Archives of Business Research – Vol. 13, No. 11
Publication Date: November 25, 2025
DOI:10.14738/abr.1311.19630.
Charfi, S. & Mallouli, Y. (2025). Technology Readiness and Artificial Intelligence Adoption by Accounting and Finance Students in Tunisia. *Archives of Business Research,* 13(11). 28-41.

Technology Readiness and Artificial Intelligence Adoption by Accounting and Finance Students in Tunisia

Souha Charfi
ORCID: 0009-0006-9867-4223
Higher Institute of Accounting and Business Administration (ISCAE), Tunisia

Yosra Mallouli
ORCID: 0009-0000-8775-6449
Higher Institute of Accounting and Business Administration (ISCAE), Tunisia

ABSTRACT

Highlighting the fundamental role of universities in preparing future accountants and financiers for an economy characterized by AI technologies progress, this study examines the relationship between accounting and finance students' technological readiness and their decision to adopt AI technologies by demonstrating the mediating effect of perceptions of use on this relationship, in the context of a developing country, Tunisia. Based on the Technology Readiness of Acceptance Model (TRAM), we designed a comprehensive survey to collect information on perceived use (PU), perceived ease of use (PEOU), technology readiness (TR), and technology adoption (TA). A total of 125 accounting and finance students from a public university in Tunisia were selected. Statistical analysis based on regressions, were performed using SPSS 25. The findings revealed the positive impact of PU, PEOU, and TR on TA. Furthermore, statistical analysis showed the mediating role of PEOU and PU on the relationship between TR and AI adoption by Tunisian students. This study contributes to the limited literature that investigates the drivers of AI adoption by accounting and finance students. Furthermore, this study confirms that the measurement scales used by the literature to measure TA, and its determinants are valid and reliable in developing countries such as Tunisia.

Keywords: AI technology, Technology Readiness Acceptance Model, Accounting and finance education, Tunisia.

INTRODUCTION

Accounting and finance professions are experiencing fundamental changes driven by many factors, including the emergence and application of new technologies based on artificial intelligence (AI). Today, AI is expanding to transform enterprises by providing more useful technologies, such as Hyper-Automation, Image Recognition, Voice Recognition, Natural Language Processing. Some of these technologies are particularly important in accounting and finance. A major element of support for AI development is university education, which can adapt to these developments and prepare the younger generations for future challenges.

In research fields- such as finance and accounting- computer technology exploitation, in particular AI-related courses, is not widespread (Damerji & Salimi, 2021; Grabinska, *et al.,* 2021). However, this situation will change as AI-related skills are increasingly required in accounting and finance professions. Tavares, *et al.* (2023) state that many universities are now incorporating courses on information technology, data analysis, cybersecurity, and database management into their accounting programs. Further research is required into how universities can best prepare their students to be technologically ready and embrace artificial intelligence technologies. This study is part of this field.

The Technology Acceptance Model (TAM) is a widely accepted theoretical framework that explains how users accept and use technology (Martin, 2022). The TAM has identified two main factors influencing user acceptance and adoption of technology: ease of use and perceived usefulness (Davis, 1986). The integration of technology readiness with technology adoption gave rise to the Technology Readiness and Acceptance Model (TRAM) (Parasuraman, 2000; Parasuraman & Colby, 2015). The TRAM provides the foundation to better understand how technology readiness influences technology adoption (Lin, *et al.*, 2007).

Drawing on these theoretical models, this study examines the relationship between perceived usefulness, ease of use, technological readiness, and artificial intelligence adoption among accounting and finance students in Tunisia. This research is significant because, on the one hand, it identifies the factors enhancing AI adoption by accounting and finance students. On the other hand, it examines students' motivation to spend time on AI-based course content, and whether they perceive it as useful and easy to use in their future careers, especially in a developing country in Africa.

Based on these findings, strategies developed by the Ministry of Higher Education can be developed to overcome barriers and improve students' motivation for AI adoption. Integrating AI into accounting and finance programs can reduce the technology adoption gap between education and business and better prepare students for their future professional careers.

LITERATURE REVIEW

Factors Determining People's Technology Adoption

With the continuous development of information and communication technologies at an unprecedented rate, researchers are interested in the factors that influence users' acceptance of a particular technology, including their intention to adopt it. The TAM, first developed by Davis (1986), is widely considered one of the most influential theories for predicting technology acceptance behaviours. Davis was the first to suggest two perceptual beliefs, perceived usefulness (PU) and perceived ease of use (PEOU) as the main determinants of an individual's attitude towards technology, which in turn predicts its adoption.

Both PEOU and PU directly influence an individual's behavioural intention and attitude towards adopting new technologies (Dwianta, *et al.*, 2024; Roy, *et al.*, 2022; Kashive, *et al.*, 2020; Asnakew, 2020; Rahi, *et al.*, 2023; Amalia, 2023; etc). Nevertheless, PEOU is assumed to be a determinant of PU, as it can affect technology adoption through PU. Indeed, a consumer's perceived use towards a specific technology may be reduced if the user is not able to use this technology (Chen & Chan, 2014; Verma & Sinha, 2018; Naranjo-Zolotov, *et al.*, 2019; etc).

Parasuraman (2000) highlighted that technology adoption can have positive or negative outcomes, that are determined by the user's technological readiness level, known as technology readiness (TR). The integration of technology readiness with technology acceptance results in the TRAM model. Parasuraman (2000) developed the Technology Readiness Index (TRI), defined as "people's readiness to adopt and use advanced technologies”. The TRI measures the overall state of mind resulting from a combination of mental motivators and inhibitors that collectively influence a person's readiness to use new technologies.

According to Parasuraman (2000) and Parasuraman & Colby (2015), individuals' perceptions of a specific technology can be separated into four distinct dimensions: optimism (a positive view of technology and the belief that it affords more control, flexibility, and efficiency in their lives), innovativeness (a tendency to be a technology pioneer and thought leader), discomfort (a perceived lack of control over technology and a feeling of being overtaken by it), and insecurity (technology distrust, stemming from scepticism about its ability to work properly and concerns about its potentially harmful consequences). Parasuraman (2000) and Parasuraman & Colby (2015) argued that optimism and innovativeness (contributors) positively influence an individual's readiness to adopt technology, whereas discomfort and insecurity (inhibitors) influence it negatively.

Based on the TRAM, several authors (Lin, *et al.*, 2007; Huang & Liaw, 2018; Kim & Chiu, 2019; Jin, 2020; Kampa, 2023; etc) showed that PU and PEOU comprehensively mediate the influence of technological readiness on the intention to use technology. Anh, *et al.* (2024) showed a positive relationship between technology readiness and AI adoption by accounting and auditing professionals in Vietnamese companies. Additionally, both PU and PEOU positively influence AI adoption and mediate the relationship between technology readiness and AI technology adoption by accountants and auditors in Vietnamese companies.

Perceptions of AI Technology Adoption in Accounting and Finance Education

The literature provides empirical evidence that it is necessary for finance and accounting professionals to acquire new skills aligned with emerging technologies (Rawashdeh, 2023; Groenewald, *et al.*, 2024; Kroon, *et al.*, 2021; Garcia & Lee, 2020; etc). With the steady advancement of AI, higher education institutions are key entities in equipping the future workforce with digital skills. Therefore, these institutions are required to upgrade their educational programs, infrastructural resources, and facilities to match the evolving industry landscape (Bond, *et al.*, 2018; Al-Maskari, *et al.*, 2022; Strong & Portz, 2015; Ballantine, *et al.*, 2024; Tavares, *et al.*, 2023; etc).

In light of the fundamental role of academics in adopting new technologies, including AI, in learning practices to make accounting and finance courses more relevant to students and to meet the needs of contemporary society, a little number of researchers have investigated the drivers of AI adoption by accounting, finance, and audit students. Indeed, AI technologies are not widely adopted in accounting and finance universities worldwide, and even less so in developing countries characterised by underdeveloped digital and energy infrastructures that are essential to the adoption of AI. Nouraldeen (2023) collected data from accounting and auditing students registered in private Lebanese universities and showed that TR and PU positively affect AI adoption, while PEOU has an insignificant impact on students' decisions to adopt AI. The results further reveal that males are more likely to adopt AI than females, and that gender moderates the associations between TR, PU, PEOU, and AI adoption.

Grabinska, *et al.* (2021) compared the perceptions of current students with graduates from the finance and accounting department at Krakow University of Economics in Poland regarding the courses' usefulness in providing knowledge about new technologies, such as AI. The research findings reveal that students and graduates are aware of the importance of technological change. However, graduates with more professional experience are more conscious of the benefits of AI technologies. Kampa (2023) attempted to empirically explore the readiness and acceptance of mobile learning (open and distance learning, ODL) among higher education students in India. The results of this study revealed that optimism, innovativeness, insecurity, discomfort, PEOU, PU, attitude, and behavioural intention, extracted from the TRI and TAM, contributed the most to e-learning readiness and acceptance.

The findings of Dwianto, *et al.* 's (2024) research on accounting students enrolled in several Indonesian universities show that technology readiness does not have a significant influence on technology adoption. However, PU and PEOU had significantly positive effects on technology adoption, highlighting the importance of these factors in students' willingness to adopt AI-based accounting software. The research conducted by Sudaryanto, *et al.* (2023) indicate that PU and PEOU have a significant impact on AI technology adoption by accounting students in West Jakarta, Indonesia. However, digital competence and technology readiness did not have an impact on AI technology adoption.

The findings of Damerji & Salimi's (2021) indicate that technology readiness has a significant influence on AI technology adoption by accounting students at two United States universities. Furthermore, these results confirmed the relationship between technology readiness, AI technology adoption, PU, and PEOU. In addition, the authors' mediation analysis revealed that the relationship between technology readiness and AI technology adoption is affected by both PU and PEOU.

RESEARCH HYPOTHESES

The objective of this study is to examine on the one hand, the relationship between TR, PU, PEOU, and AI technology adoption, as well, the mediating role of PU and PEOU in the relationship between TR and AI technology adoption by accounting and finance students in a developing country namely Tunisia. The following hypotheses arise from our research:

PEOU, PU and AI Technology Adoption

In the TAM, PU directly influences users' behavioural intention to adopt a new technology, while PEOU directly and indirectly influences new technology adoption. PEOU has an indirect impact on the intention to adopt a new technology via PU. Consequently, the following hypotheses are formulated:

- $\boldsymbol{H_1}$**:** PEOU has a direct and indirect (via PU) positive impact on TA.
- $\boldsymbol{H_{1a}}$**:** PEOU has a positive impact on TA.
- $\boldsymbol{H_{1b}}$**:** PEOU has a positive impact on PU.
- $\boldsymbol{H_2}$**:** PU has a direct positive impact on TA.

TR, PEOU, PU and AI Technology Adoption

In the domain of user adoption of new technologies, TR and TAM were integrated to obtain the TRAM model, in which TR is a strong predictor of TA's PU and PEOU (hypotheses H3a and H3b).

According to TRAM, an individual's positive (negative) perceptions of a specific technology can influence whether they are (are not) willing to adopt this technology (hypothesis H3c). Accordingly, the following hypotheses are formulated:

- $\boldsymbol{H_{3a}}$: TR has a positive effect on PEOU.
- $\boldsymbol{H_{3b}}$: TR has a positive effect on PU.
- $\boldsymbol{H_{3c}}$: TR has a positive effect on TA.

The Mediating Roles of PU and PEOU

Throughout the literature review, we found that perceptions of PU and PEOU can mediate the relationship between TR and TA in several ways. The relationship between TR and TA by accounting and finance students may be influenced by their perceptions that AI technologies are, on the one hand, useful and, on the other hand, easy to use. In other words, if a student who thinks he/she is optimistic, has an innovation capacity, is not insecure, or does not feel discomfort using AI technology, will be willing to adopt this technology, if, in addition, he/she perceives this technology as useful and/or easy to use (hence hypotheses H4a, H4c, and H4e).

Moreover, PEOU can mediate the relationship between TR and PU. For example, if a person thinks that technology is useful but difficult to use, his/her perception that he/she is ready to adopt this technology may be negative (hence, hypothesis H4d). Finally, the PU of a technology can mediate the relationship between TA and PEOU. For example, if a person thinks that technology is easy to use but not useful, he/she will not tend to adopt it (hence, hypothesis H4b).

- $\boldsymbol{H_{4a}}$: PU is a mediator between TR and TA.
- $\boldsymbol{H_{4b}}$: PU is a mediator between PEOU and TA.
- $\boldsymbol{H_{4c}}$: PEOU is a mediator between TR and TA.
- $\boldsymbol{H_{4d}}$: PEOU is a mediator between TR and PU.
- $\boldsymbol{H_{4e}}$: PEOU and PU together mediate the relationship between TR and TA.

RESEARCH METHODOLOGY

Research Population

The research was conducted at a public university in Tunisia, the Higher Institute of Accounting and Business Administration, *L'Institut Superieur de Comptabilité et d'Administration des Entreprises* (*ISCAE*). The reasons for choosing this institution were as follows: *i*) Geographical convenience of these research authors; *ii*) The institution has existed for more than 30 years and is considered a leader in accounting and financial training in Tunisia; *iii*) The institution offers undergraduate and master's programs with degrees in accounting and finance; *iv*) Each year, the institution organizes two sessions of the national examination for accountant qualifications. The research population consisted of students enrolled at *ISCAE* during the 2024/2025 academic year in a bachelor's degree in accounting sciences, a bachelor's degree in finance, a master's degree in accounting, a master's degree in audit accounting, and a master's degree in financial and banking engineering.

Survey

We started our survey with questions concerning the respondents' gender and current educational level. The remaining part of the survey contained 30 questions distributed as follows: *i*) Sixteen items (developed by Parasuraman & Colby (2015)) to measure the sub-dimensions of TR: four items for optimism, four items for innovativeness, four items for discomfort, and four items for insecurity. These items were measured on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". *ii*) Twelve items (developed by Davis (1989)) to measure the sub-dimensions of TA: six items for PU and six items for PEOU; *iii*) Two items concerning the intention to adopt AI technologies. These items were measured on a 7-point Likert scale ranging from "very unlikely" to "very likely."

Data Collection and Sample Size

The survey was prepared on Google Forms and sent in early October 2024 by email and messenger groups to 855 students in our survey population (855 students). We explained the importance of our survey to the students and asked them to respond and invite their friends to do the same. Furthermore, we asked our colleagues to encourage their students to respond. In early November, we closed the questionnaire link, and the number of collected responses was 125. Harris (2001) suggested that the number should exceed the number of variables by at least 50 to carry out regression analyses. In our case, a sample size of over 55 was considered sufficient.

Statistical Tests

SPSS 25 (Statistical Package for Social Sciences) was used to analyse the data. The statistical procedures included descriptive analysis, exploratory factor analysis, and simple linear regression (hierarchical regression analysis). The methodology for our quantitative correlation study used statistically validated and reliable survey instruments: The Technology Readiness Index (TRI 2.0) and Technology Acceptance Model (TAM).

In addition, we verified the recommended requirements of measurement theory researchers to conduct factor analysis. These include Bartlett's test of sphericity, which is used to examine correlations between variables, and the Kaiser, Meyer, and Orkin (KMO) test, which aims to determine the suitability of factor analysis. On the other hand, Cronbach's alpha is often recommended for estimating the internal consistency of the measurement instrument, that is, measurement consistency (Taber, 2018). Table 1 shows the results of the three tests.

Table 1: Results of the KMO, Bartlett's sphericity and Cronbach's Alpha tests

Variables	Notation	KMO	Bartlett's Test of sphericity		Cronbach's alpha
			Chi-square	Sig	
Technology Adoption	TA	0.5	130.997	0.000	0.895
Perceived Use	PU	0.862	639.904	0.000	0.938
Perceived Ease of use	PEOU	0.858	462.377	0.000	0.902
Technology Readiness	TR	0.568	70.681	0.000	0.632
Optimism	OPT	0.628	55.008	0.000	0.564
Innovativeness	INV	0.718	85.949	0.000	0.699
Insecurity	INS	0.668	59.583	0.000	0.602
Discomfort	INC	0.622	31.319	0.000	0.517

Source: Data processed by authors.

The KMO index for the variables PU, PEOU, and INV is > 0.7, implying that the data are well suited for factor analysis. For the variables TA, TR, OPT, INS, and INC, the KMO index lies between 0.5 and 0.7, implying that the data are suitable for factor analysis, but with caution.

URL: http://doi.org/10.14738/abr.1311.19630

Bartlett's sphericity test is an essential tool for assessing the relevance of a factor analysis. In our research, all the variables were significant ($p < 0.05$) according to Bartlett's test, which implies the existence of significant correlations between the variables and that factor analysis is appropriate.

In social science research, Cronbach's alpha must be at least equal to 0.7 to guarantee the internal consistency of the survey instrument scores (Errabi & Hamadi, 2023). According to table I, the variables TA, PU, and PEOU have scores significantly higher than 0.8, indicating excellent internal consistency. However, the scores for TR (around 0.7) and its various dimensions (INV, INS, INC, OPT) were between 0.5 and 0.7. This implies a low but acceptable level of internal consistency.

RESULTS AND DISCUSSION

Demographic Data

Demographic data were collected to determine the respondents' identities, that is, gender and educational level. Table 2 shows the respondents' demographic data.

Table 2: Respondent's demographic data

	Frequency (n)	Percentage (%)
Total number of students in accounting and finance	**125**	**100%**
Gender Man	26	20.8%
Woman	99	79.2%
Educational level Bachelor	99	79.2%
Master	26	20.8%

Source: Data processed by authors.

Table 2 demonstrates that 99 of the respondents were women and 26 were men. The sample included bachelor's degree students in accounting or finance (n = 99; 79.2%) and master's degree students in accounting or finance (n = 26; 20.8%).

Descriptive Statistics for the Variables

Table 3 provides the average and standard deviation for the variables TR, PU, PEOU, and TA for the overall sample of 125 accounting and finance students, as well as for two sub-samples (Bachelor students and Master students). Table 3 demonstrates that the average of the TR variable is 3.44 for the Bachelor group, and 3.39 for the Master group. These scores are at the upper end of the 1-5 range, indicating that the majority demonstrate a high overall level of TR and are likely to adopt AI in their professional careers in accounting and finance. The average of the PU is 5.26 for the Bachelor group and 5.72 for the Master group. These scores indicate that the majority of respondents agree with the presented statements and perceived the usefulness of AI in accounting and finance.

The average of the PEOU is 4.75 for the Bachelor group and 5.23 for the Master group. These scores indicate that the majority agreed with the presented statements and perceived AI applications in accounting and finance as potentially easy. The average of TAM's dependent variable, TA, is 4.84 for the Bachelor group and 5.57 for the Master group. These scores indicate that the majority of respondents agree with the presented statements and intentions regarding AI technology adoption in accounting and finance.

Table 3: Averages and standard deviations of variables

	Total sample	**Bachelor**	**Master**
Number	**125**	**99**	**26**
Technology Readiness (TR)			
Average	3.43	3.44	3.39
Standard deviation	0.50	0.52	0.41
Perceived Usefulness (PU)			
Average	5.36	5.26	5.72
Standard deviation	1.49	1.55	1.22
Perceived Ease of Use (PEOU)			
Average	4.85	4.75	5.23
Standard deviation	1.33	1.37	1.12
Technology Adoption (TA)			
Average	4.99	4.84	5.57
Standard deviation	1.76	1.84	1.29

Source: Data processed by authors

Furthermore, the average PU, PEOU, and TA variables are higher in the Master group than in the Bachelor group. These differences were statistically significant only for the TA. Master's students seemed to be more aware of AI's importance and its impact on their future professional careers.

Hypothesis Testing

Table 4 presents the linear regression results obtained from the data collected using SPSS.

Table 4: Path analyses of PU, PEOU, TR and TA variables

Path	**H**	**Prediction Model**	**F**	**p (F)**	**R^2**	**b**	**t**	**p (t)**
1	H1a	PEOU→TA	109.54	0.000	0.469	b1= 0.684	10.467	0.000
2	H1b	PEOU→PU	113.721	0.000	0.482	b2= 0.707	10.664	0.000
3	H2	PU→TA	90.925	0.000	0.424	b3= 0.641	9.535	0.000
4	H3a	TR→PEOU	29.260	0.000	0.187	b4= 0.511	5.409	0.000
5	H3b	TR→PU	27.341	0.000	0.178	b5 = 0.507	5.229	0.000
6	H3c	TR→TA	28.562	0.000	0.182	b6 = 0.501	5.344	0.000
7	H4a	TR→PU→TA PU→TA, control TR TR→TA, control PU	50.423	0.000	0.448	b7 = 0.564 b7' = 0.213	7.732 2.468	0.000 0.015
8	H4b	PEOU→PU→TA PU→TA, control PEOU PEOU→TA, control PU	68.541	0.000	0.527	b8 = 0.332 b8' = 0.451	3.884 5.205	0.000 0.000
9	H4c	TR→PEOU→TA PEOU→TA, control TR TR→TA, control PEOU	59.217	0.000	0.486	b9 = 0.612 b9' = 0.189	8.560 2.271	0.000 0.025
10	H4d	TR→PEOU →PU PEOU →PU, control TR TR→PU, control PEOU	60.531	0.000	0.496	b10 = 0.640 b10' = 0.175	8.770 2.063	0.000 0.041

11	H4e	TR→PEOU→PU→TA PEOU→TA, control TR PU→TA, control TR TR→TA, control PEOU et PU	47.031	0.000	0.533	b11= 0.420 b11’= 0.307 b11’’= 0.126	4.757 3.551 1.549	0.000 0.001 0.124

Note: TR= Technology Readiness; PU= Perceived Usefulness; PEOU= Perceived Ease of Use; TA= Technology Adoption. *Source*: Data processed by authors.

Table IV reveals that all links mentioned in our hypotheses have a significant Fisher's F ($p < 0.01$). Consequently, all analysed models were considered valid.

Furthermore, paths 1, 2, and 3 in the table show that PEOU has a significant impact on TA (b1 = 0.684; $p < 0.01$), PEOU has a significant influence on PU (b2 = 0.707; $p < 0.01$), and PU has a significant influence on TA (b = 0.*641*; $p < 0.01$). Both sub hypotheses H1.a. and H1.b. and hypothesis H2 were, therefore, confirmed. Paths 4, 5, and 6 in the table reveal a significant impact of TR on PEOU (b = 0.511; $p < 0.01$), PU (b = 0.507; $p < 0.01$), and TA (b = 0.501; $p < 0.01$). Three hypotheses, H3.a, H3.b, and H3.c, were also confirmed.

Mediating Effects of PU and PEOU

To test the first mediation hypothesis, H4.a, we compared the direct effect of the relationship between TR and TA while controlling PU (path 7) with the total effect of the relationship between TR and TA (path 6). A comparison of the two paths reveals the existence of a partial mediator effect of PU on the relationship between TR and TA.

Indeed, the effect of TR on TA was weakened when PU was included in the regression (b7' = 0.213 < b6 = 0.501). Additionally, the significance level was lower because P(t) increased from 1% to 5%.

To test the second mediation hypothesis, H4b, we compared the direct effect of the relationship between PEOU and TA (path 8) while controlling PU with the overall effect of the relationship between PEOU and TA (path 1). The results show a partial mediating effect of PU on the relationship between PEOU and TR. Indeed, the effect of PEOU on TA was weakened when PU was included in the regression (b8'= 0.451 < b1= 0.684).

For the third mediation hypothesis, H4c, we compared the direct effect of the relationship between TR and TA while controlling PEOU (path 9) with the overall effect of the relationship between TR and TA (path 6). The results show a partial mediating effect of PEOU on the relationship between TR and TA. Indeed, the effect of TR on TA was reduced when PEOU was included in the regression (b9'= 0.189 < b6 = 0.501). Additionally, the significance level was lower because P(t) increased from 1% to 5%.

For the fourth mediation hypothesis, H4d, we compare the direct effect of the relationship between TR and PU while controlling PEOU (path 10) with the total effect of the relationship between TR and PU (path 5). A comparison between the paths reveals the existence of a partial mediating effect of PEOU on the relationship between TR and PU. Indeed, the effect of TR on PU was reduced when PEOU was included in the regression (b10' = 0.175 < b5= 0.507). Additionally, the significance level was lower because P(t) increased from 1% to 5%.

For the fifth mediation hypothesis, H4e, we compared the direct effect of the relationship between TR and TA while controlling PEOU and PU (path 11) with the total effect of the relationship between TR and TA (path 6). The results indicated the existence of a complete mediating effect of PEOU and PU on the relationship between TR and TA. Indeed, the effect of TR on TA was reduced when PEOU and PU were included in the regression (b11''= 0.126 < b6= 0.501). In addition, the association between TR and TA was no longer statistically significant. The mediation analysis confirmed our 5 hypotheses, H4a, H4b, H4c, H4d, and H4e (figure 1).

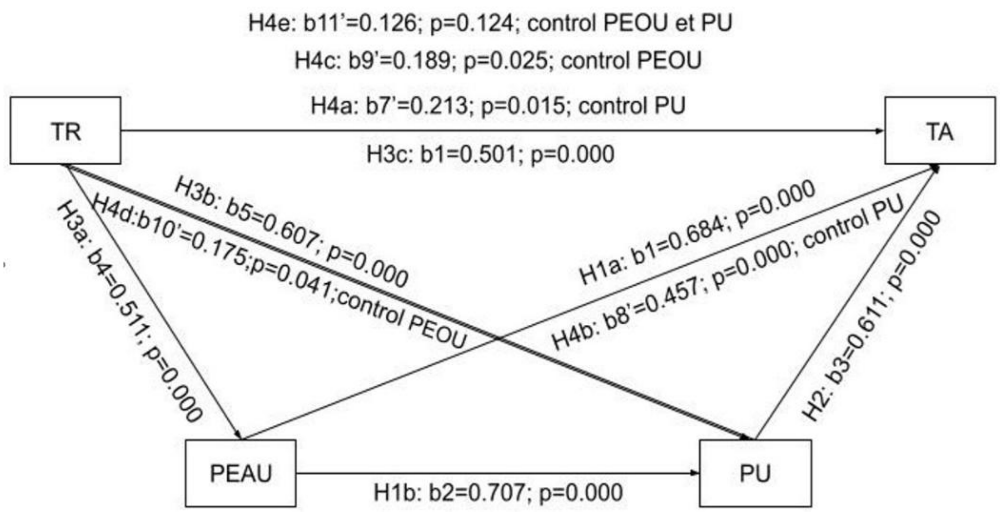

Figure 1: Mediation analysis of our hypotheses

Sources: Data processed by authors

Bootstrap Analysis

After verifying the mediating effects of PU and PEOU on the relationship between TR and TA, we tested the robustness and accuracy of these mediator effects using the bootstrapping method. This method is nowadays strongly recommended to estimate indirect effects in mediation models (Preacher & Hayes, 2004). Accordingly, we conducted our bootstrap analysis using 2000 resamples, an appropriate sample size for a multiple regression model, with a 95% confidence interval level and a type of bias corrected and accelerated confidence interval.

Table 5: Bootstrap Analysis of coefficients

Variables	b	Std. Error	T	p	LLCI	ULCI
Constant	- 0.008	0.059	- 0.143	0.886	- 0.125	0.108
Technology Readiness (TR)	0.126	0.081	1.548	0.124	- 0.035	0.287
Perceived Ease of Use (PEOU)	0.420	0.088	4.757	0.000	0.245	0.595
Perceived Usefulness (PU)	0.306	0.086	3.550	0.000	0.135	0.478

Source: Data processed by authors.

Bootstrap analysis aims to assess the strength of the indirect effect of TR, PU, and PEOU on TA using a statistical resampling method in SPSS. The bootstrap standardized the distribution of the original sample of 125 students used in the mediation analysis and then resampled several times to reach a sample size of 2000. The results of the bootstrap analysis, presented in Table V, revealed that TR was not a statistically significant predictor of TA (p = 0.124 > 0.05).

PU was identified as a statistically significant predictor of TA ($p = 0.000 < 0.01$) and PEOU ($p = 0.000 < 0.01$). While controlling for PU and PEOU, TR was not a statistically significant predictor of TA. However, PU and PEOU remained statistically significant predictors of TA; hence, PU and PEOU had a mediating effect on the relationship between TR and TA.

CONCLUSION

The results of the study concerning the positive effects of TR, PU, and PEOU on the adoption of AI technology and the mediating role of perceptions of use (PU and PEOU) on the relationship between technological readiness and the adoption of AI technology by accounting and finance students at *ISCAE*-Tunisia reveal that these students perceive themselves as prepared to adopt new AI technologies and that they will adapt to technological advances required by companies and accounting firms. These students are aware and convinced of the importance of AI technologies in their future professions.

The study, conducted in a developing country in Africa, shows that the results are not different from the results of those by Damerji & Salimi (2021) conducted in the United States universities, the studies by Sudaryanto, *et al.* (2023) and Dwianto, *et al.* (2024), conducted in universities in Indonesia. These results indicate that adoption of AI technology is unavoidable worldwide and the intention of its adoption by students is not different in the context of an African developing country, which may be characterised by a lack of financial resources, digital and energy infrastructures to be as compared with countries in other continents.

The findings are significant because they illustrate the drivers of AI adoption by accounting and finance students in universities. AI adoption will enable these students to acquire knowledge and skills that will provide them with a competitive advantage in both university and accounting, auditing, and finance industries. This study makes both theoretical and practical contributions to the literature. On the theoretical level, the results confirm that the measurement scales of Parasuraman and Colby (2015) and Davis (1989), used to measure the adoption of AI technology and its determinants, are valid and reliable in the context of a developing country such as Tunisia.

On a practical level, this study contributes to helping universities understand the factors that increase AI adoption among accounting and finance students. The findings reveal that accounting and finance students are ready for technology, and they perceive PU and PEOU to be positive. Therefore, it is encouraging for universities to invest in launching AI implementations in accounting and finance programs to enhance the technological readiness of students. The findings further imply that universities should consider that easy-to-use and useful AI technologies lead to higher adoption rates and ensure that students are more conscious of AI's importance in their future careers in accounting, auditing, and finance. Furthermore, these universities can develop strategies to overcome the obstacles (discomfort and insecurity) and strengthen the drivers, the motivators/ factors (optimism and innovative spirit) to foster the adoption of AI by accounting and finance students.

Our research has several limitations, particularly concerning the selected university, the honesty of the responses, and the self-reported perceptions of the respondents regarding the questionnaire. First, the collected data were limited to students from a single Tunisian university (*ISCAE)*. As previously explained, the selection of this institution is pertinent. However, it should be noted that *ISCAE* is not the sole institution offering accounting and finance courses in Tunisia.

The research findings may be specific to this institution and may not be generalized to all universities in Tunisia, particularly those not located in large cities such as the capital, Tunis. Second, there may be an inherent bias in taking the first respondents to the survey and respondents whom the authors know personally or have encouraged to respond to, which may result in a non-random sample of the study population. The final limitation is that respondents may not have properly understood the questions, particularly undergraduates, and therefore may have responded based on beliefs, and not necessarily based on AI technologies' knowledge and their application in the accounting and finance sector.

To conclude, we emphasize that the literature has focused on the impact of external factors, other than individuals' perceptions of technology adoption. It is recommended that the present study be reproduced, with consideration given to external factors influencing the adoption of AI technology by a larger audience and in other universities worldwide.

Disclosure Statements

The authors declare:

- That there are no known conflicts of interest associated with this publication.
- That no funding was received to conduct this study.
- Compliance with the ethical standards of the university for the collection and protection of student’s personal data.

References

Al-Maskari, A., Al-Riyami, T. and Kunjumuhammed, S. K. (2022), “Students academic and social concerns during COVID-19 pandemic”, Education and Information Technologies, Vol. 27, N°1, pp. 1–21, available at: https://doi.org/10.1007/s10639-021-10592-2.

Amalia, D.N. (2023), “Implementation of technology acceptance model (TAM) in learning management system (case study: Kalimantan Institute of Technology)”, Jurnal Nasional Komputasi et Teknologi Informasi (JNKTI), Vol. 6 No 4, pp. 576–584, available at: https://doi.org/10.32672/jnkti.v6i4.6529.

Anh, N.T.M., Hoa, L.T.K., Thao, L.P., Nhi, D.A., Long, N.T., Truc, N.T. and Ngoc Xuan, V. (2024), “The effect of technology readiness on adopting artificial intelligence in accounting and auditing in Vietnam”, Journal of Risk Financial Management, Vol. 17, No 1, available at: https://doi.org/10.3390/jrfm17010027.

Asnakew, Z. (2020), “Customers’ continuance intention to use mobile banking: development and testing of an integrated model”, The Review of Socionetwork Strategies, Vol. 14, No 2, available at https://doi.org/10.1007/s12626-020-00060-7.

Ballantine, J., Boyce, G. and Stoner, G. (2024), “A critical review of AI in accounting education: threat and opportunity”, Critical Perspectives on Accounting, Vol. 99, available at: https://doi.org/10.1016/j.cpa.2024.102711.

Bond, M., Marín, V.I., Dolch, C., Bedenlier, S. and Zawacki-Richter, O. (2018), “Digital transformation in German higher education: student and teacher perceptions and usage of digital media”, International Journal of Educational Technology in Higher Education, Vol. 15, No 1, available at: https://doi.org/10.1186/s41239-018-0130-1.

Chen, K. and Chan, A.H.S. (2014), "Gerontechnology acceptance by elderly Hong Kong Chinese: a senior technology acceptance model (STAM)", Ergonomics, Vol. 57, pp. 635–652, available at: https://doi.org/10.1080/00140139.2014.895855.

Damerji, H. and Salimi, A. (2021), "Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting", Accounting Education, Vol. 30, No 2, pp. 107-130, available at: https://doi.10.1080/09639284.2021.1872035.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", MIS Quarterly, Vol. 13, pp. 319–340, available at: https://doi.org/10.2307/249008.

Davis FD, (1986), "A technology acceptance model for empirically testing new end-user information systems: theory and results", Doctoral dissertation, MIT Sloan School of Management, Cambridge, MA (USA).

Dwianto, A., Rahman, A.N., Ulynnuha, O.I., Anam, K. and Saif, G.M.S. (2024), "The Impact of technology readiness, usefulness, and ease of use on AI-based accounting software adoption", Advances in Accounting Innovation, Vol. 1, pp. 10–11.

ERRABI, G. and HAMADI, C. (2023), "De la sélection à la structure factorielle de l'instrument de mesure: Principes et exemple d'application", Revue Internationale du Chercheur, Vol. 4, No 2, pp. 79-94.

Garcia, A. and Lee, C.H. (2020), "Equity-centered approaches to educational technology", Bishop, M.J., Boling, E., Elen, J. and Svihla, V. (Eds.), Handbook of Research in Educational Communications and Technology, Springer International Publishing, Cham. pp. 247–261. available at: https://doi.org/10.1007/978-3-030-36119-8_10.

Grabińska, B., Andrzejewski, M. and Grabiński, K. (2021), "The students' and graduates' perception of the potential usefulness of artificial intelligence (AI) in the academic curricula of finance and accounting courses", e-mentor, Vol. 92, No 5, pp. 16–25, available at: https://doi.org/10.15219/em92.1544.

Groenewald, E., Rabillas, A., Uy, F., Kilag, O.K., Bugtai, G. and Batilaran, J. (2024), "Enhancing financial management practices in public schools: a systematic literature review in southeast Asia", International Multidisciplinary Journal of Research for Innovation, Sustainability, and Excellence, Vol. 1, pp. 207–212.

Harris, R.J (2021), "A Primer of Multivariate Statistics", New York, Psychology Press, 3rd Edition, available at: https://doi.org/10.4324/9781410600455.

Huang, H.M., and Liaw, S. S. (2018), "An analysis of learner's intentions toward virtual reality learning based on constructivist and technology acceptance approaches", The International Review of Research in Open and Distributed Learning, Vol.19, No 1, available at https://doi.org/10.19173/irrodl.v19i1.2503

Jin, C.H. (2020), "Predicting the use of brand application based on a TRAM", International Journal of Human-Computer Interaction, Vol. 36, No 2, pp. 156-171, http://doi.org/10.1080/10447318.2019.1609227.

Kampa, R.K. (2023), "Combining technology readiness and acceptance model for investigating the acceptance of m-learning in higher education in India", Asian Association of Open Universities Journal, Vol. 18, pp. 105–120, available at: https://doi.org/10.1108/AAOUJ-10-2022-0149.

Kashive, N., Powale, L. and Kashive, K. (2020), "Understanding user perception toward artificial intelligence (AI) enabled e-learning", International Journal of Information and Learning Technology, Vol. 38, pp. 1–19, available at: https://doi.org/10.1108/IJILT-05-2020-0090.

Kim, T. and Chiu, W. (2019), "Consumer acceptance of sports wearable technology: the role of technology readiness", International Journal of Sports Marketing and Sponsorship, Vol. 20, No 1, pp. 109-126, available at: https://doi.org/10.1108/IJSMS-06-2017-0050.

Kroon, N., Alves, M.G, Martins, I. (2021), "The impacts of emerging technologies on accountants' role and skills: connecting to open innovation: A systematic literature review", Journal of Open Innovation Technology Market and Complexity, Vol. 7, No 3, available at: https://doi.org/10.3390/joitmc7030163

Lin, C., Shih, H. and Sher, P.J. (2007), "Integrating technology readiness into technology acceptance: the TRAM model", Psychology and Marketing, Vol. 24, pp. 641–657, available at: https://doi.org/10.1002/mar.20177.

Martin, T. (2022), "A literature review on the Technology Acceptance Model", International Journal of Academic Research in Business and Social Sciences, Vol. 12, No 11, available at https://doi.org/10.6007/IJARBSS/v12-i11/14115.

Naranjo-Zolotov, M., Oliveira, T. and Casteleyn, S. (2019), "Citizens' intention to use and recommend e-participation: drawing upon UTAUT and citizen empowerment", Information Technology & People, Vol. 32, pp. 364–386, available at: https://doi.org/10.1108/ITP-08-2017-0257.

Nouraldeen, R.M. (2023), "The impact of technology readiness and use perceptions on students' adoption of artificial intelligence: the moderating role of gender", Development and Learning in Organizations, Vol.37, No 3, pp. 7-10, available at: https://doi.org/10.1108/DLO-07-20220133.

Parasuraman, A. (2000), "Technology readiness index (TRI): a multiple-item scale to measure readiness to embrace new technologies", Journal of Service Research, Vol. 2, pp. 307–320, available at: https://doi.org/10.1177/109467050024001.

Parasuraman, A. and Colby, C.L. (2015), "An updated and streamlined technology readiness index: TRI 2.0", Journal of Service Research, Vol. 18, pp. 59–74, available at: https://doi.org/10.1177/1094670514539730.

Preacher, K.J. and Hayes, A.F. (2004), "SPSS and SAS procedures for estimating indirect effects in simple mediation models", Behavior Research Methods, Instruments, & Computers, Vol. 36, pp. 717–731, available at: https://doi.org/10.3758/BF03206553.

Rahi, S., Zaheer, M., Alghizzawi, M. and Ngah, A.H. (2023), "Investigating the role of innovativeness, technology acceptance model and theory of planned behavior towards adoption of QR mobile payment system", International Journal of Business Innovation and Research, Vol. 1, No 1, available at: doi:10.1504/IJBIR.2023.10058240.

Rawashdeh, A. (2023), "The consequences of artificial intelligence: an investigation into the impact of AI on job displacement in accounting", Journal of Science and Technology Policy Management, Vol. 16, No 3, available at: https://doi.org/10.1108/JSTPM-02-2023-0030.

Roy, R., Babakerkhell, M.D., Mukherjee, S., Pal, D. and Funilkul, S. (2022), "Evaluating the intention for the adoption of Artificial Intelligence-based robots in the university to educate the

Students", IEEE Access, Vol. 10, pp. 125666–125678, available at: https://doi.org/10.1109/ACCESS.2022.3225555.

Strong, J. and Portz, K. (2015), "IT knowledge: what do accounting students think they know? Do you know more than I do? An exploratory study", Review of Business Information Systems, Vol. 19, No 2.

Sudaryanto, M.R., Hendrawan, M.A. and Andrian, T. (2023), "The Effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students artificial intelligence technology adoption", E3S Web of Conferences, available at: https://doi:10.1051/e3sconf/202338804055.

Tavares, M.C., Azevedo, G., Marques, R.P. and Bastos, M.A. (2023), "Challenges of education in the accounting profession in the Era 5.0: a systematic review", Cogent Business & Management, Vol. 10, available at: doi:10.1080/23311975.2023.2220198.

Taber, K.S. (2018), "The use of Cronbach's Alpha when developing and reporting research instruments in science education", Research in Science Education, Vol. 48, pp.1273-1296, available at: https://doi.org/10.1007/s11165-016-9602-2.

Verma, P. and Sinha, N. (2018), "Integrating perceived economic wellbeing to technology acceptance model: the case of mobile based agricultural extension service", Technological Forecasting and Social Change, Vol. 126, pp. 207–216, available at: https://doi.org/10.1016/j.techfore.2017.08.013.