overly high Cronbach’s Alpha may indicate that variables measure the same phenomenon, they are not over 0,95 and are derived from previously conducted scientific studies [20-25]. Considering that, it is justified to keep them in the model. Results for the average variance extracted (AVE) confirm this conclusion, as its value exceeds 0,70. A common rule of thumb is that standardized outer loadings should be 0,708 or higher, as significant outer loadings can still be weak [28].

To assess the results of reflective measurement models, in addition to evaluating convergent validity, it is necessary to evaluate discriminant validity, typically assessed using the Fornell-Larcker criterion, cross-loadings, and especially the heterotrait-monotrait (HTMT) ratio of correlations [28]. Discriminant validity refers to the degree to which a construct is genuinely distinct from other constructs based on empirical standards, meaning that demonstrating discriminant validity indicates that a construct is unique and addresses phenomena not captured by other constructs in the model [28].

Table 2. Descriptive statistics and results of the measurement model.

Construct	State-ments	Mean	Std. Devi-ation	Cronbach's Alpha if Item Deleted	Standardized Factor Loadings	Cronbach's Alpha	AVE	Composite Reliability (CR)
PEU	PEU01	3,719	1,921	0,860	0,905	0,916	0,776	0,912
	PEU02	3,957	1,834	0,895	0,882			
	PEU03	3,957	2,031	0,879	0,855			
PU	PU01	4,310	1,873	0,783	0,936	0,855	0,857	0,947
	PU02	4,335	1,900	0,791	0,916			
	PU03	4,908	1,647	0,814	0,925			
ATU	ATU01	3,673	1,875	0,848	0,895	0,886	0,814	0,929
	ATU02	3,822	1,880	0,870	0,879			
	ATU03	4,032	1,975	0,790	0,932			
BIU	BIU01	4,203	1,910	0,910	0,885	0,924	0,815	0,946
	BIU02	4,238	1,992	0,897	0,910			
	BIU03	3,929	1,977	0,909	0,890			
	BIU04	4,018	1,915	0,890	0,926			
ACU	ACU01	3,527	1,948	0,909	0,896	0,925	0,817	0,947
	ACU02	3,498	1,964	0,892	0,921			
	ACU03	3,584	1,924	0,900	0,912			
	ACU04	3,765	1,973	0,909	0,885			

The Fornell-Larcker criterion is partially met, Table **3**. To satisfy the criterion, values on the diagonal, which represent the square root of the AVE, need to be higher compared to off-diagonal correlations. Thus, on the one hand, PEU and PU clearly meet the threshold. However, for BIU and ACU, the criterion is not met due to PEU. This result is not unusual for intuitive TAM-based models.

The second test for discriminant validity assesses the heterotrait-monotrait ratio of correlations between composite constructs, where a disattenuated correlation close to 1 suggests a lack of discriminant validity [28]. For all constructs, correlations are below 1; those for PEU are close to 1 i.e., above 0,90, suggesting a lack of discriminant validity. After the bootstrapping procedure, across 5 000 repetitions of creating random subsamples, one pair had a confidence interval that included the value slightly above 1, indicating a lack of discriminant validity (PEU → ACU: 1,001). However, we expected high HTMT values for PEU, as it serves as the starting point for TAM-based models and is a fundamental cognitive driver shaping attitudes, intentions, and actual technology use. When users evaluate ease of use as highly important, it has a cascading effect on other constructs, resulting in strong inter-construct correlations. Thus, PEU has direct and indirect effects on ATU, BIU, and ACU.

The table shows the cross-loadings for each statement (indicator) on each composite variable (construct). Although previous results of discriminant validity are marginal for the PEU composite construct, results of cross-loadings indicate that all indicators load very strongly on their respective construct (0,916-0.936 for PEU, 0,855-0,905 for PU, 0,879-0,932 for ATU, 0,885-0,926 for BIU, and 0,885-0,921 for ACU). There is no overlap between constructs; i.e., all indicators load only onto the intended construct. There is no evidence of cross-construct contamination, Table 4. These results prove the strong discriminant validity of the composite variables included in the model. The result is the strongest empirical confirmation of discriminant validity.

Table 3. Fornell-Larcker criterion.

	PEU	**PU**	**ATU**	**BIU**	**ACU**
PEU	**0,926**				
PU	0,714	**0,881**			
ATU	0,901	0,708	**0,902**		
BIU	0,915	0,667	0,875	**0,903**	
ACU	0,923	0,685	0,851	0,868	**0,904**

Table 4. Cross-loadings results.

	PEU	**PU**	**ATU**	**BIU**	**ACU**
PEU1	0,936	0,000	0,000	0,000	0,000
PEU2	0,916	0,000	0,000	0,000	0,000
PEU3	0,925	0,000	0,000	0,000	0,000
PU1	0,000	0,905	0,000	0,000	0,000
PU2	0,000	0,882	0,000	0,000	0,000
PU3	0,000	0,855	0,000	0,000	0,000
ATU1	0,000	0,000	0,895	0,000	0,000
ATU2	0,000	0,000	0,879	0,000	0,000
ATU3	0,000	0,000	0,932	0,000	0,000
BIU1	0,000	0,000	0,000	0,885	0,000
BIU2	0,000	0,000	0,000	0,910	0,000
BIU3	0,000	0,000	0,000	0,890	0,000
BIU4	0,000	0,000	0,000	0,926	0,000
ACU1	0,000	0,000	0,000	0,000	0,896
ACU2	0,000	0,000	0,000	0,000	0,921
ACU3	0,000	0,000	0,000	0,000	0,912
ACU4	0,000	0,000	0,000	0,000	0,885

Taking into account the existence of internal consistency, reliability and convergent validity for all composite variables, as well as excellent cross-loadings, marginal values of the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT), which are theoretically expected, considering the importance and meaning of PEU as the strongest cognitive and affective influence on attitudes, intentions, and actual usage, are not crucial for the model. Therefore, the constructs remain conceptually and empirically distinct, and it is fully justified to retain them in the model.

The results of the structural model (PLS-SEM) and the path coefficients indicate excellent predictive power for the constructs. For all but the first relation, R^2 is greater than 0,7, indicating that those relations explain more than 70% of the variance of endogenous constructs, Table 5. In the weakest relation, between PEU and PU, 50% of the variance in the endogenous constructs is explained, indicating a moderate predictive power of perceived ease of use for perceived usefulness. In all cases, VIF values are satisfactory, with values significantly below 10; they range from 2,038 to 5,578, confirming that multicollinearity is not an issue.

Table 5. Structural model results.

From	To	H	R^2	Coefficient	t-value	p-value	VIF	Result
PEU	PU	H1	0,509	0,714	21,742	0,000	2,038	Supported
PEU	ATU	H2	0,821	0,807	23,270	0,000	5,579	Supported
PU	ATU	H3	0,821	0,132	3,149	0,002	5,579	Supported
PU	BIU	H4	0,771	0,095	1,972	0,049	4,359	Supported
ATU	BIU	H5	0,771	0,808	22,331	0,000	4,359	Supported
BIU	ACU	H6	0,754	0,868	47,129	0,000	4,067	Supported

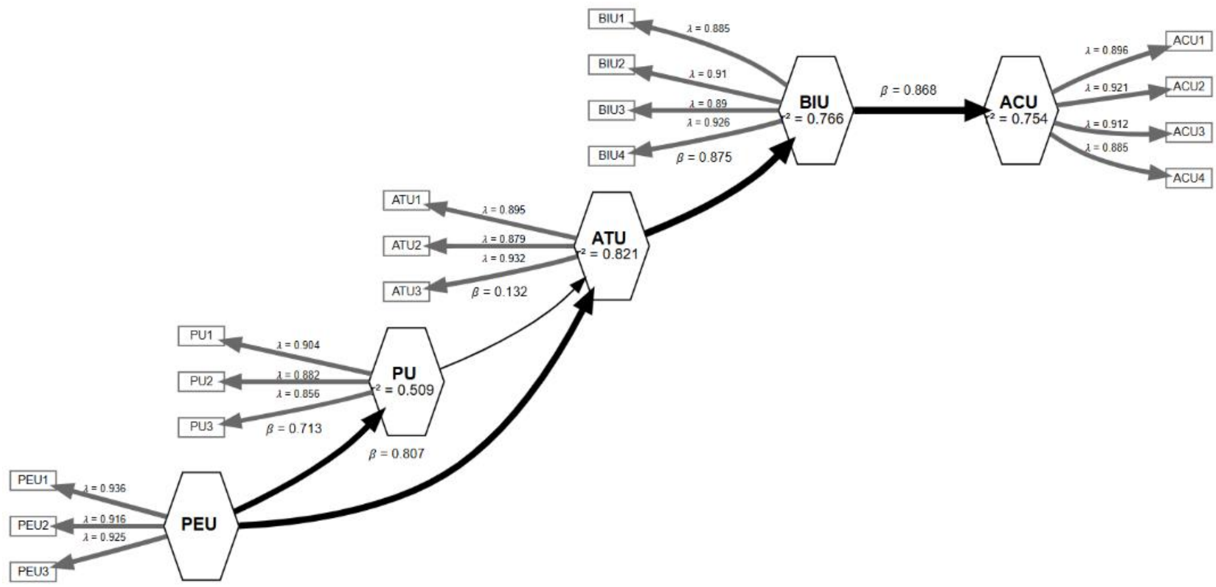

Figure 2. Results of the structural model (PLS-SEM).

The TAM results confirm all six hypotheses, Figure 2. First, PEU has a very strong positive effect on perceived usefulness (t-value = 21,74, p-value = 0,000). This result indicates that students consider AI technology more useful when it is easy to use. Results are consistent with most of the previous research [1, 4, 6-8, 10, 12-14, 16]. However, results indicate that PEU is a stronger predictor of ATU. Compared to the considerably weaker predictive power of PU, although it is statistically significant, results suggest that ease of use is a key driver of students' positive attitudes towards AI technology for learning data analytics in accounting and auditing. Furthermore, PU has a small but statistically significant direct effect on BIU AI for learning, suggesting that students who perceive it as useful are more likely to intend to use the technology. This relationship is statistically significant; however, the p-value is marginal at the 5% significance level (p-value = 0,049). On the other hand, ATU is a much stronger predictor of BIU AI for learning data analytics (t-value = 22,33, p-value = 0,000). Finally, BIU has exceptionally strong predictive power for ACU of AI technology in learning data analytics in accounting and auditing. Thus, students' intentions to use technology translate directly into real usage. Overall, the results confirm that the model performs exceptionally well, with high predictive accuracy, and all six research hypotheses are supported. Fundamental driver of perceived usefulness and attitude towards use is ease of use, and behavioral intention to use almost perfectly predicts ACU.

DISCUSSION AND CONCLUSION

The research results provide strong empirical support for the original TAM, with high predictive accuracy and a high R^2 across all composite variables. Although modifications of TAM-based models do not include ATU, in our research they represent an important channel from PU and PEU towards BIU. Furthermore, in our study, BIU has the strongest predictive power for ACU. Considering these results, we conclude that perceptions and attitudes robustly and effectively translate into behavioural intention and actual use of AI technology in learning data analytics for accounting and auditing purposes, i.e., students' intentions are highly predictive of their actual behaviour. A central finding of this study is the dominant role of PEU in shaping students' perceptions. Given the targeted population, we expected results like this.

We summarized research results in terms of their theoretical and practical implications. From a theoretical perspective, this research contributes to strengthening prior research that predominantly emphasizes ease of use as the main construct, thereby encompassing both the intention to use and the actual use of AI in the teaching process. The model emphasizes the importance of cognitive drivers. Still, there is also a need to combine them with affective drivers to obtain a more complete result, i.e., ATU is a key mediator in this process. An important contribution of this article concerns the specifics of applying AI in teaching, namely data analytics, which plays an increasingly significant role across various professions, especially in accounting and auditing, which involve the collection and analysis of objective, rational data. When it comes to practical implications, emphasizing ease of use as a key construct can help practitioners design simple, intuitive interfaces that greatly increase intention to use and, in turn, actual use of AI-based tools. The dominant role of ease of use implies that teachers must choose intuitive AI tools adapted to students with no prior technical knowledge or skills. Namely, introducing tools into education is not only a technical procedure but also a didactic challenge for teachers who must design such activities that will gradually build students' competencies for confident use of technology, on the one hand in the teaching process, and on the other hand in the accounting and auditing profession after graduation. In the context of ATU, the results confirm the importance of forming positive attitudes towards technology and of creating a supportive environment for its use, with professors playing the most important role, which is important at the organisational level of higher education institutions, where a systematic institutional approach and a clear strategy for integrating AI tools into teaching processes are needed. In doing so, it is important to establish internal regulations for AI use, train teachers, provide technical support, and regularly evaluate the tools used. Since teachers' attitudes towards technology influence students' attitudes, educating teaching staff is imperative for the successful and ethical implementation of AI in teaching.

These findings should also be interpreted in the broader context of the changing role of higher education institutions and teaching staff in digitally transformed learning environments. Previous research has shown that digital competencies among higher education professors and teachers are not only a technical issue, but are also related to teaching experience, professional adaptation, and the ability to integrate digital tools meaningfully into educational practice. In this respect, the successful use of AI-based tools in data analytics education depends not only on students' perceived ease of use but also on teachers' readiness to design pedagogically meaningful, ethically responsible, and professionally relevant learning activities. This is particularly important because higher education lecturers operate within organizational environments where psychological empowerment and organizational commitment may influence their willingness to adopt and sustain innovative teaching practices [29]. Moreover, contemporary approaches such as digital storytelling demonstrate that business and economics education can be modernized through methods that combine digital tools, creativity, and active student engagement, a shift that is especially relevant in the age of artificial intelligence [30].

From a systemic perspective, higher education institutions have a broader responsibility to support digital transformation, develop future-oriented competencies, and respond to societal and economic changes associated with emerging technological paradigms [31, 32]. Therefore, the practical implications of the present study extend beyond the selection of intuitive AI tools; they also point to the need for institutional strategies, teacher empowerment, and pedagogical innovation to support the responsible integration of AI into accounting and auditing education. The importance of this is especially emphasized in fields such as accounting and auditing, which increasingly include digital competencies as core learning outcomes. Finally, in terms of practical implications, given the importance of ease of use, programmers should be aware that improvements in ease of use can affect multiple psychological dimensions simultaneously.

The application of artificial intelligence raises numerous ethical issues, particularly in education. First, academic integrity is important when using AI tools. It is increasingly difficult to distinguish between independent and AI-assisted student work, and in this context, it is important to establish a rulebook on the ethical use of AI in teaching and in writing student essays at the institutional level. The issue of dependence on technology and its consequences is also important. In this sense, in the teaching process, it is crucial to ensure that the use of AI tools further develops, rather than replaces, students' critical and analytical thinking, especially in auditing, where professional judgment and professional skepticism are key competencies.

The limitations of this research include limited specificity, a small sample size and shortcomings in the specific courses in which AI-based tools are applied. Also, limitations in such research include reliance on self-assessment data, which may be biased. We support this with experience: at the beginning of the semester, students who enrolled in the elective course *Data Processing Methods in Accounting* had the opportunity to participate in a survey to assess their knowledge of the various data analytics tools we later used in the class. Their self-assessment of their MS Excel knowledge at the beginning of the semester was, on average, 6,8 out of 10. Still, they did not confirm this by participating in the lectures during the semester. A shortcoming of the research is the relatively long data collection period, given students' limited willingness to complete the survey questionnaires due to faculty obligations (e.g., exam deadlines, midterm exams). Finally, a limitation is the overlap among individual constructs, although results based on such data are significant for the analysis's conclusions. Future research can build on the conducted study and adopt a longitudinal design to assess changes in the acceptance of artificial intelligence in teaching data analytics in accounting and auditing over time. Also, researchers could extend the research to other business schools and faculties that offer such courses. Including variables tailored to specific use (e.g., logs and metadata) can enhance the informativeness of research results about the actual use of AI technology.

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