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Exploring Resistance to Change as a Determinant of AI Adoption among Accountants in Greece

Marios Sotiropoulos

Department of Tourism Management, University of West Attica, Egaleo, Greece
Email: msotiropoulos@uniwa.gr

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Abstract

Artificial Intelligence (AI) is reshaping accounting, yet adoption in Greece remains limited. This study examines how resistance to change, a multidimensional and relatively stable disposition, influences accountants' willingness to use AI-based tools. Grounded in Oreg's (2003) framework and supported by technology adoption models, resistance to change is explored through routine seeking, emotional resistance, cognitive rigidity, and short-term focus. A quantitative survey of 235 accountants, drawn through purposive sampling, employed a 58-item questionnaire including 18 resistance to change measures. Factor analysis validated the resistance to change structure, and logistic regression assessed its predictive effect on AI use. Findings show that higher resistance to change significantly increases the likelihood of non-adoption, with each unit increase raising the odds of avoiding AI by approximately two-thirds. The results highlight the need for change management, training, and institutional support to address psychological and organisational barriers to AI integration within the Greek accounting profession.

Keywords

Artificial Intelligence (AI), Resistance to Change, Technology Adoption, Accounting Profession, Greece, Logistic Regression, Organisational Behavior

1. Introduction

Resistance to change in organisational settings is a long-standing barrier to the successful implementation of new technologies, including Artificial Intelligence (AI) (Kotter, 1995; Oreg, 2003). Even when the technical infrastructure is available and strategic intentions are explicit, employees may hesitate to embrace new systems, delay their use in everyday work, or actively oppose their integration. This reluctance is often rooted in perceived threats to established work roles, concerns about technological complexity, and scepticism regarding the tangible benefits of adoption. Within the fields of organisational psychology and technology adoption, resistance to change has repeatedly been associated with reduced willingness to participate in training, slower behavioural adjustment, and incomplete or superficial use of digital tools (Oreg, 2003).

AI intensifies these challenges because it is not simply an incremental improvement but a potentially disruptive technology that reshapes workflows, redistributes decision-making, and affects professional identities (Sutton, Holt, & Arnold, 2016). In accounting, AI-based systems for automated classification, anomaly detection, forecasting, and document processing can alter the core of what accountants do, shifting the emphasis from routine data handling to supervisory, analytical, and advisory tasks. For many professionals, this reconfiguration raises questions about future roles, required skills, and control over outcomes. It is therefore plausible that resistance to change functions as a key determinant of AI adoption in accounting.

Greece offers a particularly relevant empirical context. The Greek accounting sector is characterised by strong regulatory demands, dense reporting requirements, and a historically conservative professional culture, with deep reliance on established tools such as spreadsheets and legacy accounting software (Giannopoulos et al., 2025). At the same time, digital initiatives (e.g. myDATA) and broader EU-driven transformations increase pressure to modernise. Preliminary evidence suggests that AI adoption in Greek businesses remains relatively low, and that professional attitudes are ambivalent: many accountants acknowledge AI's potential usefulness while hesitating to incorporate such tools into daily practice (Kottara et al., 2024).

This study examines the extent to which individual resistance to change affects the probability that accountants in Greece will use AI-based applications in their work. It integrates established technology adoption frameworks, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003), with psychological constructs of resistance to change. Conceptually, it emphasises Oreg's (2003) multidimensional view of resistance as a stable disposition combining routine seeking, emotional reactions, cognitive rigidity, and short-term focus. Empirically, it employs a quantitative research design with a structured questionnaire and a 7-point Likert scale, using a sample of professional accountants in Greece.

The aim of the paper is to examine the extent to which individual and organisational forms of Resistance to Change influence the acceptance and adoption of AI applications by accountants in Greece.

To address the research question, the paper begins by presenting an overview of the theoretical foundations of technology adoption (section 2), followed by an examination of key psychological factors shaping individuals' adoption decisions.

Chapter 3 situates Artificial Intelligence within contemporary technological and professional contexts, while Chapter 4 elaborates on prevailing conceptualizations of resistance to change within technology-related settings. The methodological framework, including the research design, quantitative approach, sampling strategy, and data collection procedures, is outlined in Chapter 5. Chapter 6 presents the findings, beginning with the demographic profile of respondents and progressing through analyses related to gender, age, education, field of accounting work, experience, and professional certifications, culminating in the assessment of how resistance to change affects the probability of AI use. Finally, Chapter 7 synthesizes the study's conclusions, highlighting theoretical and practical implications, as well as avenues for future research.

2. Theoretical Foundations of Technology Adoption

2.1. Overview of Technology Adoption Models

Research on information systems adoption has produced a rich body of models seeking to explain why individuals accept or reject new technologies. Early frameworks focused on rational assessments of benefits and costs, while more recent approaches integrate social, organisational, and psychological dimensions (Venkatesh et al., 2003).

Among the most influential models is the Technology Acceptance Model (TAM), which posits two key beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), determine attitudes toward a system and, ultimately, behavioural intention and usage (Davis, 1989). TAM and its extensions have been widely applied in accounting and auditing to study adoption of ERP systems, e-filing platforms, and decision-support tools.

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesises several prior models and emphasises performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of intention and use, moderated by factors such as age, gender, and experience (Venkatesh et al., 2003). UTAUT has proved particularly useful in organisational settings where formal structures, norms, and resources shape technology-related behaviour.

Despite their explanatory power, conventional adoption models have been criticised for giving insufficient attention to negative or ambivalent attitudes, especially resistance to change (Oreg, 2003; Oreg, Vakola, & Armenakis, 2011). They tend to treat non-adoption as the mere absence of positive drivers, rather than as the outcome of specific psychological dispositions and organisational climates. Integrating resistance to change into these models offers a more complete view of AI adoption processes.

2.1.1. Technology Acceptance Model (TAM)

TAM, developed by Davis and colleagues, adapts the Theory of Reasoned Action to the context of technology (Davis, Bagozzi, & Warshaw, 1989). Perceived Usefulness is defined as the degree to which a person believes that using a particular system would enhance job performance, whereas Perceived Ease of Use reflects the degree to which using the system is perceived as free of effort (Davis, 1989). These beliefs shape attitudes toward use, which in turn influence behavioural intention and actual usage.

In accounting, PU has been linked to expectations that technology will reduce errors, increase efficiency in data processing, and improve the quality of reporting and analysis (Greenman et al., 2024). PEOU captures concerns about the complexity of the system, required training, and compatibility with existing workflows. Numerous empirical studies in accounting settings have confirmed that both PU and PEOU are significant predictors of intention to use new systems, though PU often exhibits a stronger direct effect on behavioural intention (Adhikari et al., 2024).

Extensions of TAM have incorporated additional variables such as perceived risk, trust, enjoyment, and social norms. For AI-based tools, variables like transparency, explainability, and perceived fairness are also increasingly relevant (Mökander, 2023). Still, even in extended versions, TAM sometimes treats resistance as the inverse of acceptance rather than as a separate construct (Oreg, 2003).

2.1.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesises elements from eight earlier technology-adoption models, including the Technology Acceptance Model, the Theory of Planned Behaviour, the Model of PC Utilization, and Innovation Diffusion Theory (Venkatesh et al., 2003). It proposes that four core determinants shape behavioural intention and actual technology use: performance expectancy, or the belief that technology will enhance job performance; effort expectancy, referring to the perceived ease of learning and using the system; social influence, which reflects the perceived expectations of colleagues, supervisors, clients, or regulators; and facilitating conditions, meaning the extent to which organisational and technical infrastructure support system use. The model further suggests that these relationships are moderated by age, gender, experience, and voluntariness of use, enabling a nuanced understanding of how demographic characteristics and organisational structures shape adoption patterns (Venkatesh et al., 2003). In the specific context of AI adoption among accountants, performance expectancy relates to beliefs that AI can increase accuracy, speed, and analytical capability, while effort expectancy concerns how easy these tools are to learn and integrate into existing workflows. Social influence captures encouragement or pressure from management, peers, clients, and professional bodies, whereas facilitating conditions encompass IT support, training opportunities, and the compatibility of AI with current systems (Adhikari et al., 2024).

2.2. Psychological Factors Influencing Adoption

Beyond model-specific constructs, psychological factors play a critical role in technology adoption. These include prior experiences, personality traits (e.g. openness to experience, innovativeness), risk attitudes, and emotional responses to uncertainty (Oreg et al., 2011). Two core constructs, however, remain central.

2.2.1. Perceived Usefulness

Perceived Usefulness captures the instrumental evaluation of technology. When accountants believe that AI tools will tangibly improve their productivity, reduce errors, and enable more value-added services (such as advisory and strategic analysis), they are more likely to adopt them (Davis, 1989; Greenman et al., 2024). Empirical studies indicate that PU is often the strongest predictor of behavioural intention (Venkatesh et al., 2003).

For AI, PU may depend on whether tools are perceived as capable of handling complex and context-specific tasks, not merely routine automation. Accountants may also consider whether AI-based outputs are accepted by regulators, clients, and auditors, thereby affecting the perceived value of adoption (Sutton et al., 2016).

2.2.2. Perceived Ease of Use

Perceived Ease of Use reflects the cognitive and effort-related costs of adoption. If AI systems are seen as too complex, opaque, or unstable, accountants may resist regardless of perceived benefits (Adhikari et al., 2024). Ease of use is shaped by user interface design, training programmes, documentation, and technical support.

Age, prior exposure to digital tools, and self-efficacy influence PEOU. Younger professionals who have grown up with digital platforms may experience AI interfaces as relatively intuitive, whereas older professionals, especially those who received their training in pre-digital environments, may perceive greater difficulty and risk of errors (Alruwaili, 2025).

Both PU and PEOU are closely intertwined with resistance to change. High resistance may lead individuals to discount usefulness claims or exaggerate expected difficulties, while positive experiences may gradually lower resistance over time (Oreg, 2003).

3. Artificial Intelligence in Contemporary Contexts

3.1. Definition and Scope of Artificial Intelligence

Artificial Intelligence is commonly defined as the ability of computer systems to perform tasks that typically require human intelligence, such as learning, reasoning, pattern recognition, language understanding, and decision-making (Russell & Norvig, 2021). AI encompasses a range of techniques, from rule-based systems and expert systems to machine learning, deep learning, and natural language processing.

In contemporary organisational contexts, AI is embedded in a broad spectrum of applications. These include recommendation systems, fraud detection, predictive maintenance, chatbots, document classification, image recognition, and autonomous decision-support tools (Sutton et al., 2016). AI systems are increasingly integrated into existing enterprise platforms and workflow tools, making them less visible as standalone products and more as embedded functionalities.

For accounting, AI may be used for automated invoice processing, anomaly detection in transactions, automated journal entries, predictive cash-flow modelling, and risk scoring (Sutton et al., 2016). Large language models can assist in drafting narratives for financial reports, summarising regulatory changes, or generating client-facing explanations. The scope of AI in accounting thus extends from low-level automation to higher-level analytical and advisory support (Giannopoulos et al., 2025).

3.2. Categories of AI Applications

AI applications can be categorised in several ways, including by function, user group, and domain, but two broad categories are particularly relevant. The first involves operational and automation-oriented systems, which focus on automating routine and repetitive tasks such as data entry, matching, categorisation, and basic validation. In accounting, this includes robotic process automation combined with machine learning for invoice capture, expense categorisation, and reconciliation (Sudaryanto et al., 2023). These tools offer clear benefits in terms of speed, error reduction, and lower labour costs, yet they may also provoke concerns about job displacement and diminished human control over processes (Ayuningtyas et al., 2024).

The second category comprises analytical and decision-support systems, which generate insights, identify patterns, produce forecasts, and assess risks using large datasets. In accounting and finance, such applications are used in credit scoring, fraud detection, anomaly identification in journal entries, going-concern assessments, and scenario analysis (Silitonga et al., 2024). Rather than replacing human judgment, these tools typically augment it, shifting the professional role toward supervision and interpretation. Across both categories, however, issues of transparency, explainability, and accountability become salient. The more autonomous or opaque an AI system is perceived to be, the greater the likelihood that users will experience uncertainty and resistance (Mökander, 2023).

4. Resistance to Change in Technology Adoption

4.1. Conceptualizing Resistance to Change

Resistance to Change refers to an individual's or group's tendency to oppose or avoid changes in the status quo. Oreg (2003) conceptualises resistance to change as a relatively stable dispositional construct comprising several dimensions: routine seeking, emotional reaction to imposed change, short-term focus, and cognitive rigidity. Rather than being a purely situational response, resistance to change captures deeper cognitive and affective patterns that shape how individuals interpret and react to change initiatives.

In technology adoption contexts, resistance may manifest as delayed engagement with new systems, preference for manual or legacy procedures, scepticism about promised benefits, or active attempts to block or reverse adoption decisions

(Oreg et al., 2011). Resistance is not inherently irrational: it may be grounded in legitimate concerns about risks, workload, fairness, or the distribution of benefits and losses across organisational groups (Piderit, 2000).

Acknowledging resistance as a distinct construct allows researchers to move beyond the simple absence of acceptance and to better capture the psychological and organisational processes that hinder or slow adoption (Oreg, 2003).

4.1.1. Types of Resistance

Resistance to change is heterogeneous. One important distinction is between active and passive resistance (Piderit, 2000). Active resistance involves overt expression of opposition: openly criticising AI initiatives, arguing against investment, challenging management decisions, or undermining pilot projects. Passive resistance is more subtle and often more difficult to detect; it may include ignoring new systems, continuing to rely on familiar tools despite organisational directives, or participating in training without meaningful engagement.

A second distinction relates to behavioural vs. cognitive resistance. Behavioural resistance takes the form of observable actions, such as under-utilisation of newly implemented systems or workarounds that circumvent digital workflows. Cognitive resistance involves internalised disbelief that the change is necessary, beneficial, or feasible. Individuals may rationalise that existing methods are sufficient or that AI is not relevant to their specific tasks (Oreg et al., 2011).

A third dimension concerns habitual resistance, grounded in routine seeking and preference for stability. In professions like accounting, where standardised procedures, checklists, and regulations dominate, long-established habits can make new technologies appear as unnecessary disruptions. Individuals may not explicitly oppose AI but express lukewarm attitudes and low urgency to experiment. On standardised scales, such patterns may show as mid-range rather than extreme scores, masking reluctance behind apparent neutrality (Oreg, 2003).

4.1.2. Psychological Roots of Resistance

The psychological roots of resistance to change stem from several interconnected concerns, including fear of the unknown, loss of control, perceived threats to competence, and threats to professional identity (Oreg, 2003). AI adoption can activate each of these anxieties. Fear of the unknown arises because AI systems often rely on complex, opaque models, making their outputs difficult to interpret and creating uncertainty about reliability and outcomes (Mökander, 2023). Loss of control becomes salient when automation reduces human discretion in decision-making, generating worry that key judgments may be delegated to algorithms rather than exercised by professionals. Perceived threats to competence emerge as AI tools demand new digital and analytical skills, leading individuals to fear they may not be able to acquire these abilities or that their existing expertise may lose value (Ayuningtyas et al., 2024). Identity concerns are particularly relevant in accounting, where professional identity is built on accuracy, judgment, and responsibility; if AI appears to encroach on these defining attributes, it may be interpreted as undermining the profession itself (Sutton et al., 2016). These factors highlight that resistance is not simply a form of technophobia but a multifaceted response tied to self-concept, perceptions of fairness, and trust in both organisations and technology providers (Oreg et al., 2011).

4.2. Resistance in the Context of AI

AI-specific features amplify traditional sources of resistance. Compared with earlier systems (such as ERP or basic automation), AI often introduces partial autonomy, probabilistic outputs, and model opacity. Responsibility for errors becomes less clear, especially in high-stakes contexts such as financial reporting, auditing, or compliance (Mökander, 2023).

4.2.1. Fear of Job Displacement

One of the most salient concerns surrounding AI is the fear that machines will replace human workers. In accounting, tasks such as data entry, bank reconciliation, invoice processing, and even certain forms of auditing are increasingly automated (Prasad, 2023). This generates anxiety among accountants who may perceive AI as a direct threat to employment security or as a factor that will downgrade their role to mere supervision of automated processes (Ayuningtyas et al., 2024).

Perceived job insecurity can strengthen both cognitive and emotional resistance. Individuals may downplay AI's usefulness, emphasise rare error cases, or highlight ethical concerns as a way to justify opposition. Conversely, where organisations emphasise upskilling, role redefinition, and career development associated with AI, fear of displacement may be mitigated (Elbanna & Newman, 2016).

4.2.2. Privacy and Ethical Concerns

AI systems often process large amounts of sensitive data. Accountants are acutely aware of confidentiality obligations, regulatory requirements, and reputational risks. Concerns about data security, misuse of information, algorithmic bias, and lack of transparency can therefore be strong drivers of resistance (Silitonga et al., 2024).

From an ethical standpoint, professionals may question whether AI-based decisions are explainable, fair, and auditable. In the absence of clear governance frameworks, ethical codes, and legal guidance, AI adoption may be perceived as risky. Such apprehensions feed into resistance constructs related to distrust, perceived procedural injustice, and moral responsibility (Mökander, 2023).

5. Methodology

5.1. Research Design

The study employs a quantitative research design aimed at aligning data collection and analysis with the theoretical framework outlined above. The objective is to operationalise key constructs, particularly resistance to change and AI adoption, into measurable variables that allow for rigorous statistical testing.

The dependent variable, AI use, was defined as a binary measure indicating whether respondents currently use AI-based tools in their accounting work. Participants were coded as AI users (1) if they reported using at least one AI-enabled application, such as automated invoice processing, machine-learning-based classification, fraud or anomaly detection, predictive analytics, or AI-assisted reporting, either on a regular or occasional basis. Those who reported no use of such tools were coded as non-users (0). This approach captures actual engagement with AI in professional practice rather than intentions or general attitudes toward technology.

A structured questionnaire was developed, using a 7-point Likert scale to capture nuanced attitudes ranging from strong disagreement to strong agreement. This format facilitates fine-grained differentiation between mild scepticism and strong rejection, which is crucial when investigating resistance. The questionnaire included multiple items for each construct, improving reliability and enabling the construction of composite indices for perceived usefulness, perceived ease of use, behavioural intention, resistance to change, perceived risks, and facilitating conditions.

The research design combines cross-sectional data collection with inferential statistics, primarily logistic regression, to examine the relationship between resistance to change and the probability of AI use among accountants in Greece. Logistic regression was selected as the primary analytical technique because the dependent variable is binary in nature, making this model appropriate for estimating the probability of adoption as a function of resistance to change. Descriptive statistics are used to characterise the sample and provide context for interpretation.

5.1.1. Quantitative Research Approach

The quantitative approach is grounded in the systematic collection of numerical data through the questionnaire and their subsequent statistical analysis. It aims to transform complex perceptions surrounding AI into quantifiable scores that can be compared across individuals and subgroups.

Items relating to perceived usefulness ask respondents to evaluate whether AI can improve productivity, enhance accuracy, and reduce errors in their work. Perceived ease of use items examine whether learning and operating AI systems is considered straightforward, whether ongoing technical support is required, and whether integration into existing workflows is seen as feasible. Resistance to change was measured as a multidimensional construct following Oreg (2003), encompassing preferences for routine, emotional discomfort with change, cognitive rigidity, and a focus on short-term costs. These dimensions were combined into a composite score representing respondents' overall tendency to resist change.

Demographic variables, such as age, gender, educational level, years of experience, field of accounting work, and professional certifications, are included as control variables. This allows the study to examine whether the relationship between resistance to change and AI adoption varies across different segments of the accounting profession.

Participants were selected using purposive sampling. The key inclusion criteria were years of professional experience, the size and type of the employing organisation (e.g. small and medium-sized enterprises, large companies, independent consultants), the academic background of participants, and their previous exposure to digital tools or automation software. These criteria were chosen to ensure that the respondents had substantive familiarity with accounting processes and some degree of contact,actual or potential, with AI or advanced digital systems.

Purposive sampling is a non-probability technique often described as judgmental sampling, because the researcher intentionally selects individuals who are likely to provide rich information on the topic under study. Unlike random sampling, it does not aim at statistical representativeness but at depth and relevance. This is suitable for an exploratory study on AI adoption in a specific professional community, where it is important to capture the perspectives of those directly involved in or affected by digital transformation.

In practice, accountants were selected who had substantial professional backgrounds, occupied diverse positions within their organisations, and had experience spanning both day-to-day accounting operations and more strategic decision-making. The sample included professionals from small and medium-sized firms, accounting practices, larger companies, and independent consultants. Particular attention was paid to academic qualifications and familiarity with digital tools, as these factors are closely linked to technological readiness.

The resulting sample reflects a multilayered reality: experienced professionals alongside early-career accountants, individuals who have already integrated digital solutions into their work, and others still navigating the transition. Although purposive sampling does not yield a statistically representative sample of all accountants in Greece, it allows for an in-depth understanding of AI adoption readiness in practice.

5.1.2. Population and Sample

The target population consists of accounting and tax professionals working in Greece across a range of organisational settings. The sampling frame was designed to capture diversity in terms of organisational size, sector, and internal structure. Professionals from small accounting offices, medium-sized firms providing accounting and tax services, large corporations, and multinational enterprises with internal accounting departments were included.

This diversity is important because larger organisations typically have greater capacity to invest in advanced AI solutions, upgraded information systems, and specialised IT teams, whereas small and medium-sized enterprises and independent offices operate under constraints of limited capital, staff, and training time. Consequently, they face different priorities, constraints, and perceived risks in adopting AI.

The sample also includes both front-line accountants handling routine tasks and managerial staff, such as chief financial officers and heads of audit departments, who are responsible for strategic decisions regarding digital tools. This facilitates analysis of constructs such as social influence and facilitating conditions. Professionals with different levels of experience,from newcomers to senior staff with long careers,were included to examine how age and familiarity with digital technologies affect attitudes and adoption.

5.1.3. Data Collection Methods

Data were collected via an online questionnaire distributed through secure platforms (e.g. Google Forms) over a four-week period. Online distribution allowed for geographic dispersion and accessibility. Participants were informed about the purpose of the study, the voluntary nature of participation, and data protection measures. Anonymity and the right to withdraw at any time were explicitly guaranteed, enhancing the likelihood of honest responses.

Where necessary, alternative modes of completion were offered (such as scheduled in-person completion using printed questionnaires) to address disparities in digital access and skills. Follow-up reminders were sent to increase the response rate and to maintain balance between participants with positive experience of AI and those who were negative or undecided regarding its adoption.

Content validity was strengthened through a pilot test on a small group of professionals. Feedback from the pilot helped identify ambiguous wording and gaps in coverage, leading to revisions before full-scale administration. After collection, data were cleaned, checked for inconsistencies, and prepared for analysis. Internal consistency of multi-item constructs was examined using Cronbach's alpha, and triangulation with secondary sources (literature and industry reports) supported the interpretation of quantitative findings.

6. Results and Discussion

6.1. Demographic Information

The analysis of sample characteristics provides important context for interpreting the empirical results and understanding how accountants' professional profiles relate to AI adoption.

The demographic composition of the sample reflects the diversity of the Greek accounting sector. Age, education, professional experience, and gender function not only as descriptors but as potential predictors of technological readiness. Prior research suggests that gender, education, and nationality shape economic decision-making in small and medium-sized enterprises, and specialised training can attenuate differences between groups.

Data were collected from accounting and tax professionals with varying levels of experience and qualifications. Anonymous participation encouraged honest reporting, while inclusion of experienced staff allowed comparisons between senior and junior professionals. A total of 235 accountants participated in the study.

6.2. Gender

Regarding gender, 61.3 percent of participants identified as male, 31.9 percent as female, and 6.8 percent selected another category. This distribution indicates a predominance of men, consistent with the historical and structural gender imbalance in the accounting profession, traditionally perceived as male dominated. It may also reflect professional hierarchy, as men are more likely to hold managerial or audit-related positions that are more exposed to technological innovation.

Literature indicates that women, although technologically capable, remain underrepresented in senior positions and often face fewer opportunities for specialised technological training. At the same time, several studies suggest that women demonstrate high levels of technological adaptability and willingness to upskill, especially in innovation-related domains. In the Greek context, growing participation of women in accounting and finance programmes may gradually reduce gender disparities.

Overall, the gender imbalance in the sample does not necessarily imply substantial differences in attitudes toward AI adoption, as recent research finds that gender gaps in digital acceptance are narrowing due to widespread exposure to technology in education and work (**Table 1**).

Table 1. Frequency table on gender.

	Gender		
	Frequency	Percentage %	Cumulative Percentage %
Women	75	31.9	31.9
Men	144	61.3	93.2
Other	16	6.8	100
Total	235	100	

6.3. Age

The age distribution shows that 34.5 percent of respondents are between 31 and 40 years old, 25.5 percent between 20 and 30, 24.7 percent between 41 and 50, 11.9 percent between 51 and 60, and 3.4 percent over 61. Thus, nearly 60 percent of the sample is under 40.

This pattern reflects the phase of digital transformation experienced by the profession. Younger accountants entered the labour market in an environment already shaped by digital systems such as ERP platforms and myDATA. They tend to be more familiar with digital interfaces and may exhibit more positive attitudes toward AI. Older professionals, particularly those over 50, may be more cautious, not necessarily hostile, but constrained by training environments in which advanced technology was less central and by fewer formal opportunities for continuing education in digital tools.

These age-related differences can influence perceived ease of use, perceived usefulness, and resistance to change. Younger professionals may view AI as an opportunity to eliminate routine tasks and focus on higher value-added activities, whereas older professionals may associate AI with reduced autonomy or role ambiguity (**Table 2**).

Table 2. Frequency table on age.

	Age		
	Frequency	Percentage %	Cumulative Percentage %
20 - 30	60	25.5	25.5
31 - 40	81	34.5	60.0
41 - 50	58	24.7	84.7
51 - 60	28	11.9	96.6
61 -	8	3.4	100.0
Total	235	100	

6.4. Educational Level

Approximately 46.4 percent of participants hold a bachelor's degree, 40.4 percent a master's degree, 7.2 percent a college or vocational diploma, and 4.3 percent a PhD. The high proportion of individuals with university or postgraduate education implies substantial human capital in the Greek accounting profession.

This pattern reflects both increased demands for specialisation and the need to navigate complex technological and regulatory environments. The economic crisis of the previous decade also encouraged many professionals to pursue postgraduate degrees as a strategy for differentiation and improved career prospects.

Higher educational attainment is associated with greater technological literacy and a strong orientation toward lifelong learning. Empirical evidence suggests that accountants with postgraduate qualifications are more inclined to adopt advanced technologies, feel more confident in evaluating AI outputs, and show lower fear of job displacement compared with those with lower formal education (**Table 3**).

Table 3. Frequency table on highest educational attainment.

	Highest Educational Attainment		
	Frequency	Percentage %	Cumulative Percentage %
University Degree	109	46.4	46.4
College Degree	17	7.2	53.6
Highschool Diploma	4	1.7	55.3
Master's Degree	95	40.4	95.7
PhD	10	4.3	100.0
Total	235	100	

6.5. Field of Accounting Work

Regarding field of employment, 30.2 percent of respondents work in corporate or financial accounting, 18.7 percent in taxation, 16.2 percent in data entry, 12.3 percent in external audit, 11.9 percent in internal audit, and 10.6 percent in other areas. This distribution showcases the multidimensional nature of the profession and allows investigation of sectoral differences in AI adoption.

Professionals in corporate accounting and audit functions are more likely to interact with advanced information systems (ERP, business intelligence dashboards, audit analytics), and are therefore more exposed to AI-enabled tools. In more traditional fields, such as data entry or tax services, technological transition tends to be slower, partly due to reliance on national platforms and bureaucratic requirements (Table 4).

Table 4. Frequency table on field of accounting work.

	Field of Accounting Work		
	Frequency	Percentage %	Cumulative Percentage %
Data Entry	38	16.2	16.2
External Audit	29	12.3	28.5
Financial Accounting	71	30.2	58.7
Internal Audit	28	11.9	70.6
Other	25	10.6	81.3
Tax accounting	44	18.7	100.0
Total	235	100	

6.6. Work Experience

Work experience is distributed as follows: 20.9 percent have 1 - 5 years of experience, 37.9 percent 5 - 15 years, 23.8 percent 15 - 25 years, and 13.2 percent more than 25 years, while 4.3 percent have up to 1 year of experience. The majority thus falls into the 5 - 15 years category, corresponding to a stage of professional maturity that combines substantial practical expertise with significant exposure to digital transition.

Experienced professionals may possess strong critical skills for evaluating data and systems, which is crucial when interacting with AI outputs. At the same time, deeply ingrained routines can increase resistance to change. Less experienced professionals often show greater enthusiasm for new technologies but may underestimate associated risks, such as data quality or control issues. Overall, work experience plays a dual role: younger professionals drive innovation, while more experienced professionals provide stability and oversight (Table 5).

Table 5. Frequency table on work experience.

	Work Experience		
	Frequency	Percentage %	Cumulative Percentage %
1 year or less	10	4.3	4.3
1 - 5 years	49	20.9	25.2
5 - 15 years	89	37.9	63.1
15 - 25 years	56	23.8	86.9
25 years or more	31	13.2	100
Total	235	100	

6.7. Professional Certifications

In the sample, 68.1 percent of participants reported being certified accountants and members of the Economic Chamber of Greece, while 31.9 percent were not.

Moreover, 9.8 percent hold an ACCA qualification, 9.4 percent hold certification from the national institute for auditors, and 79.1 percent do not hold specialised international certifications.

Professional certifications indicate continuous training and alignment with national and international standards. Certified accountants often operate within professional cultures that emphasise lifelong learning, quality, and compliance. Programmes such as ACCA or national audit certifications typically include components on information systems and, increasingly, AI and data analytics, thereby enhancing technological familiarity.

The high proportion of certified accountants suggests that the sample includes many professionals with strong formal professional identities and heightened awareness of ethical, transparency, and data security issues. These characteristics may affect both perceived risks and perceived benefits of AI adoption (Table 6 and Table 7).

Table 6. Frequency table on certified accountant status.

	Certified Accountant Status		
	Frequency	Percentage %	Cumulative Percentage %
No	75	31.9	31.9
Yes	160	68.1	100.0
Total	235	100	

Table 7. Frequency table on economic chamber and ACCA certified.

	Economic Chamber and ACCA Certified		
	Frequency	Percentage %	Cumulative Percentage %
ACCA	10	4.3	4.3
ACCA & EC	49	20.9	25.2
EC	89	37.9	63.1
None	56	23.8	86.9
Total	235	87	

6.8. Effect of Resistance to Change on the Probability of AI Use

Although the broader research instrument includes 58 items, with 18 dedicated to resistance to change, this study employs only a partial factor analysis rather than a full exploratory or confirmatory factor analytic model for all constructs. The decision is methodological rather than analytical. The primary objective of the present paper is to examine the specific relationship between resistance to change and AI adoption, not to develop or validate a new multidimensional measurement model for all constructs included in the larger survey. Conducting an extensive factor analysis on the full set of items, many of which relate to additional constructs outside the scope of the current research questions, would have shifted the focus away from the central aim of estimating the predictive effect of resistance to change on accountants' use of AI.

Moreover, the resistance to change scale used in this study is theoretically grounded in Oreg's (2003) established multidimensional model and has been validated extensively in prior literature. For this reason, a factor analysis was deemed sufficient to confirm the coherence and internal structure of the resistance to change items within the context of the Greek accounting profession, without undertaking a full instrument-wide factor solution. This selective approach aligns with the analytical requirements of logistic regression, where the emphasis is on deriving reliable composite measures for the predictor of interest rather than exhaustively modelling all latent dimensions of the broader questionnaire.

The broader research project examines multiple determinants of AI adoption, including perceived usefulness, perceived ease of use, perceived risk, facilitating conditions, and organisational support. The present paper reports only one analytically distinct component of this wider study, focusing specifically on resistance to change as a psychological determinant of AI use. Other constructs are analysed separately and will be reported in complementary studies, ensuring conceptual clarity and avoiding overextension of the present model.

The first logistic regression model examines whether resistance to change toward AI influences the probability that accountants use AI-based applications in their work. The dependent variable is binary, indicating whether the respondent reports using AI tools. The key independent variable is a composite score for resistance to change, based on a 7-point Likert scale.

The model is statistically significant at the 5 percent level: the Omnibus test yields $\chi^2(1) = 4.699$, $p = 0.030$, indicating that adding resistance to change significantly improves model fit relative to the constant-only model. Pseudo-R^2 statistics suggest modest but non-trivial explanatory power: Cox and Snell $R^2 = 0.020$ and Nagelkerke $R^2 = 0.044$, indicating that the model explains about 2 - 4 percent of the variance in AI use. Given the multifaceted nature of human behaviour and the many factors affecting technology adoption, this magnitude is not negligible.

The Hosmer-Lemeshow test indicates satisfactory goodness of fit ($\chi^2(8) = 1.101$, $p = 0.998$), showing no evidence of mismatch between observed and predicted frequencies. The overall classification accuracy is approximately 91 percent, similar to the constant-only model, reflecting the high baseline proportion of accountants who do not use AI (around 91 percent of the sample).

The estimated coefficient for resistance to change is $B = 0.506$, with Wald = 4.496 and $p = 0.034$. The corresponding odds ratio Exp(B) = 1.659, with a 95 percent confidence interval of 1.039 - 2.649. The positive coefficient indicates that higher resistance to change is associated with higher log-odds of not using AI. Put differently, each one-unit increase in the resistance score is associated with a 65.9 percent increase in the odds that an accountant will not use AI tools.

This finding reflects the underlying psychological construct of resistance to change rather than a lack of awareness or access to AI tools. The persistence of non-use even in environments where AI solutions are readily visible suggests that avoidance behaviour is driven by dispositional discomfort with change and attachment to established routines, rather than informational deficits. Accountants who report greater discomfort with change, stronger attachment to routines, and more negative emotional reactions to new technologies are less likely to incorporate AI into their work.

The finding is consistent with international literature identifying resistance to change as a key human and organisational barrier to technology adoption in financial and accounting contexts. Studies have shown that employee resistance, often driven by fear of the unknown, perceived loss of control, or doubts about the relevance of new systems, can delay or undermine digital transformation projects. In the context of AI, resistance appears particularly salient because of heightened concerns over job displacement, ethical issues, and model opacity.

The empirical findings confirm that resistance to change exerts a statistically significant, though modest, negative effect on the probability that accountants will use AI. This has several implications for theory and practice.

The result supports the argument that traditional technology adoption models, which focus primarily on positive drivers (such as perceived usefulness and ease of use), are incomplete if they do not explicitly incorporate resistance. Resistance is not simply the absence of acceptance but a distinct construct rooted in psychological dispositions, professional identity, and organisational culture. Incorporating resistance into extended TAM or UTAUT frameworks can improve explanatory power and yield a more realistic depiction of adoption dynamics, especially in professions characterised by strong norms and regulatory constraints.

The modest size of the pseudo-R^2 indicates that resistance to change is only one part of a broader picture. Other factors, such as organisational resources, regulatory pressures, client expectations, leadership support, and availability of AI tools tailored to accounting, are likely to play important roles. However, the fact that resistance remains significant suggests that even in resource-rich environments, psychological and cultural obstacles can hinder AI uptake.

In addition, the Greek context provides an instructive example of how professional norms and institutional frameworks shape resistance. The accounting profession in Greece is embedded in a dense regulatory environment, with high emphasis on accuracy, documentation, and compliance. Such a context encourages risk-averse attitudes and reliance on proven methods. The introduction of AI, particularly when perceived as opaque or insufficiently regulated, may therefore clash with deeply held professional values. Resistance in this setting may not reflect irrational technophobia but a rational response to perceived uncertainty and responsibility for errors.

The demographic structure of the sample, relatively young, well-educated, and highly certified, suggests that resistance is not confined to older or less-educated professionals. Even among digitally savvy accountants, concerns about job displacement, loss of control, ethical risks, and the pace of change can generate hesitation. This challenges simple narratives in which generational or educational differences alone determine adoption (**Table 8**).

Table 8. Logistic regression coefficients.

Variable	Logistic Regression Coefficients				
	B (β)	Wald	p	Exp (B)	95% CI for OR
Resistance to Change	0.506	4.496	0.034	1.659	1.039 - 2.649
Constant	2.425	94.015	0.000	11.297	-

Note: $p < 0.05$, $p < 0.001$.

From a practical standpoint, the findings highlight the need for change management strategies. Efforts to promote AI adoption in accounting cannot focus solely on technical deployment or cost-benefit arguments. They must address the psychological and identity-related aspects of resistance. This includes:

- Transparent communication about how AI will affect roles, responsibilities, and job security.
- Clear governance frameworks covering data protection, algorithmic transparency, accountability, and error management.
- Training programmes that not only teach how to use AI tools but also explain their logic, limitations, and appropriate use cases.
- Opportunities for accountants to participate in the selection, configuration, and evaluation of AI systems, thereby reinforcing a sense of control and ownership.
- Pilot projects and proof-of-concept implementations that demonstrate tangible benefits in a controlled environment, allowing sceptical professionals to observe outcomes before full-scale adoption.

In the Greek context, professional bodies such as the Economic Chamber and national audit institutions could play a pivotal role by issuing guidelines, supporting AI literacy programmes, and coordinating pilot initiatives. Such institutional support would reduce uncertainty, signal legitimacy, and provide a framework within which individual resistance can be constructively addressed (**Table 9**).

Table 9. Logistic regression results table.

	Regression Table				
	Wald	p-value	B	Exp (B)	95% C.I. for EXP (B)
Resistance to change	4.496	0.034	0.506	1.659	1.039
Constant	94.015	0.000	2.425	11.297	
Omnibus Tests of Model Coefficients	Step sig.	0.030			
	Block sig.	0.030			
	Model sig.	0.030			
Hosmer and Lemeshow Test		Chi-square	1.101		
		df	8		
		p-value	0.998		
Pseudo R-Square		Cox & Snell	0.200		
		Nagelkerke	0.340		

7. Conclusion

This study explored the role of resistance to change as a determinant of AI adoption among accountants in Greece. Building on established technology adoption models (TAM and UTAUT) and psychological theories of resistance, it developed a quantitative framework to examine how a dispositional tendency to resist change affects the likelihood of using AI-based tools.

Using a structured questionnaire and a sample of Greek accounting professionals, the study estimated a logistic regression model with AI use as the dependent variable and resistance to change as the key predictor. The results indicate that higher resistance to change significantly increases the odds that an accountant will not use AI, even though the overall explanatory power of the model remains modest. In other words, resistance to change functions as a meaningful barrier to AI adoption, but it is not the only factor shaping behaviour.

Theoretically, the findings reinforce the importance of integrating resistance into technology adoption frameworks, particularly in professional and highly regulated environments. They also underline the need to treat resistance as a multidimensional construct encompassing cognitive, emotional, and identity-related dimensions, rather than as a simple lack of acceptance.

Practically, the results suggest that AI adoption strategies in the accounting sector must go beyond technical implementation. They should include carefully designed communication, training, and participation mechanisms that address fears of job displacement, concerns about ethical and privacy issues, and anxieties about competence and control. Institutional actors and professional bodies can support this process by providing guidance, standard-setting, and shared learning platforms.

The findings of this study have important implications beyond technology adoption, extending directly into the domains of sustainability ESG performance. In contemporary business practice, accountants are central actors in designing, implementing, and monitoring sustainability reporting systems, including ESG metrics, integrated reports, and compliance with emerging regulatory frameworks (Xanthopoulou et al., 2024; Delegkos et al., 2025; Mitroulia et al., 2025; Matsali et al., 2025). For example, resistance to adopting AI-powered carbon accounting or emissions-tracking systems may hinder firms' capacity to collect, validate, and integrate environmental data required under the Corporate Sustainability Reporting Directive (CSRD), thereby increasing compliance costs and the risk of incomplete or delayed sustainability disclosures. Limited adoption of AI-based tools among accountants in Greece therefore has consequences not only for efficiency and accuracy in traditional financial reporting, but also for the quality, reliability, and timeliness of sustainability-related information.

AI-enabled accounting systems can enhance sustainability and ESG performance by enabling granular tracking of environmental indicators (such as resource use, carbon emissions and other KPIs), improving the monitoring of social metrics (including labour costs, diversity, health and safety, and ethical sourcing), and strengthening governance through better internal controls, fraud detection and compliance with standards. Automated data collection and analysis can support more robust greenhouse gas inventories, climate risk assessments and reliable ESG reporting that meets rising stakeholder and regulatory expectations. However, high resistance to change may prevent accountants and organisations from exploiting these capabilities, leaving environmental and social data fragmented and manually processed, weakening governance mechanisms and increasing the risk of errors, lack of transparency and perceptions of "greenwashing."

The Greek context further amplifies these issues. As European and global regulatory frameworks evolve, including more stringent requirements around sustainability reporting and assurance, Greek firms will face mounting pressure to professionalise and digitise their ESG-related processes. Accountants, as gatekeepers of both financial and non-financial information, will be pivotal in determining whether AI is leveraged as an enabler of sustainable business models or remains underutilised due to psychological and organisational barriers (Skordoulis et al., 2020; Delegkos et al., 2022; Skordoulis et al., 2022, 2024). The present study shows that resistance to change significantly increases the odds of not adopting AI tools, suggesting that without targeted interventions, many firms may lag in building the technological capacity needed for credible ESG reporting and sustainable strategy execution.

Overall, this study underscores that the transition to AI in accounting is not merely a technical challenge but a socio-psychological and institutional one, with direct implications for sustainability performance. Addressing resistance to change among accountants is therefore not only a prerequisite for successful AI implementation, but also a critical step toward more transparent, reliable, and decision-useful ESG information, which underpins responsible and sustainable business practices.

However, the present study has limitations as well. The use of purposive sampling and cross-sectional data constrains statistical generalisability and prevents causal inference. The focus on a single country and profession limits external validity, although the Greek accounting sector offers a rich and relevant case. Future research could extend the analysis by incorporating additional predictors (e.g. organisational culture, leadership style, specific AI exposure), employing longitudinal designs, or comparing multiple countries and professions.

Despite these limitations, the study contributes to a more nuanced understanding of AI adoption in accounting by demonstrating that resistance to change, although not the sole determinant, is a significant and actionable barrier. Reducing resistance through informed, participatory, and ethically grounded change management is likely to be a critical precondition for realising the potential of AI in enhancing the quality, efficiency, and strategic contribution of the accounting profession in Greece and beyond.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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