Artificial intelligence usage intentions and its disruptive impact on the accounting profession: empirical evidence from Greece

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Research on intentions to use Artificial Intelligence (AI) in the accounting domain, while also considering the potential concerns stemming from its highly disruptive force, appears to be particularly limited. Our study aims to fill this gap by formulating a comprehensive model of AI acceptance in the accounting field, integrating the theoretical framework proposed by Ferri et al. (2021, 2023) with the literature-based AI Anxiety factor. By applying partial least squares structural equation modeling (PLS-SEM) to analyze the questionnaire survey data collected from accountants and auditors in Greece, our study indicates that performance expectancy (PE) and perception of external control (PEC) primarily shape accounting practitioners' AI acceptance stance. Most notably, though, the findings suggest a negative effect of the fear of AI job replacement (AIJRA) on accountants' intentions to accept AI, confirming, even partially, the overall insecurity surrounding the impact of AI on the global socio-economic landscape, particularly in the context of the post-COVID-19 world.

Keywords: accounting, auditing, artificial intelligence, technology acceptance, UTAUT, TAM3, AI anxiety

1. Introduction

The scientific field of accounting, despite its traditional form and long history (Kureljusic and Karger, 2023), is subject to rapid changes in the general environment of the new digital era (Guthrie and Parker, 2016), as it is a professional field prone to these changes due to the structured and repetitive structure of the basic accounting and auditing processes (Cooper et al., 2019; Kokina and Blanchette, 2019) and its relevance to data science (Sutton et al., 2016; Mcbride and Philippou, 2022). Therefore, the accounting and auditing professions need to evolve constantly to cope with modern technological requirements (Skrbis and Jacqueline, 2019), in the context of an unprecedented digital revolution, with the ever-changing regulatory/legislative framework accelerating this development (Andriosopoulos et al., 2019).

An important strain of these digital developments is the technology of Artificial Intelligence (AI); although the idea of implementing AI in accounting and auditing is not new (Keenoy, 1958), the current availability of substantial amounts of data and processing power brings to the forefront the potential massive impact of AI on the productivity of accounting and auditing professionals (Guthrie and Parker, 2016; Kokina and Davenport, 2017). Yet, the use of AI-based digital technologies by accounting and auditing firms is still in its early stages (Leitner-Hanetseder et al., 2021), which is partially a consequence of the costs associated with the adoption of such technology (Gotthardt et al., 2020). In numerical terms, Kommunuri (2022) lists the investment plans of the Big 4, with PWC planning to invest $12bn and hire 100,000 new staff in the AI sector by 2026, with KPMG following with $5bn over a 5-year horizon and finally Ernst & Young (EY) with around $1.5bn.

Despite the investment outline, there is an overall sentiment of uncertainty regarding the imminent reshaping of the accounting and auditing professions, stemming from the possibility of AI job displacement (Makridakis, 2017) and changes in practitioners' roles, responsibilities and necessary skills (Kommunuri, 2022; Kureljusic and Karger, 2023), thus posing a challenge to companies' smooth transition into the new digital era. Ultimately, what becomes crucial is to investigate the perceptions and expectations of the individual actors (Ferri et al., 2023), both positive and negative. These insights could be essential for developing new business models (Petkov, 2020), planning new training strategies at both organizational and academic contexts, and ensuring the successful intracompany adoption of the technology; after all, individual attributes, such as the characteristics of the managers and the effectiveness of the support team integration, have been shown to significantly affect this adoption process (A. Vasarhelyi and Romero, 2014). However, research on the factors influencing the accounting and auditing practitioner's intentions to embrace these technological developments appears to be limited (e.g. Ferri et al., 2021; Vărzaru, 2022; Norzelan et al., 2024; Abdullah and Almaqtari, 2024; Al Wael et al., 2024).

In this perspective, the research model of this study integrates the two widely used models of Unified Theory of Acceptance and Use of Technologies (UTAUT) and Technology Acceptance Model 3 (TAM3), following the example of Ferri et al. (2021, 2023) studies, with the originality value of this study stemming from the parallel use of the AI Anxiety factor, adapted in the context of the impending transformative role of AI in the wider accounting profession, with its inclusion being rather relevant in the post-COVID-19 context. The integration of both positive and negative factors will allow us to examine not only the relevance of the benefits of AI for practitioners, but also the seriousness of the concerns about its disruptive role for their profession. The data utilized in this study were collected through a literature-based Likert-type questionnaire that was distributed to Greek accountants, assistant accountants and auditors, with a total of 153 people providing full responses, and were analyzed using partial least squares structural equation modeling (PLS-SEM) in order to measure the effect of each factor on the practitioner's intentions to adopt AI technologies.

The most important findings of this study include the dominant role of performance expectancy (PE) and perception of external control (PEC) as determinants of AI use intentions, the differential impact of social influence (SI) between accountants and auditors, and finally, the negative effect that the fear of job replacement from AI (AIJRA) has on practitioners' intentions.

The rest of this paper is organized as follows. The next section describes the relationship between the fields of accounting and AI through a review of the existing literature and introduces the model used in the research. The subsequent two sections include the hypothesis development, stemming from the literature review of the acceptance and rejection factors under consideration, and outline the research methods employed. The next section presents the findings of the analysis and discusses the results. Finally, the last section concludes the study and provides guidelines for companies and regulators regarding their next steps in technology adaptation, considering the individual and social characteristics of the practitioners.

2. Foundations of the theoretical model

The history of AI applications in the accounting profession dates back to the 1980s (Abdolmohammadi, 1987; Borthick and West, 1987), with the development and use of Expert Systems being the most studied area of AI in accounting and auditing (Baldwin et al., 2006). An Expert System is defined as a computer system that imitates an expert's ability to make decisions, store knowledge and convert it into rules, with the purpose of, in the case of accounting, solving accounting problems and performing accounting tasks (Sutton et al., 2016). However, this technology's reliance on pure logic, "if-then" rules and decision trees, and the difficulty of it truly capturing human expertise, limits its capabilities (O' Leary, 2003) and renders it incapable of learning, resulting in many cases in the same mistakes over and over again (Makridakis, 2017). Yet, the recent technological breakthroughs in the AI field are opening a new page in the accounting practice, redirecting the research focus from the applications of Expert Systems to some new opportunities and challenges for accounting professionals (Sutton et al., 2016), with their broad effect on the accounting and auditing practice being widely discussed in the literature.

2.1. The AI & accounting nexus: expected opportunities and underlying threats

Since accounting data are usually rule-based and well-structured, they are suitable for automation through the use of AI models (Kureljusic and Karger, 2023), especially regarding various time-consuming and repetitive tasks (Kokina and Blanchette, 2019; Cooper et al., 2019; Diller et al., 2020). These tasks include checking payment transactions and identifying any unusual amounts recorded in them (Kommunuri, 2022), estimating inventory ratios (Baldwin et al., 2006), identifying patterns (Lehner et al., 2022), and scanning keywords in complex electronic documents to extract sales, contracts, costs, and other relevant information for decision-making (Kokina and Davenport, 2017). AI also provides more accurate information through data processing (Han et al., 2023) and facilitates auditing and accounting procedures, such as reviewing general ledgers, ensuring tax compliance, preparing work papers, conducting data analytics, maintaining expense compliance, detecting fraud (Munoko et al., 2020), and financial forecasting (Bertomeu, 2020). In summary, current research literature lauds the potential of AI to improve the productivity and efficiency of the accounting and auditing professionals and firms (Guthrie and Parker, 2016). For instance, a result of Deloitte's use of AI when extracting terms from contracts is that it allows auditors to review a much higher percentage of documents – potentially up to 100% (Davenport and Ronanki, 2018).

The expected automation of common routine processes (Gotthardt et al., 2020) and its subsequent potential impact on the accounting workforce (Guthrie and Parker, 2016) insinuate the possible disappearance of a number of jobs (Oesterreich et al., 2019; Kruskopf et al., 2020), especially in the unstable environment that characterizes the post-COVID-19 era. Indeed, Kokina and Davenport (2017) highlight the fact that, according to one Ernst & Young (EY) source, the number of new hires each year could be halved as a result of the rise of AI, drastically changing the industry's employment model. By extension, Makridakis (2017) points out that the application of AI may lead to potential income inequalities due to the diminishing need for human labor.

The possible reduction in routine accounting tasks over the next few years (Kommunuri, 2022) could lead to the development of new roles and responsibilities (Diller et al., 2020) for the accounting professionals, such as monitoring the performance of intelligent systems and providing scientific advice to IT companies during the development of new AI technologies (Kokina and Davenport, 2017). Gamage (2016) defines how accountants will stop being mere handlers of historical financial data; instead, they will begin to play a more active and strategic role within businesses. Leitner-Hanetseder et al. (2021) conclude that while core accounting and auditing roles will continue to exist, some tasks could be performed by AI technology, necessitating the conscious use of new digital tools. Therefore, in order to adapt to this new work environment and the current data-centric business context (Appelbaum et al., 2020), practitioners should develop new skills (Oesterreich et al., 2019) so that they can create value for their clients (Kureljusic and Karger, 2023), including technical skills, like analysis skills and ERP experience, as well as soft skills, such as leadership and adaptability (Kruskopf et al., 2020).

Despite the general climate of uncertainty surrounding the potential transformative role of AI technology in the broader accounting profession, research on the factors influencing accounting and auditing practitioners' intentions to embrace these technological developments appears to be limited (Ferri et al., 2023). In light of this, the construction of a representative theoretical model that also addresses key issues of concern among accounting and auditing professionals is deemed especially relevant.

2.2. Baseline model

For the initial phase of our theoretical model development, we draw on the acceptance studies of emerging technologies by Ferri et al. (2021, 2023), which integrate the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and Technology Acceptance Model 3 (TAM3) (Venkatesh and Bala, 2008). UTAUT has been effective in interpreting the acceptance of innovative technologies (Dwivedi et al., 2019; Donmez-Turan, 2020), while TAM3 is useful for understanding the key drivers underlying UTAUT. We believe this approach provides a strong explanatory basis for elucidating the general characteristics that shape accounting professionals' intentions, thereby adopting the proposed model as the backbone of our empirical analysis.

In this spirit, after discussing the topic, we concur with the logical assumptions presented by Ferri et al. (2021, 2023) regarding the overlap of variables between UTAUT and TAM3. More specifically, we agree that the performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC) of UTAUT correspond to the perceived usefulness (PU), perceived ease of use (PEOU), and perception of external control (PEC) of TAM3, respectively. Therefore, in the context of UTAUT, PE, EE, and social influence (SI) are incorporated into the research model as predictors of intention to use (INT). Similarly, in accordance with the variables proposed by TAM3, we adopt output quality (OQ), job relevance (JR), and result demonstrability (RD) as determinants of PE, while computer self-efficacy (CSE) and PEC serve as antecedents to EE, with PEC also functioning as a predictor of INT. Taking a step further from Ferri et al. (2021, 2023), we examine EE as a determinant of PE, based on the relationship suggested by TAM3 between PEOU and PU.

We also agree with the exclusion of the variables of voluntariness, image, computer playfulness, perceived enjoyment and objective usability from the research framework, as they do not appear to be related to the subject of the present research for the same reasons stated by Ferri et al. (2021, 2023).

It is, finally, important to note that, in the case of AI technologies, the factor of computer anxiety (ANX), as proposed by TAM3, is considered conceptually inadequate for their interpretation (Wang and Wang 2022) and cannot be used in this study's context.

2.3. The AI Anxiety factor

Moving away, then, from the concept of computer anxiety as framed by TAM3, the anxiety factor should be examined in terms of AI anxiety, which refers to feelings of fear or agitation concerning uncontrollable AI. It primarily arises from inaccurate perceptions of technological developments, confusion about AI's autonomy, and sociotechnical ignorance (Johnson and Verdicchio, 2017). AI anxiety can be considered a general perception or belief with multiple dimensions (Wang and Wang, 2022), by virtue of its subject matter raising, inter alia, the issues of autonomous decision-making (Leyer and Schneider, 2021; Vincent, 2021), human-independent operation (Huang and Rust, 2018; Lindebaum et al., 2020) and the ethical issues of its societal and workforce impact (Jarrahi, 2018; Munoko et al., 2020), in contrast to computer anxiety (Li and Huang, 2020), which is unidimensional, and is purely the result of the user's mere personal interaction with the computer (Howard and Smith, 1986).

Only a limited number of studies (e.g., Wang and Wang, 2022; Li and Huang, 2020) have attempted to concretize the dimensions of AI anxiety. The factors of AI learning anxiety and AI job replacement anxiety, which emerged from the bisection of the aforementioned studies through thorough discussion among the authors, are closely aligned with the primary concerns evident in the existing accounting literature regarding the impact of AI. More precisely, this conceptual correspondence is observed between the dimension of AI learning anxiety (AILA) and the possibility of new accounting roles and responsibilities and the need for new digital skills, as well as between the dimension of AI job replacement anxiety (AIJRA) and the concern of job loss due to automation, thus incorporating them into the research model. The theoretical construct and hypothesis development are explained in the next section.

3. Hypothesis development

3.1. Self-efficacy

Being a term deriving from the Social Cognitive Theory (SCT) (Wood and Bandura, 1989), self-efficacy's highly valued effect on the performance of complex activities and the levels of effort that users are willing to undertake (Bandura, 1982) has led researchers to investigate the potential relationship between self-efficacy and computer use (Compeau and Higgins, 1995). Indeed, when applied to the technological domain, the term (computer) self-efficacy (CSE), as is documented in TAM3, refers to the extent to which users believe they have the ability to perform a particular technological task (Venkatesh and Bala, 2008), based on individual skills and knowledge (Debowski et al., 2001), essentially including not only the confidence one has in attaining a specific level of difficulty, but also the perception of the difficulty level of this task (Bandura, 2001; Saadé and Kira, 2009).

Venkatesh and Bala (2008) suggest that CSE assists in determining initial perceptions of the ease of use of a system, which is also evidenced by recent AI technology acceptance studies, such as that of Wang et al. (2021). Therefore we expect CSE to have a positive effect on the professionals' EE, hypothesizing the following:

H1. CSE has a positive effect on accountants and auditors' EE of using AI.

3.2. Perception of external control

Perception of external control (PEC) is a concept derived from TAM3, defined by Venkatesh and Bala (2008) as the set of individual user perceptions of system control, viewed from the perspective of the existence or absence of organizational resources and structured support to consolidate the use of the system within the organization. According to Dwivedi et al. (2019), PEC seems to have an important effect on both EE and usage intentions, a statement that is also evident in AI technologies such as AI-Integrated CRM systems in business environments (Chatterjee et al., 2023) and AI-enabled Robo-advisors in finance (Roh et al., 2023).

In the accounting domain, the relevant literature directly highlights the need for administrative and technical support for accountants when implementing AI technologies (Gotthardt et al.. 2020), while also referencing Big 4 innovation programs (Kokina and Davenport, 2017), such as PwC's 2018 PwC Digital Accelerator Program, which targeted 1000 employees to enhance their digital capabilities in AI tools (Kruskopf et al., 2020). Therefore, given the relevance of PEC to the accounting sector, we hypothesize the following:

H2. PEC has a positive effect on accountants and auditors' EE of using AI.

H3. PEC has a positive effect on accountants and auditors' intentions to use AI.

3.3. Job relevance

Venkatesh and Davis (2000) define job relevance (JR) as an individual's belief regarding the extent to which the system under consideration can be applied in the context of their job, suggesting that it may impact the user's performance expectancy (PE) of the system. Sonntag et al., (2022), in their research on AI-based conversational agents for customer service, also highlight the positive impact of JR on PE, thus contributing to the following hypothesis:

H4. JR has a positive effect on accountants and auditors' PE of using AI.

3.4. Output quality

According to Venkatesh and Davis (2000), output quality (OQ) captures the user's perception of how well a system performs tasks necessary for their job, documenting that OQ has a positive effect on PE. Kao and Huang (2023) in their study on the acceptance of AI-boosted service robots in the hospitality industry also support this idea, thus we argue that:

H5. OQ has a positive effect on accountants and auditors' PE of using AI.

3.5. Result Demonstrability

Venkatesh and Davis (2000) refer to result demonstrability (RD) as the users' expectation of the tangibility of the results of using the innovative system and their ability to attribute the effects of its use on their work processes to the specific functions and uses of that system (Moore and Benbasat, 1991), also indicating that it positively affects PE. As aspects such as transparency and accountability of the AI-based algorithms and the potential ethical issues arising from them are subjects of intense debate in the accounting literature (Munoko et al., 2020; Lehner et al., 2022), we consider that this factor's role on the adoption process of AI could be significant, thus hypothesizing that:

H6. RD has a positive effect on accountants and auditors' PE of using AI.

3.6. Effort Expectancy

Effort expectancy (EE) is a factor stemming from UTAUT, and is defined as the users' subjective perception of the degree of ease of use of the system (Venkatesh et al., 2003). Researchers use this agent extensively, most notably in cases where the learning process of using the new technology is expected to be substantial (Ferri et al., 2023). Especially in the early stages of the new adoption behavior, because of the process barriers that need to be overcome at the outset (Szajna, 1996; Venkatesh, 1999), the less effort that is expected to be required, the more likely it is that the system will be accepted by users (Venkatesh et al., 2003).

Besides, due to the conceptual overlap of EE with TAM's perceived ease of use (PEOU) (Venkatesh et al., 2003), we also expect EE to have a positive effect on PE, thus forming two relationships involving EE in our research model. Taking into account the potential complexity of the new AI accounting systems, as well as comparable results of studies on the acceptance of AI technologies in the accounting and auditing profession (Abdullah and Almaqtari, 2024; Al Wael et al., 2024), we hypothesize the following:

H7. EE has a positive effect on accountants and auditors' intentions to use AI.

H8. EE has a positive effect on accountants and auditors' PE of using AI.

3.7. Performance Expectancy

In accordance with the researchers' general thesis that AI and its enabling technologies will have an imminent positive impact — mainly through increased productivity and accuracy and reduced time and costs (Kruskopf et al., 2020) — on various applications in the broader field of accounting, the performance expectancy (PE) construct from the UTAUT captures the extent to which each user believes that the use of the new technology will help increase their work performance (Venkatesh et al., 2003).

Having in mind that PE is regarded as the most significant predictor of intention to use within the UTAUT framework (Venkatesh et al., 2003; Williams et al., 2015), especially at the organizational level (Venkatesh et al., 2012), and is further supported by recent consistent results in AI acceptance studies in the wider accounting profession (Vărzaru, 2022; Norzelan et al., 2024), there is most likely that PE will be an important factor in the professionals' willingness to accept the new AI technologies, thus formulating the following hypothesis:

H9. PE has a positive effect on accountants and auditors' intentions to use AI.

3.8. Social Influence

As the acceptance behavior of technologies is shaped by the broader social environment (Burkhardt, 1994; Kraut et al., 1998), particularly in the case of socially impactful technologies (Vannoy and Palvia, 2010), such as AI (Vesnic-Alujevic et al., 2020), the role of social influence is increasingly recognized as important in predicting and assessing the extent of innovation acceptance (Graf-Vlachy et al., 2018).

According to Venkatesh et al. (2003), social influence (SI) — a construct derived from the UTAUT — is defined as the degree to which the user perceives that people important to them believe that they should use the new system. It serves as a significant positive determinant of the intention to use new technologies, despite the initial doubts raised by TAM (Davis, 1989), which is likely to be more evident in cases of corporate schemes (such as the Big 4), where a hierarchical staff structure is in place and the opinions of both superiors and colleagues are taken into further consideration by the individual (Ferri et al., 2021). Thus, in conjunction with similar findings of related AI acceptance studies (Strzelecki, 2023; Yu and Huang, 2020), we hypothesize that:

H10. SI has a positive effect on accountants and auditors' intentions to use AI.

3.9. AI learning anxiety

It has been established for decades by the existing literature that the computer learning process can cause anxiety (Heinssen et al., 1987; Rosen and Weil, 1995; Gordon et al., 2003), with learning distress serving as a constitutive dimension of the computer anxiety factor (Rosen et al., 1987). In addition, Li and Huang (2020) define AI learning anxiety (AILA) as the user's lack of confidence in the AI systems' learning process, which is perceived as difficult. Due to the learning aspects of computer anxiety and its conceptual proximity to AILA — both being responses to emotions generated by the prospect of personal interaction with the new technology (Wang and Wang, 2022) — we can logically assume that we may use the relationship defined by TAM3 (Venkatesh and Bala, 2008) between computer anxiety (ANX) and perceived ease of use (PEOU), and subsequently EE, to interpret AILA's effect.

In line with these, as professional accountants are exposed to new AI-centered roles, tasks and necessary skills (Guthrie and Parker, 2016; Oesterreich et al., 2019; Kruskopf et al., 2020; Leitner-Hanetseder et al., 2021), we argue that their potential discomfort towards the requirement to learn them, as a result of subjective individual observation, will have a negative effect on their EE, leading to the hypothesis that:

H11. AILA has a negative effect on accountants and auditors' EE of using AI.

3.10. AI job replacement anxiety

On the other hand, AI job replacement anxiety (AIJRA) includes emotions stemming from the possibility of unemployment and/or reduced job prospects (Li and Huang, 2020), in the overall climate of concern that AI applications may replace humans in a large portion of occupations (Makridakis, 2017; Bughin, 2018). Therefore, AIJRA is not related to the perceived system difficulty, thus rejecting the association of anxiety with

PEOU as is defined by TAM3 (Venkatesh and Bala, 2008).

The presence of concerns about job displacement and the potential degradation of occupational characteristics such as professional autonomy and status, as well as their attenuating influence on usage intentions, is evident in the AI acceptance literature at various levels and disciplines (e.g. Jussupow et al., 2022; Vu and Lim, 2022). Supported by the strong presence of this issue in the current interdisciplinary AI-accounting literature (Sutton et al., 2016; Oesterreich et al., 2019; Kruskopf et al., 2020), we believe that accounting and auditing professionals would be more reluctant to use these systems, considering that either their jobs or the broader sectoral work structure could be at risk. Thus, we hypothesize that:

H12. AIJRA has a negative effect on accountants and auditors' intentions to use AI.

Therefore, our theoretical model, after incorporating our hypotheses, is illustrated as shown in **figure 1**. Next, we provide a brief overview of the applied research methodology.

[Figure 1 near here]

4. Research design

4.1. Questionnaire

To begin with, the questionnaire that was designed to test our hypotheses, was compiled via Google Forms and consisted of 44 questions, divided into three sections; the first section contained the demographic questions, the second the questions of the TAM3 theoretical constructs, and the third the questions of the UTAUT, AI Anxiety and Intentions to Use constructs. All questions were derived from the relevant literature on technology acceptance and AI anxiety scale development (Venkatesh et al., 2003;

Venkatesh and Bala, 2008; Li and Huang, 2020; Ferri et al., 2021) by adapting existing a priori factor structures to align with the research context of the present study. A Likert-type scale of 1 (strongly disagree) to 5 (strongly agree) was used to answer the questions in order to increase response rate and quality along with reducing respondents' frustration level (Babakus and Mangold, 1992).

4.2. Sample selection and data collection

The aforementioned questionnaire was distributed by email in April and May 2024 to self-employed accountants, employees of accounting firms and accounting departments of companies, and auditors working for Big 4 companies operating in Greece. A total of 153 responses were collected from 268 contacted accounting and auditing professionals, resulting in an estimated response rate of 57.09%. All responses were deemed complete and valid. **Table 1** provides an overview of the sample demographics.

[Table 1 near here]

There is a roughly equal distribution in the gender profile of the sample between men and women, with 51.63% being men and 48.37% being women. In terms of age of respondents, the vast majority fall within the age range of 18-30 (81.70%), with 18.30% being over 30 years old. In terms of experience, 74.51% have less than 5 years of professional experience, 15.68% have between 5 and 10 years of experience, 4.58% have between 11 and 20 years of experience and finally 5.23% have more than 20 years of experience. Finally, in terms of professional status, 66.67% declare themselves as assistant accountants, 24.18% as auditors and finally 9.15% as accountants.

4.3. Statistical analysis

In order to interpret the effects of each latent variable on intentions of accounting and auditing professionals to use AI, we conducted the PLS-SEM (partial least square structural equation modeling) technique, which was evaluated as a suitable means of statistical analysis, as this study elaborates the extension of an already existing structural theory, the model consists of many constructs and items and the sample size could be characterized as relatively small (Hair et al., 2011).

However, despite its small size, the sample can be considered particularly adequate for PLS-SEM analysis. According to the minimum R-squared method (Hair et al., 2014, 21), with a maximum of 5 arrows pointing at a latent variable, a significance level of 0.05, and a minimum R^2 in the model, as estimated further below, of 0.336, the minimum accepted sample size is 70.

Additionally, since we are adapting existing and validated measures, we do not need to conduct exploratory factor analysis (Henson and Roberts, 2006; Green et al., 2016) before the baseline PLS-SEM analysis. Therefore, the research model was evaluated in two steps: the first included the measurement model, which refers to the relationships between each latent variable and its indicators, while the second covered the structural model, which deals with the causal relationships between the latent variables. The validity and reliability assessment of the model, the examination of existence of multicollinearity issues and the determination of the model's overall fit were all included in the analysis of the study's measurement model. In the next step, that of the structural model analysis, the assessment of the explanatory power and the predictive relevance of the model, the hypothesis testing and the examination of the existence of indirect relationships between the variables and, finally, the multigroup analysis testing the effect of the role of the professionals were also all carried out. The structural model calculations were conducted using the bootstrapping procedure with 5,000 bootstraps to evaluate its efficacy.

5. Results and discussion

5.1. Measurement model

We started our statistical analysis by conducting factor loading, which is recommended to be >0.7. As a result, CSE4, PEC1, RD1, AILA3 and AIJRA3 were eliminated from the model (with values of 0.395, 0.580, 0.662, 0.668 and 0.484 respectively), having outer loadings below 0.7. **Table 2** provides a summary of the descriptive statistics measures of mean and standard deviation for the remaining indicators, as well as the quality values regarding the reliability and validity of each construct.

[Table 2 near here]

Regarding the reliability of the model, we extracted the variable score values of Cronbach's alpha and composite reliability (CR), which should be >0.700 and >0.708 respectively (Hair et al., 2019). Indeed, as shown in **Table 2**, Cronbach's Alpha ranges between 0.705-0.902 and composite reliability between 0.842-0.946; as a result, all constructs remain in the model. Additionally, constructs' convergent validity is established when the average variance extracted (AVE) is >0.500, which, as can be seen in **Table 2**, is true in each case, as AVE takes values between 0.595-0.898.

Following up, in order to address the discriminant validity, the Fornell-Larcker criterion was used, according to which, discriminant validity is achieved if the square root of the AVE of each construct is greater than any inter-construct correlation, which indeed turned out to be true. For the results of this process see **Appendix** (**Table A1**).

We then applied the VIF method in order to assess the existence of multicollinearity. VIF (Variance Inflation Factor) measures and quantifies the amount of variance and indicates whether the independent variables are correlated with each other. If the VIF values are above 3 then the constructs have a collinearity problem. The VIF values are in every case below 3, which means that the study's model is free of multicollinearity symptoms (Muhaimin et al., 2019). See also **Appendix** (**Table A2**) for the exact findings.

Subsequently, the standardized root mean square residual (SRMR) was calculated to estimate the model's goodness-of-fit, which takes the value 0.080. According to the most conservative version, this value is the highest acceptable value that SRMR should take; however, some researchers are more flexible by setting the threshold at 0.1 (Hu and Bentler, 1998), while Al Wael et al. (2024), in their study exploring the factors of acceptance of AI in the accounting profession, set the upper limit at 0.085; so in any case SRMR takes a value, even if only marginally, of an acceptable level.

5.2. Structural model

Proceeding with the analysis of the structural model, we first of all analyzed the coefficient of determination (R^2) of the endogenous constructs to evaluate the explanatory power of the model used. Chin (1998) suggested that R^2 values for endogenous latent variables for PLS-SEM analysis are evaluated as follows: >0.67 (significant), >0.33 (moderate), >0.19 (weak) and <0.19 (very weak). The explanatory power of the model in terms of intention to use (INT), performance expectancy (PE) and effort expectancy (EE) is moderate (43.2%, 48.4% and 33.6% respectively), with 56.8%, 51.6% and 66.4% of their variance respectively explained by factors external to the model.

As far as predictive relevance goes, obtaining values of $Q^2 > 0$ indicates that the model is predictive of the endogenous structures under consideration. Indeed, Hair et al. (2019) suggest that Q^2 values for endogenous latent variables are evaluated as follows: 0.35 (significant), 0.15 (moderate), 0.02 (weak). The model has significant predictive ability with respect to INT (0.368) and PE (0.435), and moderate in terms of EE (0.308).

Proceeding to the hypothesis testing, the level of significance was set at 5% ($p<0.05$), and the path coefficients' values were extracted. It is noteworthy that the majority of the hypotheses of this paper are validated by the results of the statistical analysis. As shown in **figure 2**, it can be seen that eight of the hypotheses are accepted (H1, H2, H3, H5, H8, H9, H10 and H12), while the remaining four (H4, H6, H7 and H11) are rejected as their path coefficients presented a p-value above 0.05 ($p>0.05$).

[Figure 2 near here]

To enhance the interpretation of our results, we also analyzed the indirect relationships between the latent variables, setting the significance level at 5% ($p < 0.05$). The statistically significant results are discussed in the discussion section. See also **Appendix** (**Table A3**).

Finally, we examined the effect of the role of accounting professionals on the structural correlations of the model through the multigroup analysis (MGA) procedure. For this purpose, two groups of professionals were defined: accountants, which include both accountants and assistant accountants who work in the broader field of financial accounting, and auditors. The significance level was set at 5% ($p < 0.05$). Among the relationships analyzed, only SI showed a statistically significant difference in its effect on INT between accountants and auditors, as elaborated upon further in the discussion section below. **Appendix** (**Table A4**) provides the specific results of the MGA.

5.3. Discussion

Analyzing our findings, with reference to CSE, our results fully support H1. CSE has a significant positive effect on EE (coeff. 0.272, $p < 0.01$), being in line with a number of similar studies in the literature on the acceptance of AI technologies (Wang et al., 2021; Ferri et al., 2023), further establishing the broadly held position of the importance of one's confidence in his/her knowledge and abilities in shaping his/her perception of the ease of use of the system in question. As a matter of fact, by also examining the indirect relationships of the present model, it is found that CSE extends, to a small degree, its positive effect through EE on PE (coeff. 0.078, $p < 0.05$); accounting and auditing professionals who have a better self-assessment of their capabilities believe that AI will further improve their work processes, as they expect that it will not require much effort to implement it.

With reference to PEC, our results confirm both H2 and H3, as it is observed to exhibit positive effects on both EE (coeff. 0.437, $p < 0.01$) and INT (coeff. 0.287, $p < 0.01$), being consistent with a number of AI-related studies (Chatterjee et al., 2023; Roh et al., 2023; Kim et al., 2024). This dual influence highlights that accounting and auditing professionals are more likely to adopt AI technologies and adapt their work practices if they are engaged in an environment with a strong sense of organizational support, resource adequacy and corporate technological readiness (Kim et al., 2024), thus emphasizing the role of firm support in the technological change process (Ferri et al., 2023). In extension of this finding, PEC seems to have a positive effect through EE on PE (coeff. 0.125, $p < 0.01$); this makes sense since practitioners, perceiving the system as something effortless due to the existence of external support, expect AI to improve the overall performance of their professional operations.

Despite the proven relevance of AI technologies to accounting and auditing processes, there is no significant relationship between JR and PE (coeff. 0.083, $p > 0.05$), thus rejecting H4. The accountants' expectations of improvement that the application of AI would yield to their various tasks is not necessarily cultivated by its fundamental relationship to this professional discipline.

On the other hand, OQ seems to be the main predicting factor of PE, as it is shown to have a strong positive effect on it (coeff. 0.431, $p < 0.01$), thus confirming H5, being consistent with several similar studies of AI technology acceptance in other professional disciplines (Hu. 2022; Kao and Huang, 2023). Accounting and auditing professionals perceive the upgrade of the quality of their work outcome as the most important factor improving overall performance, beyond other factors such as result tangibility and effort. Furthermore, the finding of an indirect positive effect on INT through PE is derived (coeff. 0.197, $p < 0.01$), further demonstrating the importance of this factor in the explanatory power of the present model.

In contrast, RD appears to have no significant effect on PE (coeff. 0.121, $p > 0.05$), thus rejecting H6. We believe that the absence of this factor in shaping practitioners' expectations is probably attributed to the early stage of the AI adoption process, leaving practitioners incapable of forming some secure initial perceptions about its results' tangibility.

In the case of EE, the results are mixed; apart from the absence of a significant relationship between EE and INT (coeff. -0.132, $p > 0.05$), which is a common consensus of a remarkable number of previous studies on AI acceptability (Andrews et al., 2021; Ni and Cheung, 2023; Norzelan et al., 2024), a negative relationship between the two constructs is also observed, leading to the rejection of H7. Actually, our finding contradicts the general thesis in the AI literature that the chances of AI acceptance will be higher if its applications are easy to use and require less effort (Gursoy et al., 2019; Norzelan et al., 2024). However, the significant positive relationship between EE and PE (coeff. 0.285, $p < 0.01$), confirming H8, leads to the indirect, positive, relationship between EE and INT, through PE (coeff. 0.130, $p < 0.01$). This perhaps suggests that practitioners are willing to use AI applications in their accounting or auditing processes, provided that the expected ease of use is of such degree that it is conducive to their perceptions of the benefits of this technology to their work performance.

As far as PE is concerned, H9 is fully supported, as it appears to have a strong positive effect on INT (coeff. 0.456, $p < 0.01$), actually being its main predictor. Our result is in line with numerous studies of AI acceptance in different professional disciplines (Andrews et al., 2021; Ni and Cheung, 2023), including studies within the accounting and/or auditing context (Vărzaru, 2022; Norzelan et al., 2024; Abdullah and Almaqtari, 2024), thus providing even more substantial and relevant research results. From the descriptive statistics measures, as shown in **Table 2**, it is easy to conclude that accountants and auditors perceive AI as a technology that will improve the efficiency of their professional processes, and due to this they appear more willing to adopt its technologies in their professional careers.

A twofold interest arises in the case of SI, as, apart from the positive effect it has on INT (coeff. 0.154, $p < 0.05$), thus confirming H10, in parallel with numerous other AI acceptance studies (Strzelecki, 2023; Yu and Huang, 2020; Ferri et al., 2023), there is a distinct effect of this factor between accountants and auditors, based on the results of the multigroup analysis, as it plays a much more important role in AI acceptance in the case of auditors (diff. -0.412, $p < 0.05$). The interpretation of the present finding probably lies in the fact that auditors work mainly in corporate structures, such as the Big 4 firms, where collegiality and employer/employee relationships are much more evident than in the case of accountants, who in most cases are self-employed or work as assistant accountants in small accounting firms.

With reference to AI anxiety, AILA has no statistically significant relationship with EE, despite its conceptual similarity with the anxiety factor as defined by TAM3. In fact, both the measures of descriptive statistics and the existence, albeit insignificant, of a positive relationship with EE (coeff. 0.025, $p > 0.05$), in contrast to the corresponding hypothesis, indicate that accounting and auditing professionals are not particularly anxious about the possibility of having to acquire new knowledge and skills in handling AI-integrated information systems, thus rejecting H11.

On the other hand, AIJRA appears to have a negative and significant effect on INT (coeff. -0.144, $p < 0.05$), being in line with similar results of other AI acceptance studies (Vu and Lim, 2022; Jussupow et al., 2022) in the context of job insecurity and replacement risk, thus confirming H12. It is becoming evident that the fear of AI taking over jobs, in line with Vu and Lim' (2022) research, is to some extent also present in the accounting and auditing profession, creating tendencies to reject AI's use.

Summarizing the above, it is evident that PE and PEC are perceived as the key determinants of accounting and auditing professionals' intentions to use AI technologies in their daily work activities, with SI also playing a role, differentiated in terms of the type of accounting specialization. In addition, CSE, OQ and EE are indirectly influential as external factors, proven to be essential for the AI acceptance process. Finally, the anxiety factor, in the form of the AIJRA, comes through as a dissuasive force, but it appears to be counterbalanced by the effect of the other intention drivers, since, ultimately, professional accountants and auditors seem willing to embrace the new opportunities provided from the implementation of AI in their daily occupational activities.

6. Conclusions

This study was developed on the basis of the proposal that AI will lead to disruptive changes in the structure of the accounting and auditing practices and the composition of the industry's workforce; a proposal which raises the urgent need for a deeper insight into the real question of how professionals in the field will adapt to the new impending reality; a deeper insight, which was made through a search, in the relevant literature, of the factors that may influence the intentions of accepting and embracing of the new digital AI technologies.

It should be noted that this study contributes to the relevant literature from two perspectives. On one hand, by integrating the constructs of the UTAUT and TAM3 models—following the example of Ferri et al.'s (2021, 2023) studies—with the AI anxiety factor, this study successfully develops a research model of reasonable explanatory value, in order to reveal potential explanatory gaps and thus improve the explanatory power of the respective technology acceptance model. On the other hand, this study reinforces the interdisciplinary literature on accounting and AI by underscoring the main factors that shape the behavioral attitudes of accounting and auditing professionals towards the use of AI. It also considers the challenges arising from AI's disruptive impact on the industry, particularly in the context of the post-COVID-19 landscape. In this regard, the concern about human replacement by new technology is shown to be a genuine issue that influences, to a certain extent, the adoption intentions of practitioners. This finding provides empirical evidence for further research.

Keeping a more practical standpoint, our study raises important findings regarding the individual cognitive and psychological process of accepting AI technology, which should be taken into account by business entities in the accounting and auditing sector, in light of the undeniable social substance of any massive technological change. Especially companies that have already invested heavily in hiring new staff and researching AI implementations could really benefit from a deeper understanding of the attributes of the individual technology acceptance process, so that they can consider options in order to better leverage AI.

Drawing on the results of the present analysis, the strong effects of PE and PEC on acceptance intentions demonstrate the need to inform users about the opportunities that the application of AI can offer in improving the effectiveness and efficiency of accounting and auditing processes and, thus, to provide meaningful exposure to this technology, indicating the need to shape an environment of ongoing organizational support of educational and material nature, by ensuring adequate financial resources and equipment, as well as developing appropriate training and practice strategies. Particular attention should also be paid to the role of SI, constituting a crucial factor of technology acceptance by employees (Ferri et al., 2023), thereby validating the need of the adapting firms to integrate social elements of motivation and positive reinforcement into their organizational culture. Finally, the impact of the AIJRA on the intentions of accounting and auditing practitioners should also be taken into account, at least as a reminder to firms of the importance of practicing corporate social responsibility (CSR), by focusing on how they can create economic value, while also being aware of their impact on the economic and social aspects of society (Fernandez-Feijoo et al., 2014).

In any case, accounting and auditing professionals seem to be ready to move along the wave of technological change. While acknowledging the radical shift that the rise of AI is expected to bring about in the structure of the profession and in the employment landscape, our study demonstrates that accountants and auditors view the prospect of the expected increase in their work efficiency favorably, moving along a line of reflection between technology, work substance and social reality.

However, our study is not without its limitations. Firstly, the sample is deemed to be of marginal size for the needs of the model under consideration; a larger sample could lead to more reliable results. Secondly, a large portion of the sample consists of practitioners with limited experience; future studies could focus on more experienced professionals. Thirdly, the research takes place before the introduction of the technology in the accounting and auditing industry, i.e. at a very early stage, and expectations and perceptions may change over time, as experience is gained and technology matures. Fourthly, no distinction is made between mandatory and voluntary use of AI applications, aspects that could have a major impact on modulating different usage intentions. Fifthly, the research is limited within the national borders of Greece, whilst practitioners from other countries, who have different professional experiences and motivations, are very likely to have different perceptions. Finally, it jointly involves the fields of accounting and auditing, two fields characterized by processes and techniques that could be affected differently by AI. A future research, more targeted in terms of the aspects mentioned, along with the addition of other factors observed in the technology acceptance literature, could enhance the interpretability of the results of this study.

Ethics declaration

The authors of this study do not retain any personal data from the survey participants. Additionally, the respondents have remained anonymous during and after their participation and have provided informed consent for their responses to be used solely within the scope of this study. Thus, our survey is not subject to the requirement for ethics approval.

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Appendix: Supplementary tables

This appendix provides additional supportive details regarding the analyses conducted in this study. **Table A1** demonstrates the values of the square root of the Average Variance Extracted (AVE) for each construct, used in the Fornell-Larcker criterion. **Table A2** presents the Inner Model Matrix for the multicollinearity test we conducted using the values of Variance Inflation Factor (VIF). Regarding the structural model of this analysis, **Table A3** suggests the indirect relationships between the constructs of our model, with the statistically significant results discussed in the Discussion section. Finally, **Table A4** illustrates the findings of the multigroup analysis (MGA) procedure, considering the roles of accounting practitioners.

[Table A1 near here]

[Table A2 near here]

[Table A3 near here]

[Table A4 near here]

Table 1. Sample demographics

Variable	Item	n	Percentage
Gender	Male	79	51.63%
	Female	74	48.37%
	Other/no response	0	0
Age	18-30	125	81.70%
	31-40	18	11.76%
	41-50	3	1.96%
	51+	7	4.58%
Experience	<5 years	114	74.51%
	5-10 years	24	15.68%
	11-20 years	7	4.58%
	>20 years	8	5.23%
Role	Accountant	14	9.15%
	Auditor	37	24.18%
	Assistant accountant	102	66.67%

Table 2. Descriptive statistics, loading factors, Cronbach’s alpha, composite reliability and average variance extracted

	Items	Loading factors	Mean	SD	Cronbach's alpha	CR	AVE
Self-efficacy	CSE1	0.802	4.235	0.693	0.755	0.859	0.671
	CSE2	0.816	4.092	0.753			
	CSE3	0.839	4.209	0.755			
Perception of external control	PEC2	0.751	3.503	0.887	0.720	0.842	0.641
	PEC3	0.878	3.719	0.779			
	PEC4	0.767	3.765	0.869			
Job relevance	JR1	0.814	3.856	0.771	0.831	0.887	0.662
	JR2	0.810	3.725	0.834			
	JR3	0.825	3.967	0.836			
	JR4	0.805	3.752	0.924			
Output Quality	OQ1	0.887	3.667	0.943	0.902	0.932	0.773
	OQ2	0.867	3.301	1.055			
	OQ3	0.871	3.908	0.858			
	OQ4	0.891	3.477	1.127			
Results demonstrability	RD2	0.841	3.686	0.939	0.820	0.893	0.736
	RD3	0.902	3.693	0.902			
	RD4	0.830	3.301	1.109			
Effort expectancy	EE1	0.709	3.699	0.768	0.777	0.854	0.595
	EE2	0.826	3.908	0.761			
	EE3	0.802	3.817	0.851			
	EE4	0.744	3.758	0.817			
Performance expectancy	PE1	0.822	3.961	0.808	0.857	0.903	0.699
	PE2	0.886	4.065	0.773			
	PE3	0.833	3.935	0.822			
	PE4	0.800	3.810	0.913			
Social influence	SI1	0.773	3.065	1.008	0.843	0.891	0.673
	SI2	0.775	3.150	0.962			
	SI3	0.854	3.497	1.004			
	SI4	0.874	3.497	0.998			
AI learning anxiety	AILA1	0.904	2.425	0.954	0.705	0.870	0.771
	AILA2	0.851	2.503	0.833			
AI job replacement anxiety	AIJRA1	0.902	3.203	0.999	0.725	0.879	0.784
	AIJRA2	0.868	2.471	0.936			
Intention	INT1	0.949	4.046	0.795	0.887	0.946	0.898
	INT2	0.946	3.830	0.982			

Table A1. Discriminant validity findings (Fornell-Larcker criterion)

	AIJRA	AILA	CSE	EE	INT	JR	OQ	PE	PEC	RD	SI
AIJRA	0.885										
AILA	0.238	0.878									
CSE	-0.111	-0.154	0.819								
EE	0.016	-0.148	0.439	0.772							
INT	-0.148	-0.126	0.399	0.276	0.948						
JR	-0.098	-0.112	0.410	0.293	0.475	0.814					
OQ	-0.087	-0.174	0.385	0.317	0.538	0.617	0.879				
PE	-0.114	-0.031	0.433	0.495	0.587	0.484	0.614	0.836			
PEC	0.151	-0.296	0.393	0.535	0.475	0.322	0.429	0.459	0.801		
RD	-0.204	0.042	0.395	0.402	0.313	0.426	0.358	0.426	0.269	0.858	
SI	0.029	0.052	0.175	0.208	0.421	0.276	0.377	0.368	0.451	0.239	0.821

Table A2. Multicollinearity test with the VIF method (Inner model - Matrix)

	AIJRA	AILA	CSE	EE	INT	JR	OQ	PE	PEC	RD	SI
AIJRA					1.070						
AILA				1.098							
CSE				1.185							
EE					1.600			1.246			
INT											
JR								1.755			
OQ								1.682			
PE					1.561						
PEC				1.268	1.802						
RD								1.371			
SI					1.328						

Table A3. Results of indirect relationships

Indirect relationships	Coefficient	P Value	Significant
AILA → EE → INT	-0.003	0.734	No
JR → PE → INT	0.038	0.344	No
CSE → EE → INT	-0.036	0.087	No
OQ → PE → INT	0.197	0.002	Yes
AILA → EE → PE	0.007	0.713	No
CSE → EE → PE	0.078	0.022	Yes
RD → PE → INT	0.055	0.160	No
PEC → EE → INT	-0.058	0.075	No
PEC → EE → PE → INT	0.057	0.007	Yes
PEC → EE → PE	0.125	0.004	Yes
AILA → EE → PE → INT	0.003	0.705	No
CSE → EE → PE → INT	0.035	0.031	Yes
EE → PE → INT	0.130	0.001	Yes

Table A4. Results of multigroup analysis

Relationships	Difference (accountant - auditor)	2-tailed (accountant vs auditor) p value	Significant
CSE → EE	0.052	0.799	No
PEC → EE	-0.084	0.620	No
PEC → INT	0.312	0.258	No
JR → PE	0.143	0.600	No
OQ → PE	0.198	0.293	No
RD → PE	-0.263	0.162	No
EE → INT	-0.279	0.194	No
EE → PE	0.050	0.781	No
PE → INT	0.314	0.097	No
SI → INT	-0.412	0.030	Yes
AILA → EE	0.058	0.738	No
AIJRA → INT	0.268	0.188	No

Figure 1. Proposed model from Ferri *et al.* (2021, 2023) with the integrated AI Anxiety factors

Figure 2. Final model, after structural analysis, with dotted lines representing the rejected hypotheses