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EXPLORING GENDER PATTERNS IN AI ADOPTION FOR ACCOUNTING ESTIMATES. A MIXED-METHODS INVESTIGATION

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Abstract: *This study examines gender differences in the adoption of artificial intelligence (AI) for accounting estimates using a mixed-methods approach that combines statistical analysis with thematic interpretation. Data was collected from thirty semi-structured interviews with accounting professionals. Quantitative measures covering AI adoption intensity, technique diversity, and future expectations were analyzed using non-parametric tests and correlation mapping. These analyses found small to moderate gender effects that were statistically insignificant, reflecting considerable within-gender variation. The most notable quantitative finding was that men reported slightly higher perceived AI influence, while women used a broader range of AI techniques. Multiple Correspondence Analysis (MCA) mapped two main dimensions structuring attitudes, openness to AI integration (from traditional judgment to algorithmic support) and behavioral orientation (trust in AI versus algorithm aversion). These revealed distinct professional profiles, from strong acceptance to skepticism. Gender was associated with behavioral factors, including trust, perceived transparency, and openness to innovation. Qualitative findings further showed that women and men reached similar levels of openness to AI, but through different frameworks, women engaged more broadly with AI, emphasizing governance, ethics, and employment impacts, while men focused more on system capabilities and regulatory clarity. Overall, the mixed-methods design demonstrates that AI adoption for accounting estimates is shaped by technological perceptions, behavioral attitudes, and demographic factors, with gender differences manifesting in interpretive pathways rather than in overall adoption rates.*

Keywords: *artificial intelligence; accounting estimates; gender patterns; qualitative coding; MCA.*

JEL Classification: *M41; J16; O33*

1. Introduction

The integration of artificial intelligence (AI) into accounting estimates represents a burgeoning trend poised to profoundly reshape financial processes (Bunget and Trifa, 2023; Stoica and Ionescu-Feleagă, 2024; Morandini et al., 2023; Ștefan et al., 2024). AI marks a pivotal milestone in the evolution of traditional business operations, notably within accounting (Arkhipova et al., 2024; Fülöp et al., 2022; Stoica and Ionescu-Feleagă, 2024). Its implementation promises enhanced efficiency, reduced error rates, and optimized utilization of both human and technological resources (Ahmad, 2024). Nevertheless, the adoption of AI is accompanied by considerable challenges, including a scarcity of specific competencies, employee resistance to organizational change (Ionescu and Barna, 2021), technical impediments, and heightened concerns regarding security and privacy risks (Zager et al., 2020; Banciu et al., 2023). Against this backdrop, scholarly inquiry examines the ways in which accounting professionals perceive and address these emergent challenges and opportunities.

Guided by the EU's Directional Consultation on AI in the Financial Sector (EU, AI Act, 2024), this study used interviews to gain detailed insights into accounting professionals' perceptions and experiences with AI in estimates. Interviews allowed for flexible, context-rich exploration of factors like technical barriers, training, resistance to change, and risk perceptions, as well as their connection to gender. This method also helped clarify sensitive issues such as aversion or hesitancy toward AI that might not surface in surveys (Qu and Dumay, 2011). Based on semi-structured interviews with thirty accounting professionals, this study examined AI use in estimation, covering training, resources, obstacles, aversion, risk perception, and adoption intentions. While AI is increasingly used in accounting, especially in judgment-intensive tasks like provisions estimation, impairment of assets and fair value assessment, adoption varies due to factors like data quality, uncertainty, and expertise. Individual factors, including gender disparities in training and role specialization, may influence adoption and perceptions of AI's impact. The study explores whether these gender differences are reflected in interview responses.

To fill the gap in literature, this work examines also gender-based patterns in adopting AI in accounting estimates. Using survey data, it explores how gender (I27) relates to key variables emphasis on AI advantages/risks (B4), importance of accuracy (C9), breadth of AI use in estimation domains (D10), perceived AI influence (D12), variety of AI techniques used (F17), application of advanced technologies (F18), self-assessed AI proficiency (F19), and perceived adoption obstacles (G22). The aim is to address how perception and behavior influence AI adoption in accounting. The study sought answers to the following questions:

RQ1: *How do accounting professionals perceive AI's role in accounting estimates?*

RQ2: *What behavioral and technological factors affect the adoption of AI-supported tools in estimation tasks?*

RQ3: *How do trust, transparency, and integration challenges shape attitudes toward AI?*

RQ4: *Are there gender-related differences in the perception and adoption of AI among accounting professionals?*

This paper includes a literature review along with the research framework, qualitative methodology, and participant selection. Findings are discussed, followed by conclusions, implications, limitations, and directions for future research.

2. Literature review and research framework

2.1. Literature review

Research shows AI is transforming accounting, improving forecasting and anomaly detection (Sutton et al., 2016; Kokina and Davenport, 2017; Appelbaum et al., 2017). However, algorithmic decision systems raise governance challenges (Issa et al., 2016; Moll and Yigitbasioglu, 2019). Furthermore, information systems studies indicate gender can influence how technology is interpreted, perceived, and discussed (Venkatesh and Morris, 2000; Gefen and Straub, 1997; Trauth, 2013). These differences are shaped by organizational culture, experience, and social factors. Gender-focused research proved that men and women may differ in their views on risk and ethics related to technology. Also, AI integration in accounting offers benefits like greater efficiency, accuracy, and decision support (Fülöp et al., 2025). Most accountants report positive impacts, but also raise ethical concerns over data integrity, job loss, and autonomy. Similar findings by Stoica and Ionescu-Feleagă (2024) note obstacles such as resistance to change and high costs. In Jordan, AI adoption improves data quality and disclosure (Al-Okaily, 2025). Moll and Yigitbasioglu (2019) highlight that internet technologies enhance financial transparency and reduce repetitive work, but accountants must adapt and governance issues need further study. Yang and Zhou (2025) found that AI adoption significantly improves accounting disclosure quality in Chinese companies, especially with greater corporate growth and better business environments. Bin-Nashwan et al. (2025) reported that AI, supported by strong data governance, enhances financial reporting accuracy and audit efficiency, also reducing information asymmetry. Monteiro et al. (2023) highlighted that intensive AI use and internal controls transform accounting information quality. Sutton et al. (2016) showed AI techniques are now key modules in audit decision systems, driving modern financial management. Issa et al. (2016) argued that auditing is well-suited for AI-driven automation, enabling professionals to focus on judgment and ethics, and predicted a shift to continuous, proactive audits. In the same research direction, Kokina et al. (2025) described how large audit firms use AI for data mining and natural language processing, but noted challenges such as transparency, confidentiality, reliability, and regulatory costs hinder broader adoption. Similarly, Zhang et al. (2025) found AI adoption in decision-making and performance management is driven by perceived usefulness and ease of use.

Recent studies have focused on AI adoption in audit processes (Sutton et al., 2016; Issa et al., 2016; Kokina and Davenport, 2017; Thottoli, 2024; Kokina et al., 2025; Bracci et al., 2026), but few directly address its use for accounting estimates (Bin-Nashwan et al., 2025; Abdallah et al., 2025). AI adoption for accounting estimates is more challenging due to their subjectivity, whereas audits are more easily formalized. Successful AI use depends on professionals' understanding of risks like bias and data ownership (Eisikovits et al., 2025), which can be mitigated through governance and ethical frameworks (Leong and Sung, 2024). Abdallah et al. (2025) found that both organizational and individual factors influence AI adoption, with organizational culture, ease of use, and regulatory support being especially important in the private sector. Gender plays a key role in technology adoption and should be included in diffusion models (Gefen and Straub, 1997). Venkatesh and Morris (2000) found that men adopt technology based on perceived usefulness, while women rely more on ease of use and social norms. Gefen and Straub (1997) also reported women perceive more usefulness and men greater ease of use, though both use technology similarly. Trauth (2013) notes that skills, experiences, and social influences shape technology use. Song et al. (2026) observed men view AI errors as technical issues, while women see them as violations of social expectations. Examining gender differences in AI adoption for accounting estimates is a new area in literature. Thus, the current study integrates insights from accounting technology research and gender studies to explore how accounting professionals interpret the integration of AI in estimation processes, filling a gap in existing knowledge.

2.2. Research framework

This study frames AI adoption for accounting estimates as shaped by technology, organizational context, and professional interpretation. The framework brings together the Technology Acceptance Model (TAM), which emphasizes perceived usefulness and ease of use as key drivers (Davis, 1986, 1989; Ma and Liu, 2004), and research on algorithm aversion, showing that professionals may mistrust AI in judgment-heavy fields like accounting (Dietvorst et al., 2015). The model also incorporates gendered technology adoption (GTA) research, showing that demographic factors like gender can affect trust, risk perception, and confidence in digital tools. In this framework, gender acts as an antecedent, influencing perceived usefulness, ease of use, and trust in AI. These perceptions, in turn, inform the adoption of AI tools for accounting estimates, encompassing domains such as fair value estimation, impairment testing, and predictive financial analytics. As shown in Figure 1, the model proposes gender impacts perceived usefulness/relevance and ease/accessibility of use, both drive adoption, and algorithm aversion smooths the interaction between usefulness and adoption.

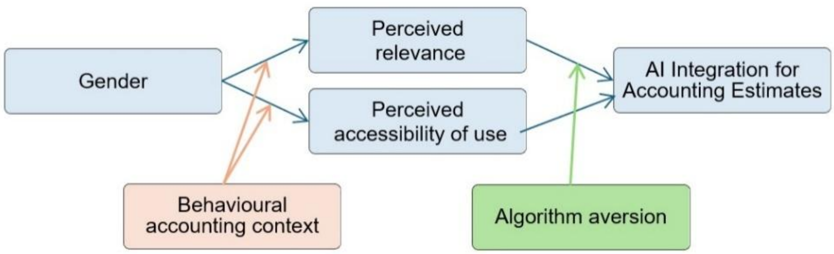

Figure 1: Research framework
Source: Authors' projection

Within this framework, gender is conceptualized as an antecedent variable that influences both the perceived relevance and perceived accessibility of AI tools use. These cognitive appraisals shape the adoption of artificial intelligence for accounting estimates, particularly in tasks that demand professional judgment, such as valuation, risk assessment, and predictive analytics. The model further integrates algorithm aversion as an agent, which may affect the extent to which perceived usefulness translates into the actual adoption/integration of AI technologies. Additionally, the broader behavioral accounting context is incorporated to recognize the influence of cognitive biases, professional judgment, and decision-making heuristics on technology acceptance among accounting professionals.

3. Methodology and participants

3.1. Methodology

This study uses a mixed-methods design, combining quantitative statistical analysis and qualitative thematic analysis. Thirty semi-structured interviews with accounting professionals were coded into structured variables reflecting AI adoption and influence. Key quantitative tools including point-biserial correlation, Mann-Whitney tests, and violin plot visualizations were used. Qualitative insights were drawn from thematic analysis of recurring narratives. Analyses were performed with Python tools, NumPy and Pandas for data structuring, Scikit-learn for dimensionality reduction and K-means clustering, and Matplotlib for figures such as the AI Integration Progress Map. Multiple Correspondence Analysis (MCA), implemented via singular value decomposition (SVD), was used to explore relationships among categorical variables (trust, transparency, integration challenges, decision quality) and reveal perceptual structures in AI adoption attitudes.

3.2. Participants profile

This study interviewed thirty Romanian accounting professionals, including economic directors, chief accountants, and financial managers. The sample shows diversity in professional experience, technological perspective, age, gender, education, and certifications. This range allowed analysis of how responsibility, training, and specialization relate to openness toward AI adoption. Most participants were aged 35–55 (73%), with 20% aged 25–35, and only one over 55. No participants were under 25. This focus on experienced professionals supports mature insights into technology adoption, while the younger group may drive innovation. Age diversity was limited, which may reflect broader employment trends (Humpert and Pfeifer, 2013). Of the thirty interviewees, twenty were women and ten were men, mirroring gender trends in accounting. This supports analysis of gender's role in AI adoption. Studies show technology can reduce barriers but may also create new risks for women (Olivetti et al., 2024; Deloitte, 2024; Singh et al., 2024). All participants reported their gender. The sample is highly educated, 41% hold master's degrees, 17% have postgraduate studies, 17% doctorates, and 7% postdoctoral experience. Professional credentials include 57% certified public accountants, 20% financial auditors, 37% tax consultants, 17% certified appraisers, and 13% liquidators. Job roles span leadership, academia, non-profit, and public sectors, providing broad expertise in accounting, auditing, taxation, and financial management.

4. Results

4.1. Descriptive statistics

Prior to investigating the associations between gender and AI-related indicators, descriptive statistics were calculated for all variables derived from interview coding. These indicators capture respondents' perceptions of artificial intelligence for accounting estimation, encompassing attitudes toward AI risks, perceived influence on estimates, range of AI techniques employed, and barriers to adoption. The analysis revealed substantial variability across these measures. Notably, perceived AI influence (D12) and diversity of techniques used (F17) exhibited considerable dispersion, reflecting heterogeneous experiences with AI across organizational and professional contexts. Indicators assessing obstacles to adoption (G22) and concerns about the reliability of AI-generated estimates (C9) also showed moderate variability, suggesting diverse assessments of technological risks and implementation challenges. Collectively, the findings confirm that the sample includes professionals with varying levels of AI exposure, from initial awareness to advanced operational use, thus providing a robust empirical foundation for examining gender-related differences in perceptions and adoption patterns.

Table 1: Descriptive statistics

Variable	Mean	Median	Std.Dev	Min	Max	Skewness	Kurtosis
B4. AI aversion	0.33	0.0	0.96	0	4	2.87	7.11
C9. Reliability concerns	1.2	1.0	0.66	1	4	3.36	10.26
D10. Innovation perception	0.7	0.5	0.95	0	4	1.85	3.64
D12. Perceived future AI influence	3.39	4.0	0.92	1	4	-1.44	1.11
F17. AI technology diversity	0.7	0.0	1.15	0	4	1.86	2.57
F18. AI use examples	0.33	0.0	0.96	0	4	2.87	7.11
F19. AI tools effectiveness	3.03	3.0	1.03	0	4	-1.21	1.13
G22. AI obstacles	0.48	0.0	1.12	0	4	2.23	3.63

Source: Authors' projection

4.2. Correlation Matrix

To investigate potential associations between gender and interview-coded indicators of AI adoption and perception, point-biserial correlations were computed. As gender is coded as a binary variable, the point-biserial coefficient is mathematically equivalent to the Pearson correlation for dichotomous-continuous variable pairs. The resulting correlation matrix is presented in Figure 2.

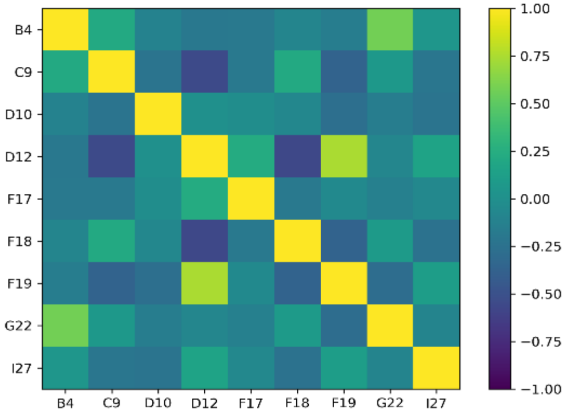

Figure 2: Correlation matrix
Source: Authors' projection

The correlation matrix reveals that most relationships between gender and AI-related indicators are weak. The strongest positive association is for perceived influence of AI on accounting estimates (D12) ($r \approx 0.16$), indicating that male respondents report slightly higher expectations regarding AI's transformative potential in estimation processes. Negative correlations are observed for innovation perception (D10) ($r \approx -0.23$) and reported AI use examples (F18) ($r \approx -0.25$), show that female respondents demonstrate somewhat greater practical engagement with AI tools and applications. The correlation for diversity of AI techniques used (F17) is negligible ($r \approx -0.06$), confirming minimal gender differences in operational exposure to AI technologies. Other variables show little or no association with gender, AI aversion (B4) ($r \approx 0.05$), reliability concerns regarding AI estimates (C9) ($r \approx -0.22$), self-assessed AI skills (F19) ($r \approx 0.12$), and perceived obstacles to AI adoption (G22) ($r \approx -0.10$). Overall, most coefficients indicate small effects, supporting the conclusion that perceptions of AI adoption are largely consistent across genders.

4.3. Mann–Whitney non-parametric tests, effect size estimation and bootstrapping validation

Given the small sample size and the ordinal nature of several interview-coded indicators, additional robustness checks were performed using Mann–Whitney U tests. This non-parametric approach assesses whether distributions of AI-related indicators differ significantly between female and male respondents without presuming normality. As shown in Table 2, none of the variables achieve conventional statistical significance ($p < 0.05$). The largest effect appears for F18 (reported AI use examples), showing a notable difference between gender groups, though statistical significance remains marginal due to sample size constraints. Moderate effects are observed for D10 (innovation perception) and F17 (diversity of AI techniques), indicating some gender-based variation in technological engagement. Basically, the findings reveal that gender differences in AI adoption indicators are limited and context dependent. Substantial overlap in response distributions also evident in violin plot analyses reveal that professional experience and organizational context likely exert greater influence than gender alone on perceptions of AI integration for accounting estimation. These results corroborate the general pattern observed in the correlation analysis, differences between gender groups are modest and fall short of statistical significance. Nonetheless, distributional comparisons indicate slightly higher median values for perceived AI influence among male respondents, while female respondents report somewhat greater diversity in AI techniques used. Thus, although gender does not yield strong statistical differences in AI adoption indicators, subtle variations in technological engagement and perception may persist.

Table 2: Statistical association between gender and AI adoption in AE

Variable	Mann–Whitney U	p-value	Rank-biserial effect size	Bootstrap 95% CI (mean difference)	Interpretation
B4. AI aversion	4.50	1.000	-0.13	[-0.72, 0.68]	Negligible association
C9. Reliability concerns	4.50	1.000	-0.13	[-0.61, 0.65]	Negligible association
D10. Innovation perception	6.50	0.396	-0.63	[-1.21, 0.37]	Moderate association
D12. Perceived future AI influence	5.00	0.633	-0.43	[-0.98, 0.54]	Small–moderate association
F17. AI technology diversity	6.00	0.502	-0.50	[-1.08, 0.43]	Moderate association
F18. AI use examples	0.00	0.063	1.00	[0.12, 1.75]	Large association
F19. AI tools effectiveness	3.50	1.000	0.13	[-0.63, 0.71]	Negligible association
G22. AI obstacles	4.00	0.755	-0.33	[-0.84, 0.49]	Small association

Source: Authors' projection

To enhance the interpretation of gender differences, rank-biserial correlation effect sizes were computed for the Mann–Whitney comparisons. Effect size analysis is particularly important in small samples, where statistical significance tests may lack sufficient power to detect differences. The rank-biserial coefficient estimates the strength of association between a binary variable (gender) and a continuous or ordinal outcome. Across the tested variables, effect sizes were generally in the small-to-moderate range, according to Cohen's (1988) conventional thresholds. Given the limited sample size (n = 30), bootstrap resampling was employed to assess the stability of the estimated gender differences, generating empirical confidence intervals through repeated resampling and recalculation of relevant statistics. Using 5,000 bootstrap iterations, confidence intervals were estimated for mean differences between female and male respondents across key AI adoption indicators. The bootstrap analysis corroborates the findings from the correlation and Mann–Whitney tests, most variables exhibit negligible to moderate effect sizes. The largest effect, observed for F18 (reported AI use examples), remains only marginally significant due to the small sample size. Bootstrap confidence intervals for most indicators include zero, indicating that observed differences lack statistical robustness. These results further support the conclusion that gender differences in AI adoption indicators are limited in this sample and that observed variations are more likely attributable to contextual or professional factors than to systematic gender effects.

4.4. Distribution of AI adoption scores. The violin plot

To illustrate the distribution of AI adoption perceptions by gender, a violin plot was generated using the composite AI adoption indicator from interview coding. This visualization integrates boxplot and kernel density features, capturing both central tendency and distributional shape. As shown in Figure 3, the distributions for female and male respondents overlap substantially, indicating that gender is not a primary determinant of AI adoption perceptions for accounting estimates. Considerable within-group variability exists, with both groups demonstrating a wide range of attitudes toward AI technologies. However, male respondents tend to cluster slightly higher in perceived AI influence, while female respondents exhibit a broader range of reported AI techniques and operational engagement. These patterns align with previous statistical findings, reinforcing the conclusion that gender differences are subtle rather than deterministic.

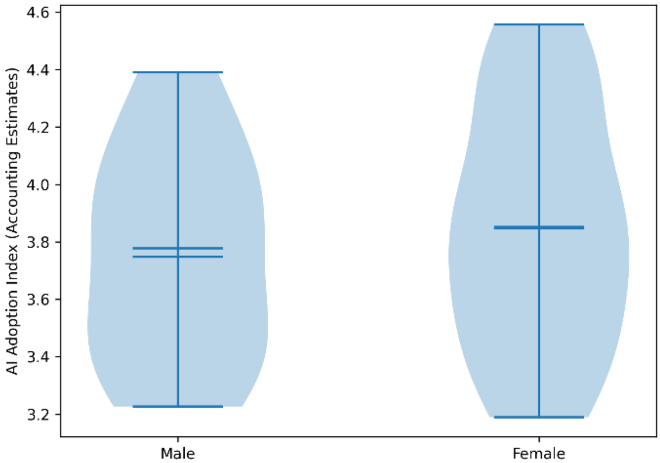

Figure 3: Distribution of AI adoption scores by gender
Source: Authors' projection

4.5. Multiple Correspondence Analysis (MCA)

To investigate the multidimensional relationships among AI adoption indicators, Multiple Correspondence Analysis (MCA) was employed. MCA is well-suited for analyzing categorical or coded qualitative variables and facilitates the visualization of relationships between respondents and variables in a reduced-dimensional space. The resulting MCA map, presented in Figure 4, delineates the perceptual structure of thematic attitudes toward AI adoption/integration for accounting estimation. The horizontal axis represents a continuum of AI integration progress, while the vertical axis captures behavioral orientations from algorithm aversion to greater trust in AI-assisted judgment. Respondents are depicted with gender-specific markers, and convex hulls delineate distinct adoption profiles within the sample. Directional vectors highlight the influence of key thematic drivers, including governance, technological capabilities, and behavioral perceptions of AI in accounting practice.

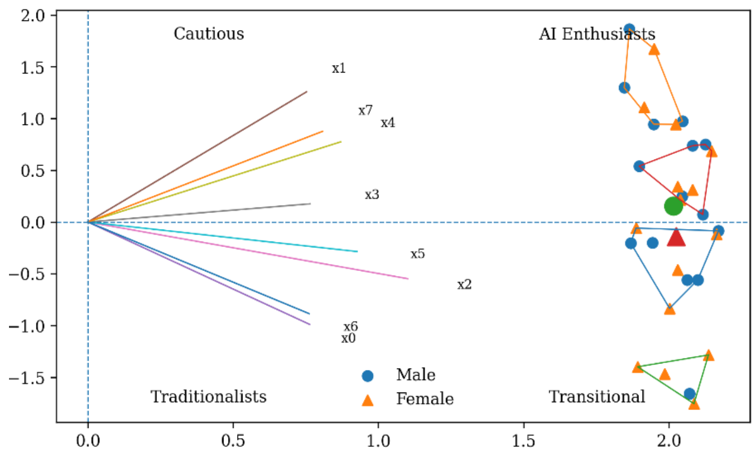

Figure 4: AI integration progress map in accounting estimation processes
Source: Authors' projection

The first dimension shows overall acceptance of AI for accounting estimates, those on the positive side embrace AI tools for efficiency and consistency, while those on the negative side prefer traditional judgment and are more skeptical of algorithms. The second dimension reflects trust in AI, upper quadrants indicate higher confidence in AI reliability, while lower quadrants show greater algorithm aversion. Together, these dimensions capture attitudes and psychological factors behind AI adoption in accounting. The AI integration progress map illustrates attitudes toward AI adoption in accounting. The horizontal axis shows the range from minimal to extensive AI use, while the vertical axis ranges from algorithm aversion to high trust in AI. Respondents are grouped into four conceptual adoption areas, AI enthusiasts (high trust and integration), Cautious adopters (see AI's potential but have transparency and ethical concerns), Transitional users (adopting AI but still use traditional methods), and Traditionalists (prefer conventional judgment and are skeptical of AI). These areas capture key drivers like trust, transparency, ethics, and perceive improvements in decision quality. AI enthusiasts are respondents who strongly align with themes of trust, enhanced decision quality, and seamless integration of AI tools. Cautious adopters recognize AI's analytical potential but harbor reservations concerning transparency and ethical issues. Traditionalists rely predominantly on conventional professional judgment and express heightened skepticism toward algorithmic decision support. Transitional users are professionals who are gradually adopting AI-supported analytical processes while continuing to use traditional methods. Cluster centroids further highlight distinct adoption profiles within the respondent population, underscoring the heterogeneity of attitudes toward AI integration for accounting estimation.

5. Discussion

This study aimed to determine whether gender is systematically associated with the adoption and perceived influence of artificial intelligence for accounting estimation processes. By integrating statistical analysis of interview-coded indicators with thematic interpretation, the research offers a nuanced perspective on how accounting professionals perceive AI integration in estimation tasks. The findings indicate that gender is not a decisive factor in AI adoption among accounting professionals. Instead, gender appears to shape interpretive orientations toward technological change, while actual adoption patterns are primarily influenced by professional context, organizational environment, and individual exposure to digital tools.

5.1. Interpretation of statistical results

Statistical analysis shows gender differences in AI adoption indicators are generally small. Correlations between gender and variables like AI aversion (B4), reliability concerns (C9), self-assessed skills (F19), and perceived obstacles (G22) are weak, with no significant differences found in most cases. Bootstrap validation also supports this, suggesting observed differences are likely due to sampling variability. However, moderate effect sizes for D10 (perception of innovation) and F17 (diversity of AI techniques used) indicate that women may engage more broadly with AI, while men emphasize innovation, though these are not statistically significant. The largest difference found was for F18 (examples of AI use), where gender had a marginal effect, possibly reflecting differences in exposure to AI within organizations. These patterns align with Venkatesh and Morris (2000), Gefen and Straub (1997), Trauth (2013), and Song et al. (2026), who argue that technology perceptions are influenced more by professional role and context than by gender. Therefore, the results highlight the need to consider both general attitudes and specific experiences (like F18) when analyzing AI implementation for accounting estimates.

5.2. Interpretation of the MCA

Whereas statistical tests elucidate pairwise associations between gender and individual variables, *Multiple Correspondence Analysis (MCA)* provides a multidimensional perspective on AI adoption within the sample. The MCA map reveals several distinct profiles of AI adoption and perception, mirroring the thematic patterns identified in the qualitative interview analysis. These profiles reflect the diverse professional orientations toward AI integration for accounting estimation processes. The first two MCA dimensions serve as the axes for the perceptual representation in the AI integration progress map.

Dimension 1. AI integration progress. The horizontal axis principally reflects respondents' openness to adopting artificial intelligence for accounting estimation. Individuals on the positive side of this dimension perceive AI as a beneficial tool that enhances analytical capabilities, efficiency, and consistency in professional judgment. In contrast, those on the negative side rely more heavily on traditional judgment and express greater skepticism toward algorithmic decision support. Thus, Dimension 1 represents a continuum of AI integration progress in accounting practice.

Dimension 2. Behavioral trust versus algorithm aversion. The vertical axis captures behavioral attitudes toward algorithmic decision-making systems. Respondents in the upper region of the perceptual space exhibit higher levels of trust in AI-assisted tools, whereas those in the lower region display characteristics of algorithm aversion, indicating reluctance to rely on automated recommendations in professional judgment contexts. This behavioral dimension is especially relevant in accounting, where professional judgment and accountability are central to decision-making.

5.3. Gender patterns across adoption profiles

This study aimed to identify gender differences in AI adoption within accounting estimation. Gender was analyzed using Multiple Correspondence Analysis (MCA) to visually compare male and female respondents' positions in the perceptual space of AI integration and trust. Gender differences in technology adoption are well documented (Venkatesh and Morris, 2000; Gefen and Straub, 1997; Trauth, 2013; Song et al., 2026). Drawing on the *Technology Acceptance Model (TAM),* perceived usefulness and ease of use may affect adoption differently by gender. Other studies emphasize the roles of perceived risk, trust, and digital experience in shaping adoption patterns while research on algorithm aversion highlights how transparency, accountability, and error tolerance influence responses to automated systems. The MCA perceptual map reveals that, although there are no sharply defined gender clusters in AI adoption profiles, subtle patterns are evident. Male respondents are somewhat more concentrated in regions associated with strong beliefs in AI's transformative potential and innovation, whereas female respondents are more widely distributed across profiles emphasizing operational and exploratory uses of AI. Statistical analyses reinforce these observations, men typically anticipate a greater degree of change from AI, while women tend to report more diverse, hands-on engagement with AI tools in practice. Importantly, these trends do not reflect differences in technological competence or readiness but rather illustrate the distinct ways each gender interprets and interacts with AI adoption in accounting. These nuanced differences highlight the need to consider both innovation perspective and practical experiences when examining gendered approaches to AI integration.

6. Conclusion and implications

This mixed-methods study explored gender differences in the adoption of AI among thirty accounting professionals, with twenty women and ten men participating. Women were more represented and generally more willing to take part, reflecting a strong social context influence. The research found some moderate gender differences, women reported greater perceived innovation and used a wider variety of AI techniques, but these differences were not statistically significant. Across most measures including concerns about AI reliability, reluctance to adopt AI, perceived self-effectiveness, and perceived obstacles, men and women showed minimal variation. The findings revealed that, while there are some nuanced, context-dependent differences, overall professional attitudes toward AI risks, reliability, and barriers do not significantly differ by gender in the accounting field. This highlights the importance of considering social context and individual experience over broad gender-based assumptions when integrating AI into professional practices.

Analysis of perceived future AI influence on accounting estimates showed a small-to-moderate, but not statistically significant, difference, with men slightly more likely to view AI as transformative. This observed difference may be due to sampling variation, not a consistent gender pattern. A greater difference appeared in reported examples of AI use, showing variability in how respondents mention AI applications, though this also approached only marginal statistical significance. Due to the small, unbalanced sample, these findings should be interpreted cautiously. Altogether, the study found only selective, context-dependent gender differences in AI engagement, with no significant differences in perceptions of risk, reliability, or implementation barriers. Gender does not appear to be a primary determinant of AI adoption for

accounting estimates, though it may influence how professionals frame AI's role in innovation and practice. Core professional attitudes toward AI remain consistent across genders.
The main contribution of the study relies on the qualitative analysis (MCA) which shows women in accounting emphasize ethics, social responsibility, and organizational safeguards in AI adoption, often focusing on data security, accountability, and workforce impact. Their support for AI depends on transparency and proper controls. Men, however, tend to focus on technical integration, system reliability, and operational control, stressing concerns like cyber-vulnerability and the need for strong regulatory frameworks. While both genders consider ethics, women prioritize social impact and responsibility, while men emphasize reliability and technical aspects. The mixed-methods approach reveals that, while gender has little statistical impact on AI openness, women and men interpret AI adoption differently. Women's openness is tied to governance, ethics, and employment issues, whereas men's is linked to technical reliability and system capabilities. Rather than indicating one gender is more for AI adoption than the other one, the findings show that gender shapes the interpretation of AI's usefulness, trust, and ease of use. For women, trust and professional responsibility are significant while for men, system transformation and reliability matter most. These differences prove that effective AI adoption in accounting needs both technical training and governance-focused measures to address the distinct concerns of each gender.
In summary, gender shapes how AI is adopted for accounting estimates, more than it affects overall adoption rates. Men see AI as transformative, while women engage more with AI tools and focus on ethics, data protection, and responsibility. These differences reflect distinct adoption logics, not outright gender opposition. AI adoption is a complex process influenced by trust, accountability, and experience. Analysis shows two main dimensions, openness to AI and attitudes like trust versus skepticism. Gender interacts with these behavioral factors, highlighting that AI adoption involves technology, behavior, and demographics. The study also contributes to research by introducing a new framework using correlation analysis and mapping to visualize different professional approaches to AI adoption. Nevertheless, this study's insights into AI adoption for accounting estimates are limited by a small, context-specific sample, reducing generalizability. The use of exploratory methods identifies patterns but not causal links, and self-reported data may not reflect actual AI use. Gender results should be interpreted cautiously since the focus is on perceptions, not proven skill differences. Future research should use larger, more diverse samples to examine if these findings apply broadly. Longitudinal and experimental work could show how attitudes and actual AI use change over time. Research should also examine how explainable AI affects trust and adoption, and develop frameworks that combine technological, behavioral, and organizational perspectives to better understand AI's impact on accounting estimates and professional judgment.

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