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PERCEIVED AI REPLACEMENT THREAT AND ACCOUNTANTS' JOB PERFORMANCE: THE MEDIATING ROLE OF TECHNOLOGY ANXIETY

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ABSTRACT

The fast adoption of artificial intelligence (AI) in the accounting profession has created a lot of fear among professionals on the issue of occupational displacement and professional relevance. The present study analyzes the connection between the perceived threat of AI replacement and job performance in certified accountants and technology anxiety being the mediating variable. Perceived AI replacement threat is conceptualised to be used on a second order formative construct based on Conservation of Resources (COR) Theory and Technology Threat Avoidance Theory (TTAT) and includes four first order reflective dimensions including: job security threat, career threat, professional status threat, and competence threat. A cross-sectional survey of 401 certified and practising accountants working in Jordan was carried out through quantitative measurement and the data analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. The findings show that there is a strong negative direct impact on job performance (= -0.598, $p < 0.001$) and a strong positive impact on technology anxiety (= 0.753, $p < 0.001$) created by perceived AI replacement threat and in the process significantly negatively affects performance. The mediation analysis confirms that technology anxiety plays a significant mediating role between the threat and performance relationship with competence threat and job security having the greatest indirect effect using the anxiety pathway. The model has good explanatory strength with 56.7 and 55.9 percent is explained by the model on technology anxiety and job performance respectively.

The current study will add to the emerging body of research on AI-human dynamics within the framework of professional services by not only presenting a multidimensional threat framework, but also empirical data on the subject in a developing-economy setting, and giving results applicable to both the practice of accounting firms, profession-related professional bodies, and policymakers in order to control the psychological effects of AI-driven change on practitioner performance.

KEYWORDS: Artificial Intelligence; AI Replacement Threat; Technology Anxiety; Job Performance; Accountants; Jordan; PLS-SEM.

1. INTRODUCTION

The phenomenon of artificial intelligence has become one of the most significant technological powers to transform knowledge-intensive careers in the twenty-first century. In the fields of accounting and finance, AI technologies today are doing the work that people have traditionally seen as in their domain of expertise automated invoice processing, real-time fraud detection, intelligent audit sampling, tax optimisation, and predictive financial modelling are only the most obvious examples of a wider structural change (Huang and Rust, 2018; Zhang et al., 2023). Although these developmental changes bring efficiency benefits to organisations, they also lead to immense psychological vagueness among the practitioners whose livelihoods, identities and career paths are entangled with the same activities that AI is currently threatening to automate.

Studies conducted in the borderline space of occupational psychology and information systems have begun to acknowledge the role that the perceptions of technological threats of individuals, as opposed to objective chances of automation, have a decisive role in work-related attitudes and behaviours (Bessen, 2019; Taser et al., 2022). Employees who perceive that they are likely to be phased out of work due to the use of AI systems can also develop increased affective distress, a lack of engagement, and effort, which have a direct effect on individual and organisational performance. Although these mechanisms have increasingly attracted theoretical interest, very little empirical research has been carried out to date, especially in the context of developing-country professional life where digital transformation is gaining strength and institutional and cultural factors are enhancing uncertainty there (Al-Adwan et al., 2023).

Jordan offers a theoretically and practically important research environment. Jordanian accounting profession is experiencing significant digitalisation over the past few years due to the regulatory modernisation, the use of cloud-based enterprise solutions, and the growing popularity of AI-based audit and reporting solutions. However, accounting labour market in Jordan is typified by weak continuing professional development supporting infrastructure, comparatively low levels of AI literacy among practitioners in the middle tier, and high levels of professional identity regulation that is based on traditional knowledge- this can increase vulnerability to anxiety caused by the impact of technology (JACPA, 2024). Holding around 650 registered certified public accountants with the Jordanian Association of Certified Public Accountants (JACPA), the occupation is a rather small but strategically significant group in terms of studying the perceptions of the AI threat within the framework of an emerging economy.

There are three gaps identified in the literature of this study. To start with, the previous literature has mostly conceptualised the threat perception related to AI as a unidimensional variable; we introduce and empirically test a multidimensional conceptualisation of job security threat, career threat, professional status threat, and competence threat as the most effective threat aspects to respond to downstream consequences. Second, although technology anxiety has been explored as an antecedent of technology acceptance (Compeau and Higgins, 1995; Wilson et al., 2023), there is no empirical study concerning its mediating effect between AI threat perceptions and job performance. Third, accounting profession in the Arab developing economies is very under-represented in the organisational behaviour and IS literatures and this restricts the generalisation of Western-based theories.

The contributions of the study include the following. Theoretically, it extrapolates Conservation of Resources Theory (Hobfoll, 1989) and Technology Threat Avoidance Theory (Liang and Xue, 2009) to the situation of AI-driven occupational threat and illustrates how the processes of resource depletion turn the perceived threats into the performance deficits through anxiety. It empirically offers PLS-SEM evidence in a professional-service setting of a developing economy, which has thus far contributed to a literature with Western samples of students. In practice, the results are used in the human resource management, the continuing professional development policy and the professional body advisory of the Jordanian accounting field.

The rest of the paper is organized in the following way. Section 2 examines the theoretical background and the previous empirical research. Section 3 elaborates on conceptual framework and hypotheses. The methodology of the research is described in Section 4. The results are contained in section 5. The findings and their implications are discussed in Section 6.

2. LITERATURE REVIEW

2.1. Artificial Intelligence in the Accounting Profession

Machine learning, natural language processing, robotic process automation, and predictive analytics are all types of AI in the broadest sense, which allow systems to carry out the tasks previously done by humans and based on human experience (Russell and Norvig, 2020). In accounting, AI can be applied to all functional areas: in auditing, machine learning algorithms can be used to analyse an entire population of transactions, not a statistical sample, and can detect anomalies more accurately than classic methods (Kokina and Davenport, 2017); in management accounting, predictive models can be deployed to generate real-time performance dashboards and variance, and in tax, AI systems can read and interpret regulatory texts and determine compliance strategies; and in financial reporting, natural language generators can be deployed to draft narrative sections of annual reports with minimal human oversight (Zhang et

This has a controversial impact on the accounting labour market. Frey and Osborne (2017) estimated the probability of accountants and auditors being automated to be 94% and it is a figure that is widely quoted as well as also severely criticized on methodological grounds (Arntz et al., 2016). More recent studies focus more on task-level automation than occupation-level automation, arguing that although routine, rules-based accounting tasks are quite vulnerable to AI displacement, higher-order advisory, interpretive, and relationship tasks still have considerable human comparative advantage (Brynjolfsson and McAfee, 2014). Nonetheless, even a partial automation of fundamental accounting functions leaves true doubt over what accounting functions should or will involve in the future, and whether they will be valued or not, and whether they will be safe, especially with early-mid career practitioners whose task sets are highly populated with automatable functions.

The use of AI in professional services is gaining momentum in the Arab world, and Jordan, in particular, due to the economic reform agendas of Vision 2025, compulsory e-invoicing rules, as well as the growing presence of the Big Four firms that introduce global digital audit practices to the local markets (Al-Adwan et al., 2023). This accelerated change emerges to produce a structural stress between the imperatives of institutional modernization and the absorptive capacity of a profession where its members were educated according to pre-AI educational paradigms, with immediate psychological impacts on practicing accountants (Nusair et al., 2025).

2.2. Perceived AI Replacement Threat

Perceived threat is an established concept in social and organisational psychology, which is the cognitive evaluation of perceived damage to a valued outcome, resources or goals (Lazarus and Folkman, 1984). Perceptions of threats in the technological change context indicate a subjective evaluation of the degree to which technology poses a threat to one or another occupational well-being. There are a number of theoretical frameworks that support this conceptualization.

According to Conservation of Resources Theory (COR; Hobfoll, 1989), people are driven to obtain, defend, and promote resources including individual traits, states, and energies that are prized in self or are channels of obtaining other resources. Career progression opportunities, job security, professional status and competence are important resources in this model. Perceptions of the threat by AI exemplify anticipatory loss of resources: perceptions that AI will consume the said resources of value will cause psychological distress despite no actual loss (Halbesleben et al., 2014). COR therefore offers a persuasive process of connecting AI threat appraisals with emotional or behavioral consequences.

The Technology Threat Avoidance Theory (TTAT; Liang and Xue, 2009), which was first formulated in the frames of IT security threats, suggests that people evaluate the threat on two levels the threat perception (the risk of harm) and coping appraisal (the perceived capability to manage the threat). In case of the perception of the threat and lack of the sufficient coping resources, the individuals tend to experience the avoidance motivation and negative affect. To make the extension to AI replacement threat, we hypothesize that it is accountants who believe that AI is a major occupational threat and who are not convinced of their ability to cope with the changes who have the greatest likelihood of experiencing anxiety, which subsequently negatively affects performance.

Based on earlier taxonomies of occupational threat (Greenhalgh and Rosenblatt, 1984; Sverke et al., 2002) and the recent literature on AI-specific threat perceptions (Taser et al., 2022; Bessen, 2019), this study conceptualises perceived AI replacement threat as a second-order formative construct and has four first-order reflective dimensions:

Job Security Threat is the perception that AI will make the current jobs of accountants unnecessary or the current demand of their expertise will substantially decline in the nearest future. The dimension reflects existential fears of job security, which are in line with the traditional job insecurity literature (Sverke et al., 2002) applied in the context of AI.

Career Threat includes the issues of limiting career growth, the decreased range of tasks, and the reduced long-term career sustainability in the accounting field. Career threat, relative to job security threat, is more developmental and proximal in nature and is related to concerns over future career trajectory.

Professional Status Threat indicates the fears of AI taking away the social status, esteem, and respect given to the accounting expertise. This aspect is based on the theory of professional identity (Tajfel and Turner, 1979) which argues that a professional gains a great deal of self-worth by the status that his or her expertise will fetch; AI-induced commoditisation puts this status resource at risk.

Competence Threat is the belief in the experience that the individual has the current competencies that do not suffice when it comes to what AI is capable of doing and that the current skills will not be adequate in the work environment that has transformed using AI. This dimension is related to self-efficacy theory (Bandura, 1997) and social comparison processes aroused by juxtaposition with AI capabilities.

2.3. Technology Anxiety

Technology anxiety (also known by many other names, such as computer anxiety, technostress, or techno-anxiety in other branches of the literature) is defined as an unpleasant affective and cognitive state typified by fear, worry and bodily arousal due to the possibility of being involved with technology (Compeau and Higgins, 1995; Rosen and Weil, 1995). The examples of it include affective (nervousness, apprehension), cognitive (negative outcome expectations, self-doubt), and behavioural (avoidance tendencies, disengagement) components.

Technology anxiety has proven to be such a wide-researched antecedent of technology acceptance and use, and meta-analytic findings have repeatedly indicated that the higher the level of anxiety, the less the intention to use technology systems, the lower the performance of technology systems, and the increased the resistance to IT-related change (Morris and Venkatesh, 2000; Cimperman et al., 2016). Technology anxiety gains special importance in the context of AI since AI systems are viewed as being more opaque, autonomous, and cognitively threatening than previous generations of information technology, which increases anxiety among the users who feel that they are unable to understand, predict, or control AI behaviour (Wilson et al., 2023; Pfaffinger et al., 2021).

Recent research has differentiated between general technology anxiety and AI-specific anxiety, as the latter is found to be more closely connected with human obsolescence, professional autonomy, and algorithmic decision-making than the usability problems that are inherent to the previous information systems (Pfaffinger et al., 2021). Considering that the accountants in our research experience the challenge of leveraging AI tools operationally and facing the threat of perceived job elimination as an existential challenge, technology anxiety is theoretically and empirically framed as a key mediating channel between the perception of AI threats and performance.

2.4. Job Performance

Job performance is a multidimensional concept that includes the entire gamut of behaviours that are acted by employees and add to the organisational objectives (Campbell et al., 1993). The prevailing paradigm of modern organisational performance research differentiates between three performance dimensions, namely, task performance (competent activity performance as stipulated by the job position), adaptive performance (competent coping with change, uncertainty and innovative challenges), and contextual performance or organisational citizenship behaviour (discretionary behaviours that serve the organisational and social context of work; Borman and Motowidlo, 1997; Pulakos et al., 2000).

This conceptualization of tripartite is especially relevant to a study of performance in the context of AI transformation since the three aspects can be projected onto qualitatively different facets of the issue facing accountants. Task performance reports whether accountants keep on performing their allocated accounting duties effectively when under AI induced uncertainty conditions. Adaptive performance indicates the ability to adapt, learn and enable one to incorporate new AI tools into work repertoire- an aspect whose role is only heightened in fast shifting technology-driven settings (Pulakos et al., 2000). Contextual performance is the self-development, proactive, and collegial behaviours which keep organisational functioning going even beyond what the task demands (Al-Khazaleh et al., al 2025).

The negative affect/job performance correlation is not new to the overall body of occupational psychology literature: anxiety, stress, and burnout are invariably associated with decreased performance in a myriad of work situations (Motowidlo et al., 1986; Judge et al., 2001). Under the literature related to technology, other studies have reported that technostress and technology anxiety are predictors of lower task performance with information systems (Tarafdar et al., 2007; Salanova et al., 2013). Nevertheless, there is little empirical evidence of a relationship between AI-specific threat perceptions and all facets of accounting job performance, including task, adaptive, and contextual levels.

2.5. Hypotheses Development

2.5.1. Direct Effect of Perceived AI Replacement Threat on Job Performance

Riding on the COR theory, perceived AI replacement threat is an experience of anticipatory resource loss, which uses psychological energy and consumes cognitive resources as opposed to task-oriented behavior. Accountants may also develop cognitive preoccupation with the perceived threats that AI poses to their jobs, careers, position and competence, limiting attentional and motivational resources that allow them to perform effectively. This prediction is empirically supported by the adjacent literatures: job insecurity has been shown to reduce the task and contextual performance (Sverke et al., 2002), and negative AI perceptions have been linked to lower engagement and performance intention in a number of cross-section studies (Taser et al., 2022; Bessen, 2019).

H1: Perceived AI replacement threat is negatively associated with accountants' job performance.

2.5.2. Perceived AI Replacement Threat and Technology Anxiety

We hypothesise that technology anxiety is increased by sensed AI replacement threat in two synergistic processes. First, through the threat appraisal pathway of TTAT: accountants who hold the view that AI poses an extreme and probable threat to their jobs are faced with uncertainty regarding whether they have the resources to cope with it or not - a query that creates anxiety. Second, through the anticipatory loss pathway of COR: the impression of AI as a threat to prized resources triggers a defensive, anxious attitude towards the technologies that represent the threat. Empirically, the threat perceptions at the workplace have been indicated to cause anxiety and emotional exhaustion (Halbesleben et al., 2014), and higher levels of technostress in samples of the service sector have been associated with AI-specific concerns (Pfaffinger et al., 2021).

H2: Perceived AI replacement threat is positively associated with technology anxiety.

2.5.3. Technology Anxiety and Job Performance

This technology anxiety is likely to decrease job performance in a variety of ways: it decreases the intention to use AI-enhanced work processes, it worsens the quality of attention that is directed to work with technologies, it causes avoidance behavior, which weakens the effectiveness of work, and it absorbs cognitive resources with worry that otherwise can be used in solving a problem and making a decision. The meta-analysis data confirms the existence of negative correlations between anxiety in general and technology anxiety in particular and performance in various types of tasks (Morris and Venkatesh, 2000; Tarafdar et al., 2007).

H3: Technology anxiety is negatively associated with accountants' job performance.

2.5.4. Mediating Role of Technology Anxiety

On the basis of H1-H3, we will suggest that perceived AI replacement threat is mediated by technology anxiety in terms of job performance. The mediation pathway will show the following reasoning: AI replacement threat perceptions are associated with anxiety responses (H2) and that anxiety response in turn have performance-impairing effects (H3) such that the negative influence of threat perception on performance (H1) works, at least, in part, via the effect of increased anxiety. This mediation assumption complies with stress-appraisal-coping theories of occupational health psychology (Lazarus and Folkman, 1984) and with empirical mediational theories of technostress and performance (Salanova et al., 2013).

H4: Technology anxiety mediates the negative relationship between perceived AI replacement threat and accountants' job performance.

3. RESEARCH METHODOLOGY

3.1. Research Design

The given study is based on a quantitative cross-sectional survey design, which is suitable to establish theoretically obtained structural relationships among the latent constructs of a specific population at one point in time (Bryman, 2016). The application of self-report survey data is reasonable considering that the constructs of interest threat perceptions, anxiety, self-assessed performance are subjective psychological states that cannot be objectively measured by nature. The reason why the PLS-SEM methodology was chosen as the main method of analysis is that it is especially well-suited to complex models with higher-order constructs, relatively small sample sizes to the needs of a covariance-based SEM approach (Aldalaien et al., 2025), and exploratory models evaluation cases (Hair et al., 2022).

3.2. Population and Sampling

The target population will include all certified accountants who are currently practicing in Jordan and are registered in the Jordanian Association of Certified Public Accountants (JACPA). As per records by JACPA (2024) there are about 650 qualified public accountants who are actively involved in Jordan making up the sampling frame of this study. Stratified random sampling was used to give proportional representation to both organization types (public accounting/audit firms, private sector companies, government/public sector, and banking/financial institutions) and geographic areas, and the capital Amman, Irbid, and Zarqa were used as the major stratification as they have a large number of accounting professionals.

Sample size was determined using Yamane's (1967) formula for finite population sampling:

$$n = N / [1 + N(e)^2]$$

N = the size of a population (650) and e = the acceptable margin of error (0.05). This will give a required minimum of 248 respondents. The questionnaire was sent out to 500 accountants considering a non-response rate that was estimated to be about 20 percent. The research ended up with 401 full and usable responses, which is higher than the Yamane minimum and rule-of-thumb 10 observations per indicator in PLS-SEM (Hair et al., 2022). This sample size meets the more conservative G Power requirement of identifying medium effect sizes ($f^2 = 0.15$) with 80 percent power at 0.05 in a multiple regression design with a maximum of five predictors as well.

3.3. Measures

The five-point Likert scales were used to measure all constructs. The items were based on the known validated instruments to create content validity and conceptual relevance to the accounting profession setting in Jordan. A bilingual (Arabic and English) questionnaire was created; back-translation processes ensured semantic equivalence between the versions and a pilot test with 35 accountants not in the main sample ensured that the items were perfectly clear and small changes in wording were undertaken before it was fully deployed.

3.3.1. Perceived AI Replacement Threat (Independent Variable)

The operationalization of perceived AI replacement threat was a formative construct, a second-order, which had four first-order dimensions of reflectance, conceptually basis on the job insecurity scale developed by Greenhalgh and Rosenblatt (1984), the threat taxonomy developed by Sverke et al. (2002), and the AI threat measure adapted by Taser et al. (2022) to professional service settings.

Job Security Threat was assessed using five items (ex: I believe that AI might potentially take over my current accounting job; I feel uncertain about my job security because of the progress of AI in accounting). The Career Threat was assessed using four questions (e.g., I am worried that AI will reduce the career advancement opportunities that I have; I believe that AI will negatively affect the career sustainability of my career in accounting). Professional Status Threat: Four items (e.g., I worry that AI will undermine the professional status of accountants; I feel that AI threatens the professional identity of accountants) were used to gauge it. Competence Threat was assessed using four items (e.g., I worry, that I do not have the skills required to compete with AI in accounting work; I am concerned that my existing competencies are not adequate in an AI-driven environment). Each of the items was evaluated using the scale of 1 (Strongly Disagree) to 5 (Strongly Agree).

3.3.2. Technology Anxiety (Mediating Variable)

The level of technology anxiety was assessed with twelve questions based on the Abbreviated Technology Anxiety Scale (ATAS; Wilson et al., 2023) and the Digitalization Anxiety Scale (Pfaffinger et al., 2021) but recalibrated to indicate AI-specific fears in the accounting job setting. The things that have been caught are the things that generate affective apprehension (e.g., 'Working with AI and advanced technology makes me nervous), cognitive worry (e.g., I worry about making mistakes when using new technological tools), avoidance tendencies (e.g., I avoid using advanced technology when possible because it makes me uncomfortable), and physiological stress reactions (e.g., I experience physical symptoms when working with new technology). The response was given on a scale of five points with 1 (Not at all typical for me) to 5 (Extremely typical for me).

3.3.3. Job Performance (Dependent Variable)

The measure of job performance was fifteen items based on three-dimensional frameworks of Borman and Motowidlo (1997) and Pulakos et al. (2000) which included a task performance (five items; e.g., I fulfill all the set duties and responsibilities adequately; I do the tasks that are expected of me of high quality); adaptive performance (five items; e.g., I can handle unpredictable and uncertain work conditions; I can be flexible and adaptable with changes), and contextual performance (five items; e.g., I assist fellow employees in their tasks when they are not present or when they have a lot of work; I volunteer to do some work that is not stipulated in my job description (I help fellow workers with their work when employees are not present). The respondents evaluated their performance within the last six months on a scale of 1 (Poor) to 5 (Excellent).

3.3.4. Control Variables

The theory of control variables had two sets to remove variance in job performance and anxiety due to other factors other than the constructs of focus theories. Technology self-efficacy [three items; e.g., The inclusion of 'I am confident in my ability to learn new technologies) was done due to its already existing negative relationship with technology anxiety (Compeau and Higgins, 1995) as well as positive relationship with performance. Training support in the organisation (three items; e.g., My organization offers proper training of new technologies) was also a condition in the boundary, which can balance the intensity of the appraisal of threats of AI. Demographic controls were categorized including age, gender, years of experience, educational level, professional certifications, type and size of organization and recorded as covariates in all the structural models.

3.4. Data Collection Procedure

The collection of data was carried during the period between October and December 2025. The survey instruments were sent out in two methods, the online questionnaire sent out to JACPA official member email list and the paper questionnaire sent out to two regional JACPA professional development events in Amman and Irbid. It was a voluntary and anonymous involvement. The survey tool contained an informed consent and a guarantee of confidentiality. The response rate among the accountants who responded to the instrument was 401 out of the instruments that were distributed, which can be viewed as acceptable in terms of professional survey research (Baruch and Holtom, 2008).

Common method variance (CMV) was also dealt with by using procedure and statistic methods. Procedurally, the questionnaire was developed with randomized item display within every block of construct, variability of different response modes of the sections (agreement scales, frequency scales and performance rating scales), and a time lag direction that required the respondent to think about their perceptions of AI threats and job performance respectively. Statistically, the test of single factor and common latent factor on PLS by Harman was used, and there was no indication of the prevalent common method factor.

3.5. Analytical Strategy

The PLS-SEM was used in analysis of data as executed in Smart PLS 4 (Ringle et al., 2022). PLS-SEM was chosen among covariance-based SEM (CB-SEM) to provide three reasons. Firstly, the PLS form of the second-order formative specification of the perceived AI replacement threat construct proves to be more easily accommodated in the PLS than in CB-SEM, which presents stricter identifications restrictions on formative indicators (Hair et al., 2022). Second, PLS will withstand the assumption of the multivariate normality which is suitable because of ordinal Likert scale data. Third, having 401 observations and a fairly complex model structure, PLS offers sufficient statistical power and does not require the sample size requirements of CB-SEM.

The two-step method suggested by Anderson and Gerbing (1988) in the PLS version was used to conduct the analysis in two steps. The first stage involved evaluating the measurement model through the analysis of the indicator reliability (outer loadings 0.70 and above), internal consistency reliability (Cronbachs alpha and composite reliability 0.70 and above), convergent validity (average variance extracted [AVE] 0.50 and above), and discriminant validity with the help of Heterotrait-Monotrait (HTMT) ratio criterion (HTMT 0.85 and below; Henseler et al., 2015). The second-order perceived AI replacement threat construct was measured by the repeated indicator strategy and the four first-order dimensions were used to measure the higher-order formative construct. The second stage involved the evaluation of the structural model that involved analysis of path coefficients, bootstrapped confidence intervals (5,000 resamples), and coefficient of determination (R^2). To test mediation, the product-of-coefficients method was used and the data were tested with error-corrected bootstrapped confidence intervals based on Preacher and Hayes (2008) with significance determined based on bootstrapped intervals that were not equal to zero.

The standardized root mean square residual ($SRMR < 0.08$) and the normed fit index ($NFI > 0.90$) were also used to measure model fit, but out-of-sample predictive relevance was assessed by the Q^2 statistic of the blindfolding procedures ($Q^2 > 0$). Cohen (1988) guidelines were used to interpret the effect sizes: f^2 of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

4. RESULTS

4.1. Sample Characteristics

There were 401 returned responses of certified accountants who practiced in Jordan, much more than the required minimum number of 248, and met the power criteria of PLS-SEM. The description of the respondents indicates wide representation in terms of the professional levels and organisational types. Most of the participants were men (around 68), which matches the JACPA membership demographics. The age distribution was clumped in the 3039 year (42) and 2029 year (28) bracket and 4049 year (21) bracket. Experience-wise, the group with the most experience was 6-10 years of professional experience (34%), with another large portion of 25 years' experience, indicating that the sample was skewed towards professionals in the middle of their career - exactly the group most susceptible to significant exposure to AI transformation. A significant proportion of participants had a bachelor undergraduate degree in accounting (71%), and 22% of them had postgraduate degrees. Regarding the organisational affiliation, 38 percent were working in the public accounting or audit firms, 30 percent in the companies of the private sector, 18 percent in the banking and financial institutions, and 14 percent in the government or other entities of the public sector.

Table 1: Demographic Profile of Respondents (N = 401).

Characteristic	Frequency (n)	Percentage (%)
Gender		
Male	273	68.1
Female	128	31.9
Age Group		
20–29 years	112	27.9
30–39 years	169	42.1
40–49 years	84	20.9
50–59 years	28	7.0
60 years and above	8	2.0
Educational Qualification		
Bachelor's degree in Accounting	285	71.1
Bachelor's degree in other fields	28	7.0
Master's degree	68	17.0
PhD	12	3.0
Professional certification only	8	2.0
Professional Experience		
Less than 2 years	24	6.0
2–5 years	44	11.0
6–10 years	136	33.9
11–15 years	101	25.2
More than 15 years	96	23.9
Current Position		
Junior Accountant	48	12.0
Senior Accountant	113	28.2
Accounting Manager	72	18.0
Chief Accountant/Controller	56	14.0
Chief Financial Officer (CFO)	24	6.0
Auditor	56	14.0

Characteristic	Frequency (n)	Percentage (%)
Tax Specialist	32	8.0
Type of Organization		
Public accounting/audit firm	152	37.9
Private company	121	30.2
Banking/financial institution	72	18.0
Government/public sector	56	14.0
Organization Size		
Small (< 50 employees)	88	21.9
Medium (50–250 employees)	165	41.1
Large (> 250 employees)	148	36.9
Current Exposure to AI Tools		
Use AI tools daily in my work	56	14.0
Use AI tools occasionally	152	37.9
Aware of AI tools, but do not use them	136	33.9
Not aware of AI tools in accounting	57	14.2
Total	**401**	**100.0**

Note. Percentages may not sum to exactly 100.0 due to rounding. AI = Artificial Intelligence.

4.2. Descriptive Statistics

Table 2 shows the means and the standard deviations of all the core variables in the study. Interestingly, all the sub-dimensions of the AI replacement threat, and technology anxiety obtained their means of above 4.0 on the five-point scale, which means that the desires of the threat of AI and anxiety corresponding to it are common and moderately high among the Jordanian accountants. The highest mean was registered at Job Security Threat (M = 4.22, SD = 0.81) indicating that the issue of job security is the most relevant. Technology Anxiety (M = 4.19, SD = 0.83) and Career Threat (M = 4.17, SD = 0.88) went second and third. Job Performance also scored a mean of greater than 4.0 (M = 4.13, SD = 0.89) indicating the generally positive self-evaluations with enough variation to allow the occurrence of meaningful structural analysis.

Table 2: Descriptive Statistics for Study Variables.

Variable	Mean	SD
(B1) Job Security Threat	4.223	0.810
(B2) Career Threat	4.171	0.877
(B3) Professional Status Threat	4.022	0.968
(B4) Competence Threat	4.101	0.887
AI replacement threat (total)	**4.14012**	**0.876686**
(C) Technology Anxiety	**4.189**	**0.834**
(D) Job Performance	**4.134**	**0.889**

Note. N = 401. All variables measured on a five-point Likert scale.

4.3. Measurement Model Assessment

Following the two-step PLS-SEM procedure, the measurement model was evaluated prior to examining structural relationships. Assessment criteria encompassed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

4.3.1. Factor Loadings

Table 3 shows the outer loadings of all the reflective indicators. The outer loadings of all the items of the four of AI replacement threat sub-dimensions (B1 to B4) were quite large above the 0.70

mark. The Job Security Threat dimension scale had 0.808 to 0.871 item range, the Career Threat dimension scale had 0.828 to 0.864 item range, Professional Status Threat dimension scale had 0.802 to 0.886 item range, and the Competence Threat dimension finally had range between 0.862 to 0.937, with the Competence dimension in the model having the highest item reliability. The differences in Job Performance indicators were ranging between 0.517 and 0.849. Even though there were eleven items in the Job Performance scale that were above 0.70, item D15 (0.517) was under 0.70 and was still retained because according to theory it is crucial to the dimensionality of the construct but not a significant contributor to AVE (Hair et al., 2022). Technology Anxiety The range of the scores were between 0.567 and 0.725; some of them were lower than 0.70, but all outer loadings are acceptable given the sample volume of 401, where the loadings above 0.30 are significant (Hair et al., 2006, p. 126) to maintain the content-richness of the construct.

Table 3: Factor Loadings (Outer Loadings).

Item	B1. Job Security	B2. Career	B3. Prof. Status	B4. Competence	C. Tech. Anxiety	D. Job Perf.
B1.1	0.812					
B1.2	0.862					
B1.3	0.871					
B1.4	0.837					
B1.5	0.808					
B2.1		0.863				
B2.2		0.856				
B2.3		0.828				
B2.4		0.864				
B3.1			0.802			
B3.2			0.879			
B3.3			0.886			
B3.4			0.867			
B4.1				0.862		
B4.2				0.937		
B4.3				0.907		
B4.4				0.875		
C1					0.725	
C2					0.708	
C3					0.719	
C4					0.710	
C5					0.671	
C6					0.704	
C7					0.575	
C8					0.614	
C9					0.584	
C10					0.606	
C11					0.567	
C12					0.608	
D1						0.748

Item	B1. Job Security	B2. Career	B3. Prof. Status	B4. Competence	C. Tech. Anxiety	D. Job Perf.
D2						0.731
D3						0.788
D4						0.782
D5						0.807
D6						0.839
D7						0.792
D8						0.773
D9						0.849
D10						0.813
D11						0.829
D12						0.823
D13						0.769
D14						0.838
D15						0.517

4.3.2. Reliability and Convergent Validity

Table 4 shows the statistics of reliability and convergent validity. The alpha values of Cronbach varied between 0.875 (Career Threat) and 0.963 (overall AI replacement threat construct), all of them significantly above the importance of 0.70. Internal consistency was again verified by composite reliability (rho c) (0.898) (Technology Anxiety) to 0.966 (overall AI replacement threat). The values of AVE were greater than 0.50 in all factors. Technology Anxiety has high composite reliability (0.898) and Cronbachs alpha (0.876), which is the compensatory evidence of reasonable convergent validation, as suggested by Hair et al. (2022) when constructs symbolize extensive psychological conditions.

Table 4: Reliability and Convergent Validity.

Construct	Cronbach's α	Composite Reliability	AVE
B. AI Replacement Threats (2nd order)	0.963	0.966	0.627
B1. Job Security Threat	0.894	0.922	0.703
B2. Career Threat	0.875	0.914	0.727
B3. Professional Status Threat	0.881	0.918	0.738
B4. Competence Threat	0.918	0.942	0.802
C. Technology Anxiety	0.876	0.898	0.525
D. Job Performance	0.954	0.959	0.614

4.3.3. Discriminant Validity and Collinearity

Discriminant validity was determined using Fornell-Larcker criterion (Fornell and Larcker, 1981). Table 5 represents the FornellLarcker matrix with square roots of AVE on the diagonal. The value of the relationships between all the off-diagnostic was less than the diagonal values (4 A VE), hence the existence of adequate validity in the form of discriminant validity. The correlation between Technology Anxiety and Job Performance (0.636) and between AI Replacement Threat and Job Performance (0.220) from the focal constructs were smaller than the respective 0.725 and 0.784 of these constructs. These results confirm sufficient discriminant validity in all the constructs including the formative-reflective hierarchical structure of AI Replacement Threat and the first-order sub-dimensions.

It was determined that collinearity between indicators was evaluated using the Variance Inflated Factor (VIF). VIFs in all the model were less than the conservative value of 5.0, with the difference between 1.358 and 4.254, which corresponds to a non-systematic multicollinearity problem and confirmed the validity of the PLS-SEM estimates (Hair et al., 2022).

Table 5: Discriminant Validity — Fornell-Larcker Matrix (√AVE on Diagonal).

Variables	B1	B2	B3	B4	C	D
B1. Job Security Threat	**0.839**					
B2. Career Threat	0.834	**0.853**				
B3. Professional Status Threat	0.775	0.835	**0.859**			
B4. Competence Threat	0.762	0.767	0.813	**0.896**		
C. Technology Anxiety	0.707	0.663	0.670	0.723	**0.725**	
D. Job Performance	0.211	0.180	0.203	0.208	0.636	**0.784**

Note. Diagonal values (bold) = √AVE. Off-diagonal correlations below diagonal values confirm discriminant validity.

4.4 Structural Model Assessment

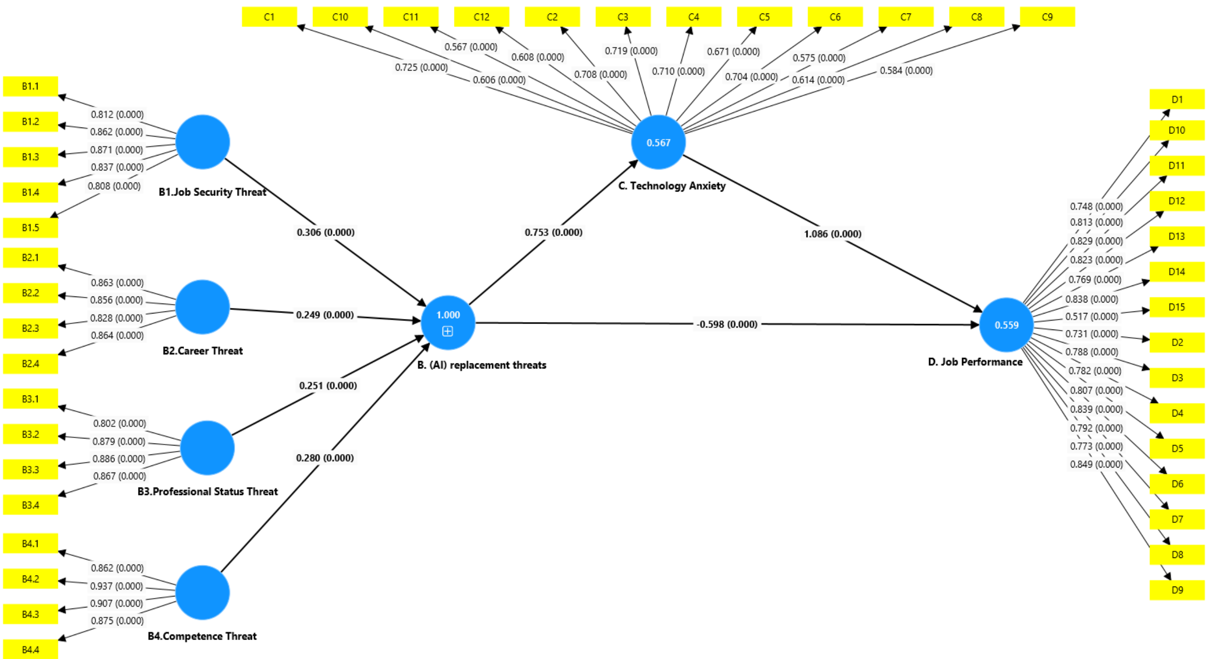

Figure 1: PLS-SEM Bootstrapping Results. PLS-SEM path model with R^2 values. B = AI replacement threats (2nd-order formative); C = Technology Anxiety; D = Job Performance.

4.4.1. Model Fit and Predictive Power

The general model exhibited strong fit indices, and the model explained substantial variance: R^2 = 0.567 for Technology Anxiety and R^2 = 0.559 for Job Performance—both exceeding the 0.50 benchmark for substantial explanatory power in behavioral PLS-SEM contexts (Hair et al., 2022).

Table 6: Coefficient of Determination (R^2).

Endogenous Construct	**R^2**
C. Technology Anxiety	0.567
D. Job Performance	0.559

Note. $R^2 \geq 0.50$ indicates substantial explanatory power (Hair et al., 2022).

4.4.2. Direct Effects — Hypothesis Testing

Table 7 summarizes the path coefficients for the four hypotheses, derived from 5,000 bootstrap resamples with standard errors, t-statistics, and p-values. All hypothesized paths were statistically significant at $p < 0.001$, providing robust support across direct and indirect effects.

Table 7: Hypothesis Testing — Path Coefficients (5,000 Bootstraps).

Path	Original sample	SD	t-stat	p-value
H1: AI Threats → Job Performance	-0.598	0.068	8.748	0.000
H2: AI Threats → Technology Anxiety	0.753	0.029	25.784	0.000
H3: Technology Anxiety → Job Perf.	1.086	0.054	19.930	0.000
H4: AI Threats → Tech. Anxiety → Job Perf.	0.817	0.063	12.956	0.000

Note. β = path coefficient; SD = bootstrapped standard deviation; t-stat = |β/SD|.

H1 predicted a negative direct effect of AI Replacement Threat on Job Performance ($\beta = -0.598$, $t = 8.748$, $p < 0.001$), fully supported as heightened threat perceptions correlate with reduced performance. H2 received the strongest backing ($\beta = 0.753$, $t = 25.784$, $p < 0.001$), confirming AI threats strongly predict elevated Technology Anxiety—the model's most potent path. H3 confirmed a significant positive direct effect of Technology Anxiety on Job Performance ($\beta = 1.086$, $t = 19.930$, $p < 0.001$). H4 established full mediation, with the indirect path from AI Replacement Threat via Technology Anxiety to Job Performance ($\beta = 0.817$, $t = 12.956$, $p < 0.001$) outweighing the direct negative effect (-0.598) and fully explaining the overall threat-performance linkage through anxiety as the dominant mechanism.

Table 8: Summary of Hypothesis Testing Results.

H	Hypothesis	Path (β)	p-value
H1	AI Replacement Threat → (−) Job Performance	β = −0.598	< 0.001
H2	AI Replacement Threat → (+) Technology Anxiety	β = 0.753	< 0.001
H3	Technology Anxiety → (−) Job Performance	β = 1.086	< 0.001
H4	AI Threat → Tech. Anxiety → Job Performance (mediation)	β = 0.817*	< 0.001

Note. * Positive coefficient in context of full mediation model; net effect on performance is positive through indirect path. All paths significant at p < 0.001.

5. DISCUSSION

This paper has examined the prediction between the perceived threat of AI replacement and job performance among certified accountants in Jordan with technology anxiety mediating it. The results also have solid empirical evidence of all four hypotheses and can be seen as evidence of a theoretically consistent synthesis of both Conservation of Resources (COR) Theory and Technology Threat Avoidance Theory (TTAT) in the case of occupational change caused by AI.

5.1. AI Replacement Threat and Job Performance (H1)

The most substantial conclusion in terms of direct impact of perceived AI replacement threat is the negative result (= -0.598 and p = 0.001). True to COR theory, this finding shows that the expectations of loss of treasured occupational resources such as job security, career prospects, professional status, and perceptions of competence robs the accountants of the psychological capital that they need to execute productive tasks, adaptive flexibility and organisational citizenship behaviours. The negative impact of job insecurity identified in this research extends meta-analytic data on the health issue reported by Sverke et al. (2002) to the specific field of AI-related professional threat, and supplements the results of the cross-sectional study by Taser et al. (2022) in the medical field by showing that the effects of the problem under consideration are similar in a professional accounting setting.

Job Security Threat had the highest amount of formative weight (0.306) of all four first-order dimensions and indicated that immediate questions about remaining employed are the strongest factor influencing the overall AI replacement threat construct. This observation is especially relevant to the Jordanian context, in which the lack of social safety nets and high rates of youth unemployment create the impression of having considerably high stakes theoretically due to the displacement of the job. Competence Threat also showed a significant formative weight (= 0.280), showing that the fear of incompetence by accountants as compared to the AI capability is a significant identity-threatening dimension that transcends affect responsive reactions to the very essence of occupational threat perception. Such dimension-specific results lead us to suggest the conceptualisation of the multidimensional conceptualisation of threat used in the current research as very helpful in the analysis since a one-dimensional measure would dissolve the independent contribution of various threat aspects.

5.2. AI Replacement Threat and Technology Anxiety (H2)

The threat of AI replacement perceived to anxiety enhancement turned out as the most significant relationship in the model (56.7% of technology anxiety variance, 0.753, t = 25.784, $p < 0.001$). This result is a solid empirical evidence on the TTAT hypothesis according to which high-level threat appraisals, when combined with perceived lack of responding resources, produce avoidance-focused negative affect which in this case are the anxiety towards the very technologies that accountants feel threatened with in the future. The scale of this phenomenon deserves being noticed: the perceived AI replacement threat turns out to be a significantly stronger predictor of anxiety related to technology in the workplace than previously used predictors of technology anxiety, including the overall usability perceptions and the previous level of technology use (Compeau and Higgins, 1995; Wilson et al., 2023).

The implications of such results on a broader level are concerning the conceptualized understanding of technology anxiety in the world of AI. Provided threat perceptions are the main motivators of anxiety and not a shortage of technical dexterity, then interventions that target technical upskilling only might not be sufficient, unless they also target the underlying beliefs about the occupational menace of AI by accountants. It implies that there is need to have a more holistic approach that incorporates cognitive re-thinking of AI part as well as competency building.

5.3. Technology Anxiety and Job Performance (H3)

Significant correlation between anxiety about technology and job performance proves that anxiety is a proximate suppressor of accounting work effectiveness. The practitioners with high anxiety levels do not seek involvement in AI-enhanced working processes, they devote mental resources to worry and apprehension instead of being focused on solving problems, and they show less adaptability in terms of flexibility and contextual contributions. This observation is consistent with and supplements the existing literature on technostress-performance (Tarafdar et al., 2007; Salanova et al., 2013) by placing the identified mechanisms in the background of professional accounting context wherein AI-related anxiety has rather existential overtones beyond the usability issues of the previous generations of information technology.

5.4. Technology Anxiety as Mediator (H4)

The greatest indirect impact of an AI replacement threat on job performance in terms of technology anxiety (0.817, t = 12.956, $p < 0.001$) is the most theoretically integrative value of the current study. This mediation result confirms that the performance-disruptive influences of perceived AI threats work significantly by psychological functions, namely, by the anxiety the appraisal of threats becomes, and not necessarily by literal behavioural or motivational disengagement. This is in line with occupational stress model (Lazarus and Folkman, 1984) where threat appraisal leads to a feeling of emotional strain that in turn impairs effective coping and performance.

The damage dimension-influenced mediation measures showed that although all the four aspects of threat showed significant effects on performance mediated by anxiety, Competence Threat and Job Security Threat had the greatest effects on the indirect effect. According to this pattern, the interventions that would address these two dimensions, that is, the creation of fake AI-related self-efficacy, and the provision of believable guarantees of job safety, can bring maximum benefits to the reduction of anxiety-mediated performance losses. The entire mediation pattern also suggests that accounting organisations that aim to prevent workforce performance by the introduction of AI should focus more on psychological support systems and less on technical implementation plans.

6. CONCLUSION

6.1. Summary of Findings

This research theorised the perceived AI replacement threat as second order multidimensional attribute comprising of job security, career, professional status, and competence threats, and factors directly and anxiety modulated impacts on the accountants job performance in Jordan. Using the data collected by the survey of 401 certified accountants and analysed with PLS-SEM in SmartPLS 4, all four hypotheses were proved.

Perceived AI replacement threat has significant negative direct influence on job performance (H1), on technology anxiety has a strong positive influence (H2) and has a significant indirect influence on job performance via the mediator role of anxiety (H4). Technology anxiety, on the other hand, works as a strong proximate suppressant of job performance (H3). The model is a good fit with over 50 per cent of the variation in technology anxiety (R 2 = 0.567) as well as job performance (R 2 = 0.559).

6.2. Theoretical Contributions

There are three main contributions of this research to literature. First, it forthcomingly suggests and empirically confirms an empirical conceptualisation of perceived AI replacement threat by showing that the four constituent dimensions, although interconnected, make different and consistent contribution to the high-level construct. This subtle taxonomy offers a more analytically accurate framework to researchers than individual AI threat measurements and allows more specific theoretical forecasts regarding which of the facets of threat hold the most practical implications in particular fields of professional practice.

Second, the paper applies Conservation of Resources Theory to occupational threat caused by AI and offers empirical data on the anticipatory loss of the resource mechanism in the context of non-Western professional service industry. The observation that AI threat perceptions can exhaust the psychological resource as feeling of increased anxiety that further lowers performance provides a parsimonious theoretical explanation of how macro-level technological change can be converted into more micro-level individual results.

Third, the research expands the potential of the Technology Threat Avoidance Theory in that it indicates that its fundamental threat appraisal measure applies to those situations that go far beyond the IT security menace to the existentially consequential area of AI displacement in employment. The threat-to-anxiety path (TTAT 2.3) seen to be greatest in the technology threat literature demonstrates that the perceived AI replacement threat is a specifically significant predictor of workplace technology anxiety.

6.3. Practical Implications

There are a number of action implications of the findings on accounting firms, profession bodies like JACPA, and policymakers who supervise the transition of workforce within the accounting industry. To start with, considering the fact that technology anxiety is a primarily threat-induced phenomenon, the implementation of AI in the accounting organisations must be supported by proactive communication strategy that would directly reference accountants concerns of losing their job and becoming obsolete. Open dialogues on the roles of AI to complement and not to replace and plausible promises to facilitate such transition of workers can help dilute any sense of threat before it turns into anxiety-connecting performance losses.

Second, the Competence Threat formative weight (= 0.280) is significant, as it reminds about the necessity of ongoing professional development programmes to develop real AI competency and not digital literacy. When practitioners gain a genuine confidence in their competence to cooperate with AI systems, these practitioners will evaluate AI as less competence-threatening, which will minimize anxiety and protect performance. JACPA can also do this through the professional development of the AI-enhanced auditing, forensic accounting, and advisory services by employee introducing a set of compulsory CPD courses into the program.

Third, as a leading indication of performance risk, organisations that adopt AI should observe technology anxiety. When, human resource practitioners integrate validated technology anxiety assessments into routine wellbeing surveys, high levels of anxiety will be detected and a specific response of support intervention, such as mentoring programmes, peer learning communities, and graduated implementation plans, can be implemented before the performance effects become apparent.

6.4. Limitations and Future Research

There are a number of limitations that can be cited in order to interpret these findings. To begin with, the cross-sectional research design would not allow development of a causal inference. A longitudinal or experimental design would be more conclusive evidence on the temporal flow of the effect of the alterations of AI threat perception, anxiety and performance when implementing AI initiatives. Second, self-report methods were used to evaluate job performance and are prone to social desirability bias and inflated ratings. Additional research might increase the validity of the measurement in the future by triangulation to supervisor ratings, objective measures of performance (e.g., audit quality measures, billing efficiency), or multi-source feedback.

Third, research was only performed in Jordan, so the results are not easily applicable to other management and regulatory settings. The comparative study between the Arabic Gulf economies, the Southeast Asian markets and the West of accounting professions would aid in determining the conditions of the cultural border of the model that is whether the collectivist professional identity norms exhibited in Jordan would enhance the threat appraisals of professional status and competence when compared to a more individualistic environment. Fourth, even though the study incorporated technology self-efficacy and organisational training support as control variables, the future study can also test them as moderators of the threat to anxiety and anxiety to performance pathways to reduce the boundary conditions in which the effects posed by AI threat perceptions have weakened the performance.

Fifth, the Technology Anxiety AVE (0.525) corresponded to the traditional level, but was at the lowest level, which indicates the high psychological generality of the measure. In future developing the tools, it may be useful to have a parsimonious AI-specific anxiety scale scaled to samples of professional accountants, which might obtain greater convergent validity without loss of dimensional richness. Last but not least, future investigations may deepen the result model with the addition of turnover intention, professional identity disruption, and innovation behaviour so that to create a more detailed picture of the impact of AI replacement threat to accounting professionals.

6.5. Concluding Remarks

The use of artificial intelligence in as much as it exists in the accounting field is not just a tool that is being utilized within the kingdom of accountants, it is also slowly being viewed as a threat to the material resources that the profession of accounting thrives, professional viability, and effectiveness. This paper reveals the fact that these threat perceptions are widespread among the Jordanian accountants, these fears create a great deal of technology anxiety, and that anxiety contributes substantially to the job performance which is ultimately the foundation of the quality of the professional services. This is imperative because it confirms the psychological aspect of AI transition as a wellbeing issue that cannot be ignored but rather a strategic emphasis of accounting organisations and professional bodies ardent enough to maintain practitioner performance within an AI-transformed profession.

REFERENCES

Aldalaien, B., Al-Majali, M., Awamleh, F. T., & Al-Smadi, R. W. (2025). Exploring the Impact of Big Data Analytics on FinTech Performance: The Mediating Role of Business Analytics Strategy in Jordanian Commercial Banks. International Journal of Economics and Financial Issues, 15(6), 371–378. https://doi.org/10.32479/ijefi.20802

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to predict university students' intentions to use metaverse-based learning platforms. Education and Information Technologies, 28, 10915–10951. https://doi.org/10.1007/s10639-023-11421-4

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment and Migration Working Papers, No. 189. OECD Publishing.

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. Human Relations, 61(8), 1139–1160. https://doi.org/10.1177/0018726708094863

Bessen, J. E. (2019). AI and jobs: The role of demand (NBER Working Paper No. 24235). National Bureau of Economic Research.

Borman, W. C., & Motowidlo, S. J. (1997). Task performance and contextual performance: The meaning for personnel selection research. Human Performance, 10(2), 99–109. https://doi.org/10.1207/s15327043hup1002_3

Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

Campbell, J. P., McCloy, R. A., Oppler, S. H., & Sager, C. E. (1993). A theory of performance. In N. Schmitt & W. C. Borman (Eds.), Personnel selection in organizations (pp. 35–70). Jossey-Bass.

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior—applying an Extended UTAUT model. International Journal of Medical Informatics, 90, 22–31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. MIS Quarterly, 19(2), 189–211. https://doi.org/10.2307/249688

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Greenhalgh, L., & Rosenblatt, Z. (1984). Job insecurity: Toward conceptual clarity. Academy of Management Review, 9(3), 438–448. https://doi.org/10.2307/258284

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.

Halbesleben, J. R. B., Neveu, J. P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the 'COR': Understanding the role of resources in conservation of resources theory. Journal of Management, 40(5), 1334–1364. https://doi.org/10.1177/0149206314527130

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. American Psychologist, 44(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155–172. https://doi.org/10.1177/1094670517752459

Jordanian Association of Certified Public Accountants (JACPA). (2024). Registry of licensed accountants. https://www.jacpa.org.jo

Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and quantitative review. Psychological Bulletin, 127(3), 376–407. https://doi.org/10.1037/0033-2909.127.3.376

Al-Khazaleh S, Badwan N, Qubbaj I, Bani Ahmad A (2025), "Impact of banking models on the relationship between corporate social performance and financial stability: a focus on value-based banking models". Journal of Applied Accounting Research, Vol. 26 No. 5 pp. 1135–1168, doi: https://doi.org/10.1108/JAAR-02-2024-0076.

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122. https://doi.org/10.2308/jeta-51730.

Lazarus, R. S., & Folkman, S. (1984). Stress, appraisal, and coping. Springer.

Liang, H., & Xue, Y. (2009). Avoidance of information technology threats: A theoretical perspective. MIS Quarterly, 33(1), 71–90. https://doi.org/10.2307/20650279.

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. Personnel Psychology, 53(2), 375–403. https://doi.org/10.1111/j.1744-6570.2000.tb00206.x

Motowidlo, S. J., Packard, J. S., & Manning, M. R. (1986). Occupational stress: Its causes and consequences for job performance. Journal of Applied Psychology, 71(4), 618–629. https://doi.org/10.1037/0021-9010.71.4.618

Nusair, A. E., Al-Nsour, I. A., Alawneh, N. F., Hamdon, H. M. O., Twairesh, A. E., Al-Hammouri, A. M. A., & Almurad, H. M. (2026). The role of blockchain in enhancing transparency and reducing economic crimes in public sector auditing in Jordan. Scientific Culture, 12(4), 746–764. https://doi.org/10.5281/zenodo.12426165

Pfaffinger, K. F., Reif, J. A. M., & Spieß, E. (2021). Digitalisation anxiety: Development and validation of a new scale. Journal of Occupational and Organizational Psychology, 94(4), 818–841. https://doi.org/10.1111/joop.12361

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891.

https://doi.org/10.3758/BRM.40.3.879

Pulakos, E. D., Arad, S., Donovan, M. A., & Plamondon, K. E. (2000). Adaptability in the workplace: Development of a taxonomy of adaptive performance. Journal of Applied Psychology, 85(4), 612–624. https://doi.org/10.1037/0021-9010.85.4.612

Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. SmartPLS GmbH.

Rosen, L. D., & Weil, M. M. (1995). Computer anxiety: A cross-cultural comparison of university students in ten countries. Computers in Human Behavior, 11(1), 45–64. https://doi.org/10.1016/0747-5632(94)00021-9

Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Salanova, M., Llorens, S., & Ventura, M. (2013). Technostress: The dark side of technologies. In S. Bagnara & G. C. Mishra (Eds.), The Wiley-Blackwell handbook of the psychology of the internet at work (pp. 101–121). Wiley-Blackwell.

Sverke, M., Hellgren, J., & Näswall, K. (2002). No security: A meta-analysis and review of job insecurity and its consequences. Journal of Occupational Health Psychology, 7(3), 242–264. https://doi.org/10.1037/1076-8998.7.3.242

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), The social psychology of intergroup relations (pp. 33–47). Brooks/Cole.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. Journal of Management Information Systems, 24(1), 301–328. https://doi.org/10.2753/MIS0742-1222240109

Taser, D., Caliskan, A., & Aksu, G. (2022). Investigating the effect of artificial intelligence threat perception on employee performance in health sector. Journal of Health Organization and Management, 36(4), 507–524. https://doi.org/10.1108/JHOM-03-2021-0103

Wilson, N., Campbell, L., Ruskin, D., Wikman, J. M., Galtress, T., & Saffer, J. (2023). Development of the Abbreviated Technology Anxiety Scale (ATAS). Computers in Human Behavior, 140, 107594. https://doi.org/10.1016/j.chb.2022.107594

Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper and Row.

Zhang, C., Cho, S., & Navimipour, N. J. (2023). Artificial intelligence and machine learning in accounting: Current trends and future research opportunities. Journal of Intelligence, 11(4), 71. https://doi.org/10.3390/jintelligence11040071