FROM BASICS TO INTELLIGENT TOOLS: ACCOUNTING INFORMATION AND AI IN PUBLIC-SECTOR INTERNAL AUDITING

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ABSTRACT
This study examines the integration of artificial intelligence (AI) in public sector internal auditing, focusing on the extent of AI adoption, the types of AI tools used, and the challenges faced by auditors in implementation. The research employs both descriptive statistical analysis and inferential techniques, including Spearman's correlation and ANOVA, to assess the relationships between AI adoption and institutional factors. Findings indicate that while data analytics is the most commonly used AI tool, a significant proportion of respondents do not utilize AI in their auditing practices. The primary barriers to AI adoption include a lack of training, high costs, and concerns regarding data privacy. The study further reveals that AI usage varies depending on the type of institution in which they work. These insights contribute to the ongoing discussion on digital transformation in auditing, emphasizing the need for enhanced training programs and strategic investments to facilitate AI integration.

Keywords: *Internal auditing, Accounting information, Artificial Intelligence (AI), Public sector*

JEL classification: *M42, H83*

1. INTRODUCTION

The increasing complexity of public sector financial management requires effective internal auditing practices to ensure accountability, transparency, and governance. Internal auditors play a crucial role in interpreting and applying accounting information to assess fiscal health, mitigate risks, and support evidence-based decision-making. In recent years, digital transformation has introduced new tools and technologies that are reshaping traditional audit functions, with artificial intelligence (AI) emerging as a key driver of change.

AI has the potential to revolutionize public sector internal auditing by automating complex tasks, improving fraud detection, and enhancing data analysis accuracy. Recent studies emphasize that AI-driven technologies enable auditors to process vast amounts of data efficiently, identify patterns of financial anomalies, and strengthen risk assessment mechanisms (Aldemir and Uysal, 2024). However, while AI presents significant opportunities, its integration also raises concerns regarding data privacy, ethical risks, and the potential diminishing role of human judgment in auditing decisions (Fedyk *et al.,* 2022). The balance between leveraging AI for efficiency and maintaining the core principles of accountability and transparency remains a critical challenge for auditors in the public sector (Setyaningrum *et al.,* 2022).

Given the rapid advancements in AI adoption, it is essential to assess how public sector internal auditors are adapting to these changes and whether they possess the necessary competencies to effectively utilize AI-driven tools. The Institute of Internal Auditors (IIA) has recognized this need by outlining a framework for AI competencies, emphasizing the importance of continuous professional development (IIA, 2017a). However, gaps remain in understanding how internal auditors in different national contexts, such as North Macedonia, integrate AI into their audit processes and whether current training initiatives adequately prepare them for an AI-enhanced environment.

This paper aims to explore how internal auditors in the public sector currently use accounting information in their auditing activities. Understanding their reliance on traditional accounting records versus AI-generated financial data will provide insights into the dynamic role of accounting information in public sector audits. Additionally, the research seeks to evaluate both the perceived and actual impacts of AI integration on audit efficiency, data accuracy, risk assessment, and decision-making processes. Furthermore, this research analyzes the benefits and challenges internal auditors face when adopting AI technologies. At the same time, the study assesses potential barriers to AI adoption, including issues related to ethical concerns, regulatory compliance, and organizational resistance.

2. LITERATURE REVIEW

AI has significantly influenced internal auditing by enhancing automation, improving fraud detection, and optimizing decision-making processes (Fedyk *et al.,* 2022). AI-driven auditing techniques, including machine learning and data analytics, enable auditors to efficiently analyze large datasets, identify anomalies, and streamline financial assessments (Allami, 2022). De Sousa *et al.* (2019) emphasize that AI's role in auditing is expanding beyond automation, providing auditors with predictive capabilities and deeper insights into risk assessment and compliance. Babina *et al.* (2020) suggest that AI adoption in auditing correlates with improved firm performance and innovation, particularly when leveraged for advanced data-driven decision-making. However, while existing literature explores AI's impact on private sector auditing, there remains a gap in understanding how AI is transforming internal auditing in the public sector, particularly in countries like North Macedonia.

The integration of AI requires auditors to develop specific competencies that bridge traditional auditing skills with technological advancements (Aldemir and Uysal, 2024). The Institute of Internal Auditors (IIA, 2017a) highlights that while auditors do not need to become data scientists, they must develop a foundational understanding of AI tools and their application in audit functions. Setyaningrum *et al.* (2022) argue that competency gaps among auditors remain a challenge, as many professionals lack adequate training in AI-related technologies, impacting their ability to conduct efficient audits. Issa *et al.* (2016) further emphasize the need for universities and professional organizations to incorporate AI-related auditing courses in their curricula to bridge this knowledge gap.

AI enhances fraud detection capabilities in auditing by using predictive analytics and anomaly detection to identify fraudulent transactions (Rehman and Hashim, 2022). Fedyk *et al.* (2022) further illustrate how AI-powered algorithms can improve risk assessment by identifying patterns of financial misstatements and fraudulent activities that might be overlooked by traditional methods. Raji and Buolamwini (2022) explore how AI audits can expose biases in algorithmic decision-making, ensuring transparency and accountability in automated auditing systems. The use of AI in fraud detection is particularly significant in the public sector, where financial mismanagement and corruption remain pressing concerns (Wirtz *et al.,* 2019).

Recent empirical research demonstrates that AI investments lead to improvements in audit quality and efficiency (Fedyk *et al.,* 2022). AI adoption has been shown to reduce audit restatements by 5%, lower audit fees, and enhance the overall reliability of financial reporting (Bughin *et al.,* 2017; Babina *et al.,* 2020). The ability of AI to process vast datasets and apply predictive analytics allows auditors to detect anomalies more effectively and focus on high-risk areas (Rock, 2020). Frey and Osborne (2017) argue that auditing is one of the professions most exposed to technological advancements, making AI integration essential for maintaining audit integrity and effectiveness.

While AI offers various benefits in internal auditing, it also presents ethical challenges, particularly in data privacy, bias, and algorithmic transparency (Wirtz *et al.,* 2019). The OECD (2018) emphasizes the importance of ethical AI adoption, calling for robust regulatory frameworks to ensure fairness and accountability. Minkkinen *et al.* (2022) discuss the need for continuous auditing of AI applications to prevent biases and inaccuracies in financial reporting. The IIA (2017b) underscores that AI should be used as an enhancement tool rather than a replacement for human auditors, ensuring that ethical considerations remain at the forefront of AI integration. Burton and Rezaee (1994) advocate for ongoing ethics training for auditors to address these emerging challenges. Despite these discussions, research has not yet provided sufficient insights into how public sector internal auditors perceive and manage AI-related ethical dilemmas, particularly in countries like North Macedonia, where regulatory frameworks for AI auditing may still be evolving.

As AI continues to develop, its role in internal auditing is expected to grow, necessitating continuous professional development for auditors (Burton and Rezaee, 1994). Issa *et al.* (2016) propose that AI-driven auditing will become the standard practice in the future, requiring internal auditors to adopt new methodologies and tools for enhanced financial governance. The IIA (2021) suggests that organizations should invest in AI training programs to equip internal auditors with the necessary skills to navigate this dynamic environment. Further, the integration of blockchain with AI is emerging as a future trend that could enhance the transparency and security of audit processes (Frey and Osborne, 2017). However, while the theoretical benefits of AI in auditing are widely acknowledged, research gaps remain regarding how internal auditors in the public sector can best leverage AI to improve transparency and accountability, and what barriers - whether technological, organizational, or regulatory - hinder full adoption.

3. METHODOLOGY

3.1. Research design

This study employs a quantitative research design using a structured survey to collect data from internal auditors working in public sector institutions in North Macedonia. The survey aims to assess how auditors utilize accounting information, their perceptions and use of AI in internal auditing, and the benefits and challenges associated with AI adoption in the public sector. The collected data is analyzed using statistical techniques to identify trends, correlations, and comparative differences based on the internal auditors' institutional affiliations.

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3.2. Survey structure

The survey is divided into six distinct sections, each designed to capture specific aspects of the research objectives (see Table 1).

Table 1: Survey's structure

Section	Description	Question	Type of answers
General Characteristics of Respondents	Demographic and professional background information of respondents	Job title	Open-ended response
		Years of experience in internal auditing	Categorical response: Less than 2 years, 2–5 years, 6–10 years, More than 10 years
		Educational background	Accounting, Audit, Finance, Information Technology, Other
		Type of organization	Local government, Central government, Government agency, Public enterprise, Other
Use of Accounting Information in Internal Auditing	Role of accounting information in public sector audits	1 question for use of paper-based vs. AI-generated accounting records	5-point Likert scale: Never to Always
		6 questions for agreement with statements on the importance of accounting information in auditing	5-point Likert scale: Strongly Disagree to Strongly Agree
Perception and Use of AI in Internal Audit	Auditors' familiarity and use of AI tools	1 question for self-reported familiarity with AI in auditing	5-point Likert scale: Not familiar at all to Very familiar
		1 question for frequency of AI tool usage (e.g., data analytics, anomaly detection)	5-point Likert scale: Never to Always
		8 questions for perceptions of AI's impact on audit accuracy, efficiency, fraud detection, and workload	5-point Likert scale: Strongly Disagree to Strongly Agree
		1 question for current AI tools used in auditing	e.g., machine learning, predictive modeling, process automation (Multiple-choice)
Benefits of AI in Internal Audit	Auditors' perceptions of AI's effectiveness in various audit aspects	6 questions for the usefulness of AI in efficiency, fraud detection, and decision-making	5-point Likert scale: Not useful to Very useful
		1 question for the extent to which AI has transformed the approach to accounting information in auditing	5-point Likert scale: Not at all to Completely
Challenges and Concerns with AI in Internal Audit	Barriers to AI adoption	6 questions for concerns regarding data privacy, ethics, complexity, and costs	5-point Likert scale: Strongly Disagree to Strongly Agree
		1 question for the perceived difficulty of integrating AI into audit practices	5-point Likert scale: Not a challenge at all to Extremely challenging

		1 question for key barriers to AI implementation	Multiple-choice: Lack of training, High cost, Privacy concerns, complexity, Resistance to change, Lack of support from management
Future Perspectives on AI in Public Sector Internal Audit	Auditors' expectations regarding AI's future role	6 questions for agreement with statements on AI's growing importance, evolving auditor roles, and the necessity for continuous learning	5-point Likert scale: Strongly Disagree to Strongly Agree
		Overall optimism about AI's impact on public sector auditing	Open question

(Source: Authors' research)

3.3. Data collection

The data for this study was collected through an online survey (Appendix 4) distributed to internal auditors in the public sector of North Macedonia. The Ministry of Finance provides a publicly accessible list of internal auditors, including their names, institutional affiliations, and contact details (email addresses) - LINK (internal auditors at the central level) and LINK (internal auditors at the local level). This list was last updated in December 2024, ensuring the accuracy and completeness of the sampling frame.

The study population initially consisted of 189 internal auditors employed at both central and local government levels. However, due to the unavailability of email addresses for some individuals, the survey was electronically distributed to 173 internal auditors for whom valid contact information was available. Following the email distribution, 18 messages were returned as undeliverable due to inactive or non-existent email addresses. Consequently, the final sample size for the study comprised 155 internal auditors.

Participation in the survey was entirely voluntary and anonymous, ensuring adherence to ethical research standards and maintaining data confidentiality. A total of 48 responses were received, yielding a response rate of 30.97%. This response rate provides valuable insights into internal auditors' perspectives on the utilization of accounting information and the integration of AI in public sector internal auditing. This rate aligns with findings from Nulty (2008), who suggests that response rates for online surveys can be lower than those for paper-based surveys yet still yield meaningful data for analysis. Furthermore, a study by Fincham (2008) indicates that response rates between 30% and 40% are considered acceptable in social science research, providing sufficient data for reliable statistical analysis.

3.4. Data analysis

The collected data is analyzed using SPSS software, employing a combination of descriptive and inferential statistical techniques:

- *Descriptive statistics* were used to summarize and present key characteristics of the dataset, providing insights into central tendencies, variability, and distribution patterns of the variables.
- *ANOVA (Appendix 1)* was applied to determine whether there were statistically significant differences between groups based on institutional affiliation (local government vs. central government agencies), making it a suitable method for comparing means across these categories and identifying potential variations in responses.

- *Spearman's rank correlation coefficient (Appendix 2)* was used to assess the strength and direction of the relationship between familiarity with AI auditing and the frequency of AI use, as it is a non-parametric measure suitable for examining associations between ordinal or non-normally distributed variables. This method allows for identifying monotonic relationships without assuming linearity or homoscedasticity in the data.
- *Descriptive analysis of multiple-choice responses*.

4. RESULTS AND DISCUSSION

Before any further analysis of the results, a reliability analysis was carried out. The reliability of the survey instrument was assessed using Cronbach's alpha, which yielded a value of 0.719 for the 36 items. According to established guidelines (Taber, 2018; Tavakol and Dennick, 2011), a Cronbach's alpha value of 0.70 or higher is considered acceptable, indicating good internal consistency among the items. Therefore, the result suggests that the items in the survey demonstrate strong reliability in measuring the intended constructs, providing confidence that the responses are consistent and the instrument is effective in capturing the relevant dimensions of the study.

The demographic characteristics of the survey respondents are presented in the following table.

Table 2: Demographic characteristics of the respondents

Feature	Description	Number	Percent
Years of Experience in Internal Auditing	0-2 years	4	8.3%
	3-5 years	11	22.9%
	6-10 years	7	14.6%
	more than 10 years	26	54.2%
	Total	**48**	**100%**
Educational Background	Accounting	12	25%
	Auditing	6	12.5%
	Law	4	8.3%
	Finance	20	41.7%
	Other	6	12.5%
	Total	**48**	**100.00%**
Institution Type	Local Government	14	29.2%
	Central Government	16	33.3%
	Government Agency	9	18.8%
	State or local owned enterprise	9	18.8%
	Total	**48**	**100%**

(Source: Author's calculation)

The demographic characteristics of the respondents indicate that the majority have more than 10 years of experience in internal auditing (54.2%), followed by those with 6-10 years (14.6%), 3-5 years (22.9%), and 0-2 years (8.3%), suggesting that most participants are seasoned professionals. In terms of educational background, Finance (41.7%) and Accounting (25.0%) are the most common fields, while others come from Auditing (12.5%), Law (8.3%), and other disciplines (12.5%), reflecting a diverse academic profile with a strong financial focus. Regarding institutional affiliation, respondents primarily work in Central Government (33.3%) and Local Government (29.2%), with additional representation from Government Agencies (18.8%) and State or Locally Owned Enterprises (18.8%), ensuring a broad perspective on auditing practices across different public sector entities.

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4.1. Descriptive statistics

Below in Table 3 are the results of the descriptive statistics of the questions asked on a Likert scale and Yes/No questions.

Table 3: Descriptive statistics

	N	Mean	Std. Deviation
Section 2: Use of Accounting Information in Auditing			
Frequency_Accounting_Info_Use	48	3.625	1.2653
Accounting_Essential_Audit	48	3.104	1.1893
Accounting_Improves_Transparency	48	4.229	.6270
Audit_Reports_Rely_Accounting	48	4.271	.7363
Training_Accounting_Data	48	3.958	.9444
Accounting_Data_Accuracy	48	3.646	.9563
Access_Accounting_Info	48	3.979	.9563
Section 3: Perception and Use of AI in Auditing			
Familiarity_AI_Auditing	48	2.771	1.0766
Frequency_AI_Use	48	2.500	1.0106
AI_Improves_Accuracy	48	1.792	.8742
AI_Detects_Fraud	48	3.354	.6681
AI_Increases_Efficiency	48	3.396	.6760
AI_Reduces_Workload	48	3.563	.7118
Confidence_AI_Use	48	3.521	.9891
Org_Provides_AI_Resources	48	3.250	1.0000
Training_AI_Audit	48	1.833	1.0383
Section 4: Benefits of AI in Internal Auditing			
AI_Increases_Efficiency	48	1.604	.8440
AI_Improves_Data_Accuracy	48	3.688	.7192
AI_Enhances_Fraud_Detection	48	3.542	.6510
AI_Supports_Decision_Making	48	3.583	.6790
AI_Reduces_Human_Error	48	3.563	.7693
AI_Assists_Data_Analysis	48	3.625	.7033
AI_Transforms_Accounting_Info_Use	48	3.833	.7244
Section 5: Challenges and Concerns with AI in Auditing			
AI_Data_Privacy_Concern	48	2.438	1.0897
AI_Ethical_Concern	48	3.500	.9453
AI_Lack_Guidelines	48	3.417	.7945
AI_Tool_Complexity	48	4.396	.8184
AI_Cost_Barrier	48	3.667	.9528
AI_Reduces_Human_Auditors	48	3.458	1.0306
AI_Integration_Challenge	48	2.875	1.2484
Section 6: Future Perspectives on AI in Public Sector Auditing			
AI_Essential_Next_5_Years	48	3.646	1.1011
AI_Benefits_Outweigh_Drawbacks	48	3.271	1.0051
AI_Creates_New_Roles	48	3.417	.7672
AI_Requires_Continuous_Learning	48	3.479	.8503
Optimism_AI_Public_Auditing	48	4.083	.6469
AI_Impact_Public_Auditing	48	3.625	.9368

(Source: Author's calculations)

Section 2: Use of Accounting Information in Auditing

The findings indicate that internal auditors frequently use accounting information in their auditing activities, with a mean score of 3.625. This suggests that accounting data is an integral part of the auditing process, though some variation in frequency exists. Additionally, the perception of accounting information as essential for auditing recorded a mean score of (3.104), indicating that while many auditors recognize its importance, some may not view it as indispensable.

The role of accounting information in improving transparency was strongly affirmed, with a high mean score of 4.229. Similarly, the reliance of audit reports on accounting information was emphasized, with a mean of (4.271), demonstrating the fundamental role of financial data in reporting processes. In terms of training, auditors reported a moderate level of training in the use of accounting data, with a mean score of 3.958.

When assessing the accuracy of accounting data, the responses yielded a mean score of 3.646, indicating a general trust in data reliability but also pointing to possible concerns about inconsistencies or errors. Moreover, access to accounting information was reported with a mean score of 3.979, reflecting relatively good availability of financial records within public sector auditing.

Section 3: Perception and Use of AI in Auditing

The level of familiarity with AI in auditing was relatively low, with a mean score of 2.771, indicating that many auditors are still in the early stages of understanding AI's applications. Furthermore, the frequency of AI use in auditing was reported at 2.500, reinforcing the notion that AI adoption remains limited in practice.

Auditors expressed skepticism regarding AI's role in improving accuracy, with a mean score of 1.792. In contrast, AI's potential to detect fraud was acknowledged, with a mean of (3.354). The perceived ability of AI to increase efficiency received a mean score of 3.396, while its potential to reduce workload scored slightly higher at 3.563.

Confidence in using AI tools was moderate, with a mean score of 3.521, suggesting that while some auditors feel comfortable with AI applications, others may still lack confidence. However, organizational provision of AI-related resources was reported at (3.250), indicating that while some institutions provide support, there is still room for improvement. Additionally, the availability of training on AI in auditing received a low mean score of 1.833, highlighting the need for more education and skill-building initiatives.

Section 4: Benefits of AI in Internal Auditing

The perception of AI as an efficiency-enhancing tool was low, with a mean score of 1.604, suggesting that many auditors are not yet convinced of its operational benefits. However, AI was seen as improving data accuracy, with a mean score of (3.688), and as enhancing fraud detection, with a mean of (3.542).

AI's role in supporting decision-making received a mean score of 3.583, while its potential to reduce human error was acknowledged with a mean of 3.563. The ability of AI to assist with data analysis was also rated positively, with a mean score of 3.625. Additionally, AI's transformative impact on the use of accounting information was rated relatively high, with a mean of 3.833, indicating that many auditors recognize its potential to redefine traditional processes.

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Section 5: Challenges and Concerns with AI in Auditing
Concerns about AI's impact on data privacy were notable, with a mean score of 2.438, reflecting apprehensions about security risks. Ethical concerns surrounding AI usage were moderately high, with a mean of 3.500, indicating awareness of potential biases and ethical dilemmas.

A lack of clear guidelines for AI adoption was identified as a significant challenge, with a mean score of 3.417. Additionally, the complexity of AI tools emerged as a major barrier, receiving the highest mean score in this section at 4.396, suggesting that many auditors find AI systems difficult to implement and use.

The cost of AI adoption was also seen as a barrier, with a mean score of 3.667, reinforcing the notion that financial constraints hinder widespread AI integration. Concerns about AI replacing human auditors were moderately high, with a mean score of 3.458, suggesting that some auditors fear job displacement. Lastly, challenges related to AI integration received a mean score of 2.875, indicating that while some progress has been made, integrating AI into existing audit processes remains a hurdle.

Section 6: Future Perspectives on AI in Public Sector Auditing
Internal auditors generally perceived AI as essential in the next five years, with a mean score of 3.646, signaling an expectation of increased reliance on AI. However, the belief that AI's benefits outweigh its drawbacks received a moderate mean score of 3.271, indicating some lingering skepticism.

The potential of AI to create new roles within auditing was recognized, with a mean score of 3.417, highlighting expectations of evolving job functions. The necessity for continuous learning in AI auditing received a mean score of 3.479, emphasizing the need for ongoing education and skill development. Optimism regarding AI's role in public sector auditing was relatively high, with a mean score of 4.083, reflecting positive attitudes toward future advancements. Lastly, the perceived impact of AI on public auditing was recorded at 3.625, demonstrating a general consensus that AI will play a transformative role in the field.

4.2. ANOVA
The ANOVA analysis (Appendix 1) reveals several statistically significant differences in responses based on the type of institution where internal auditors are employed.

In the domain of accounting information use, significant differences were observed for the perception that accounting improves transparency ($p=.004$), the necessity of training in accounting data ($p = .016$), and the perceived accuracy of accounting data ($p=.004$). These findings suggest that auditors from different institutional backgrounds may have varying experiences and levels of confidence in the reliability and role of accounting information in auditing.

Regarding AI-related training and resources, a statistically significant difference was found in access to AI training ($p = .002$), indicating that some institutions provide more structured AI-related training opportunities than others. Additionally, perceptions of AI's ethical concerns ($p = .028$) and the lack of clear guidelines for AI use ($p = .011$) were significantly different among

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auditors from different institutions. These results highlight the potential discrepancies in institutional approaches to AI governance and ethical considerations in auditing.

Furthermore, the belief that AI requires continuous learning ($p = .003$) also varied significantly among respondents, implying that institutional differences might shape attitudes toward AI adoption and skill development in auditing.

4.3. Spearman's rank correlation coefficient

Spearman's rank correlation coefficient between familiarity with AI auditing and the frequency of AI use revealed a significant positive correlation ($r=.307$, $p=.034$). This suggests that individuals who are more familiar with AI in auditing tend to use it more frequently. Additionally, significant correlations were observed with other variables. For instance, the frequency of AI use showed a strong positive correlation with the perception that AI improves accuracy ($r=.597$, $p<.001$) and with the provision of AI-related resources by organizations ($r=.457$, $p=.001$). Conversely, familiarity with AI auditing was negatively correlated with the perceived complexity of AI tools ($r=-.411$, $p=.004$), indicating that those who find AI tools more complex tend to be less familiar with AI auditing. These findings highlight the importance of training and organizational support in fostering both AI familiarity and its adoption in auditing practices.

4.4. Descriptive analysis of multiple-choice questions

Finally, Table 4 presents the results of the descriptive analysis of the two multiple-choice questions.

Table 4: Descriptive analysis of multiple-choice questions

Which AI tools do you currently use in auditing?	**Responses**	**Percent**
☐ ChatGPT	2	4.17%
☐ Data Analytics	14	29.17%
☐ Anomaly detection	3	6.25%
☐ None	32	66.67%
What are the main barriers to AI implementation in your work?	**Responses**	**Percent**
☐ Lack of training	29	60.42%
☐ High cost	16	33.33%
☐ Data privacy concerns	14	29.17%
☐ Complexity of AI tools	11	22.92%
☐ Resistance to change	6	12.50%
☐ Lack of support from management	17	35.42%

(Source: Author's calculations)

The responses indicate that AI adoption in auditing remains limited, with the majority of respondents (66.7%) reporting that they do not use any AI tools. Among those who do, data analytics tools (29.2%) are the most commonly utilized, followed by anomaly detection (6.3%) and ChatGPT (4.2%), suggesting that AI applications are primarily used for data-driven insights rather than language-based support.

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Regarding the barriers to AI implementation, the lack of training (60.4%) is the most significant challenge, highlighting the need for skill development in AI technologies. Other major obstacles include lack of support from management (35.4%), high costs (33.3%), and data privacy concerns (29.2%), which reflect both organizational and financial constraints. Additionally, the complexity of AI tools (22.9%) and resistance to change (12.5%) further hinder adoption, indicating that both technical and cultural factors influence AI integration in auditing practices.

5. CONCLUSION

This study provides valuable insights into the current use of accounting information and AI in internal auditing within the public sector. The findings confirm that accounting information remains a cornerstone of auditing practice, especially in enhancing transparency and informing audit reports. However, perceptions about its indispensability vary, and there is a moderate level of training and trust in the reliability of accounting data.

In contrast, the use and understanding of AI in auditing are still in their infancy. Although auditors recognize AI's potential in areas such as fraud detection, decision-making, and reducing human error, actual adoption remains limited. The low frequency of AI use and training, combined with concerns about complexity, cost, and ethical considerations, underscores significant barriers to integration. Importantly, auditors who are more familiar with AI tend to use it more frequently, suggesting that targeted training and institutional support could accelerate adoption.

The analysis also reveals notable differences between institutions regarding access to training, ethical concerns, and perceptions of AI’s impact - highlighting the need for standardized guidelines and broader capacity-building efforts. Most auditors believe that AI will become essential in the near future, yet their optimism is tempered by the challenges they currently face.

Based on the current state identified in this study, i.e., low familiarity with AI tools, infrequent training, and barriers related to complexity, cost, and uneven institutional support, internal audit units should: (i) start with low-risk pilots using currently familiar analytics (e.g., exception and anomaly detection) on high-volume, high-risk processes; (ii) adopt a basic AI governance pack (usage policy, privacy checklist, bias/ethics notes, documentation templates) and designate an “AI champion” per unit; (iii) deliver short, role-based training linked to live audit tasks and pair it with supervised practice; (iv) improve data readiness through standardized data extracts and secure access protocols; (v) pool procurement and share models/dashboards across peer institutions to reduce costs and duplication; and (vi) monitor adoption with simple KPIs (share of audits using analytics, exception rates, rework/clarification cycles) and review lessons learned.

The results are derived from a cross-sectional, self-reported survey of public-sector internal auditors in North Macedonia with a modest sample size, which may limit generalizability. The constructs emphasize perceptions rather than observed behavior, and the design lacks longitudinal tracking of AI adoption over time. Future work should broaden the sample, integrate qualitative evidence, and follow AI-enabled audit workflows longitudinally to capture capability maturation and impact.

Ultimately, for AI to fulfill its transformative promise in public sector auditing, investments in education, clearer policies, and supportive organizational cultures will be essential. Bridging the gap between current practices and future potential will require a strategic, inclusive, and well-resourced approach to digital innovation in audit processes.

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Appendix 1: ANOVA

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Frequency_Accounting_Info_Use	Between Groups	11.678	3	3.893	2.694	.057
	Within Groups	63.572	44	1.445		
	Total	75.250	47			
Accounting_Essential_Audit	Between Groups	7.891	3	2.630	1.975	.132
	Within Groups	58.588	44	1.332		
	Total	66.479	47			
Accounting_Improves_Transparency	Between Groups	4.724	3	1.575	5.037	.004
	Within Groups	13.755	44	.313		
	Total	18.479	47			
Audit_Reports_Rely_Accounting	Between Groups	3.597	3	1.199	2.411	.080
	Within Groups	21.882	44	.497		
	Total	25.479	47			
Training_Accounting_Data	Between Groups	8.662	3	2.887	3.820	.016
	Within Groups	33.255	44	.756		
	Total	41.917	47			
Accounting_Data_Accuracy	Between Groups	11.233	3	3.744	5.190	.004
	Within Groups	31.746	44	.722		
	Total	42.979	47			
Access_Accounting_Info	Between Groups	2.566	3	.855	.931	.434
	Within Groups	40.413	44	.918		
	Total	42.979	47			
Familiarity_AI_Auditing	Between Groups	6.761	3	2.254	2.078	.117
	Within Groups	47.718	44	1.085		
	Total	54.479	47			
Frequency_AI_Use	Between Groups	4.460	3	1.487	1.502	.227
	Within Groups	43.540	44	.990		
	Total	48.000	47			
AI_Improves_Accuracy	Between Groups	1.238	3	.413	.524	.668
	Within Groups	34.679	44	.788		
	Total	35.917	47			
AI_Detects_Fraud	Between Groups	3.058	3	1.019	2.502	.072
	Within Groups	17.922	44	.407		
	Total	20.979	47			
AI_Increases_Efficiency	Between Groups	2.007	3	.669	1.512	.225
	Within Groups	19.472	44	.443		
	Total	21.479	47			
AI_Reduces_Workload	Between Groups	3.376	3	1.125	2.423	.078
	Within Groups	20.437	44	.464		
	Total	23.813	47			
Confidence_AI_Use	Between Groups	5.327	3	1.776	1.922	.140
	Within Groups	40.652	44	.924		

	Total	45.979	47			
Org_Provides_AI_Resources	Between Groups	4.421	3	1.474	1.523	.222
	Within Groups	42.579	44	.968		
	Total	47.000	47			
Training_AI_Audit	Between Groups	14.365	3	4.788	5.804	.002
	Within Groups	36.302	44	.825		
	Total	50.667	47			
AI_Increases_Efficiency	Between Groups	3.129	3	1.043	1.512	.225
	Within Groups	30.350	44	.690		
	Total	33.479	47			
AI_Improves_Data_Accuracy	Between Groups	1.066	3	.355	.673	.573
	Within Groups	23.246	44	.528		
	Total	24.313	47			
AI_Enhances_Fraud_Detection	Between Groups	2.480	3	.827	2.086	.116
	Within Groups	17.437	44	.396		
	Total	19.917	47			
AI_Supports_Decision_Making	Between Groups	2.480	3	.827	1.896	.144
	Within Groups	19.187	44	.436		
	Total	21.667	47			
AI_Reduces_Human_Error	Between Groups	2.955	3	.985	1.744	.172
	Within Groups	24.857	44	.565		
	Total	27.813	47			
AI_Assists_Data_Analysis	Between Groups	1.750	3	.583	1.194	.323
	Within Groups	21.500	44	.489		
	Total	23.250	47			
AI_Transforms_Accounting_Info_Use	Between Groups	3.301	3	1.100	2.266	.094
	Within Groups	21.366	44	.486		
	Total	24.667	47			
AI_Data_Privacy_Concern	Between Groups	2.407	3	.802	.661	.580
	Within Groups	53.406	44	1.214		
	Total	55.813	47			
AI_Ethical_Concern	Between Groups	7.745	3	2.582	3.316	.028
	Within Groups	34.255	44	.779		
	Total	42.000	47			
AI_Lack_Guidelines	Between Groups	6.570	3	2.190	4.172	.011
	Within Groups	23.096	44	.525		
	Total	29.667	47			
AI_Tool_Complexity	Between Groups	2.301	3	.767	1.156	.337
	Within Groups	29.179	44	.663		
	Total	31.479	47			
AI_Cost_Barrier	Between Groups	3.801	3	1.267	1.434	.246
	Within Groups	38.866	44	.883		
	Total	42.667	47			
AI_Reduces_Human_Auditors	Between Groups	4.794	3	1.598	1.558	.213
	Within Groups	45.123	44	1.026		
	Total	49.917	47			

AI_Integration_Challenge	Between Groups	6.063	3	2.021	1.324	.279
	Within Groups	67.187	44	1.527		
	Total	73.250	47			
AI_Essential_Next_5_Years	Between Groups	7.090	3	2.363	2.084	.116
	Within Groups	49.889	44	1.134		
	Total	56.979	47			
AI_Benefits_Outweigh_Drawbacks	Between Groups	4.153	3	1.384	1.406	.254
	Within Groups	43.326	44	.985		
	Total	47.479	47			
AI_Creates_New_Roles	Between Groups	2.837	3	.946	1.676	.186
	Within Groups	24.829	44	.564		
	Total	27.667	47			
AI_Requires_Continuous_Learning	Between Groups	9.224	3	3.075	5.465	.003
	Within Groups	24.755	44	.563		
	Total	33.979	47			
Optimism_AI_Public_Auditing	Between Groups	1.877	3	.626	1.547	.216
	Within Groups	17.790	44	.404		
	Total	19.667	47			
AI_Impact_Public_Auditing	Between Groups	6.571	3	2.190	2.779	.052
	Within Groups	34.679	44	.788		
	Total	41.250	47			

Appendix 2: Spearman's rank correlation coefficient

		Familiarity_AI_Auditing	Frequency_AI_Use
Frequency_Accounting_Info_Use	Correlation Coefficient	-.150	-.422**
	Sig. (2-tailed)	.310	.003
	N	48	48
Accounting_Essential_Audit	Correlation Coefficient	.416**	.388**
	Sig. (2-tailed)	.003	.006
	N	48	48
Accounting_Improves_Transparency	Correlation Coefficient	.169	-.001
	Sig. (2-tailed)	.252	.997
	N	48	48
Audit_Reports_Rely_Accounting	Correlation Coefficient	.246	-.055
	Sig. (2-tailed)	.092	.709
	N	48	48
Training_Accounting_Data	Correlation Coefficient	.472**	.320*
	Sig. (2-tailed)	.001	.027
	N	48	48
Accounting_Data_Accuracy	Correlation Coefficient	.206	.061
	Sig. (2-tailed)	.160	.680
	N	48	48
Access_Accounting_Info	Correlation Coefficient	.471**	.154
	Sig. (2-tailed)	.001	.296
	N	48	48
Familiarity_AI_Auditing	Correlation Coefficient	1.000	.307*
	Sig. (2-tailed)		.034
	N	48	48
Frequency_AI_Use	Correlation Coefficient	.307*	1.000
	Sig. (2-tailed)	.034	
	N	48	48
AI_Improves_Accuracy	Correlation Coefficient	.273	.597**
	Sig. (2-tailed)	.061	.000
	N	48	48
AI_Detects_Fraud	Correlation Coefficient	-.185	.016
	Sig. (2-tailed)	.208	.912
	N	48	48
AI_Increases_Efficiency	Correlation Coefficient	.007	.169
	Sig. (2-tailed)	.961	.252
	N	48	48
AI_Reduces_Workload	Correlation Coefficient	.095	.038
	Sig. (2-tailed)	.522	.797
	N	48	48
Confidence_AI_Use	Correlation Coefficient	-.029	-.093
	Sig. (2-tailed)	.847	.528
	N	48	48
Org_Provides_AI_Resources	Correlation Coefficient	.002	.457**
	Sig. (2-tailed)	.991	.001
	N	48	48

Training_AI_Audit	Correlation Coefficient	-.078	.017
	Sig. (2-tailed)	.599	.906
	N	48	48
AI_Increases_Efficiency	Correlation Coefficient	.260	.278
	Sig. (2-tailed)	.074	.055
	N	48	48
AI_Improves_Data_Accuracy	Correlation Coefficient	.047	-.222
	Sig. (2-tailed)	.752	.130
	N	48	48
AI_Enhances_Fraud_Detection	Correlation Coefficient	-.291*	-.264
	Sig. (2-tailed)	.045	.070
	N	48	48
AI_Supports_Decision_Making	Correlation Coefficient	-.119	-.106
	Sig. (2-tailed)	.422	.473
	N	48	48
AI_Reduces_Human_Error	Correlation Coefficient	-.141	-.043
	Sig. (2-tailed)	.339	.771
	N	48	48
AI_Assists_Data_Analysis	Correlation Coefficient	-.062	-.233
	Sig. (2-tailed)	.678	.112
	N	48	48
AI_Transforms_Accounting_Info_Use	Correlation Coefficient	-.025	.146
	Sig. (2-tailed)	.868	.322
	N	48	48
AI_Data_Privacy_Concern	Correlation Coefficient	.084	.296*
	Sig. (2-tailed)	.570	.041
	N	48	48
AI_Ethical_Concern	Correlation Coefficient	-.276	-.040
	Sig. (2-tailed)	.058	.785
	N	48	48
AI_Lack_Guidelines	Correlation Coefficient	-.217	.066
	Sig. (2-tailed)	.138	.657
	N	48	48
AI_Tool_Complexity	Correlation Coefficient	-.411**	-.164
	Sig. (2-tailed)	.004	.266
	N	48	48
AI_Cost_Barrier	Correlation Coefficient	-.188	-.137
	Sig. (2-tailed)	.200	.352
	N	48	48
AI_Reduces_Human_Auditors	Correlation Coefficient	.039	-.142
	Sig. (2-tailed)	.792	.336
	N	48	48
AI_Integration_Challenge	Correlation Coefficient	-.162	-.269
	Sig. (2-tailed)	.271	.064
	N	48	48
AI_Essential_Next_5_Years	Correlation Coefficient	.077	-.114
	Sig. (2-tailed)	.603	.440
	N	48	48
AI_Benefits_Outweigh_Drawbacks	Correlation Coefficient	-.095	-.208
	Sig. (2-tailed)	.522	.156

	N	48	48
AI_Creates_New_Roles	Correlation Coefficient	.029	-.157
	Sig. (2-tailed)	.843	.286
	N	48	48
AI_Requires_Continuous_Learning	Correlation Coefficient	.008	.067
	Sig. (2-tailed)	.956	.649
	N	48	48
Optimism_AI_Public_Auditing	Correlation Coefficient	-.188	-.068
	Sig. (2-tailed)	.201	.645
	N	48	48
AI_Impact_Public_Auditing	Correlation Coefficient	-.181	.083
	Sig. (2-tailed)	.219	.574
	N	48	48

Appendix 3: Case summaries

		Frequency_Accounting_Info_Use	Accounting_Essential_Audit (Likert 1–5)	Accounting_Improves_Transparency (Likert 1–5)	Audit_Reports_Rely_Accounting (Likert 1–5)	Training_Accounting_Data (Likert 1–5)	Accounting_Data_Accuracy (Likert 1–5)	Access_Accounting_Info (Likert 1–5)	Familiarity_AI_Auditing	Frequency_AI_Use	AI_Improves_Accuracy (Likert 1–5)	AI_Detects_Fraud (Likert 1–5)	AI_Increases_Efficiency (Likert 1–5)
Total	N	14	14	14	14	14	14	14	14	14	14	14	14
	Mean	4.214	3.071	4.571	4.500	4.071	3.714	4.286	3.286	2.571	1.929	3.429	3.500
	S.D	1.2514	1.2067	.5136	.7596	.7300	.9945	.8254	.9945	1.2839	.6157	.5136	.5189
Total	N	16	16	16	16	16	16	16	16	16	16	16	16
	Mean	3.688	3.313	4.313	4.438	4.313	4.000	4.000	2.625	2.750	1.625	3.063	3.125
	Std. Deviation	1.2500	1.0145	.4787	.5123	.4787	.8165	.8165	1.0247	.7746	.7188	.6801	.7188
Total	N	9	9	9	9	9	9	9	9	9	9	9	9
	Mean	2.778	3.556	3.667	4.111	4.000	3.889	3.778	2.778	2.556	2.000	3.333	3.444
	Std. Deviation	1.0929	1.3333	.8660	.7817	1.0000	.7817	.9718	1.2019	1.0138	1.0000	.7071	.5270
Total	N	9	9	9	9	9	9	9	9	9	9	9	9
	Mean	3.444	2.333	4.111	3.778	3.111	2.667	3.667	2.222	1.889	1.667	3.778	3.667
	Std. Deviation	1.1304	1.1180	.3333	.8333	1.3642	.7071	1.3229	.9718	.7817	1.3229	.6667	.8660
Total	N	48	48	48	48	48	48	48	48	48	48	48	48
	Mean	3.625	3.104	4.229	4.271	3.958	3.646	3.979	2.771	2.500	1.792	3.354	3.396
	Std. Deviation	1.2653	1.1893	.6270	.7363	.9444	.9563	.9563	1.0766	1.0106	.8742	.6681	.6760

		AI_Reduces_Workload (Likert 1–5)	Confidence_AI_Use (Likert 1–5)	Org_Provides_AI_Resources (Likert 1–5)	Training_AI_Audit (Likert 1–5)	AI_Increases_Efficiency (Likert 1–5)	AI_Improves_Data_Accuracy (Likert 1–5)	AI_Enhances_Fraud_Detection (Likert 1–5)	AI_Support_Decision_Making (Likert 1–5)	AI_Reduces_Human_Error (Likert 1–5)	AI_Assists_Data_Analysis (Likert 1–5)	AI_Transforms_Accounting_Info_Use (Likert 1–5)	AI_Data_Privacy_Concern (Likert 1–5)
Tot	N	14	14	14	14	14	14	14	14	14	14	14	14
	Mean	3.643	3.357	2.786	1.286	1.286	3.786	3.357	3.357	3.286	3.500	4.071	2.286

		al	Std. Deviation	.4972	.4972	1.1217	.4688	.4688	.4258	.4972	.6333	.7263	.5189	.7300	.8254
		Total	N	16	16	16	16	16	16	16	16	16	16	16	16
			Mean	3.250	3.688	3.500	1.750	1.563	3.500	3.500	3.625	3.500	3.500	3.813	2.688
			Std. Deviation	.9309	1.1383	.6325	.8563	.7274	.8165	.8165	.8062	.8165	.8165	.8342	.8732
		Total	N	9	9	9	9	9	9	9	9	9	9	9	9
			Mean	3.556	3.000	3.444	2.889	2.000	3.667	3.444	3.444	3.667	3.667	3.333	2.556
			Std. Deviation	.5270	1.4142	1.0138	1.4530	1.3229	.8660	.5270	.5270	.8660	.8660	.5000	1.1304
		Total	N	9	9	9	9	9	9	9	9	9	9	9	9
			Mean	4.000	4.000	3.333	1.778	1.778	3.889	4.000	4.000	4.000	4.000	4.000	2.111
			Std. Deviation	.5000	.5000	1.2247	.8333	.8333	.7817	.5000	.5000	.5000	.5000	.5000	1.6915
	Total	N		48	48	48	48	48	48	48	48	48	48	48	48
		Mean		3.563	3.521	3.250	1.833	1.604	3.688	3.542	3.583	3.563	3.625	3.833	2.438
		Std. Deviation		.7118	.9891	1.0000	1.0383	.8440	.7192	.6510	.6790	.7693	.7033	.7244	1.0897

				AI_Ethical_Concern (Likert 1–5)	**AI_Lack_Guidelines** (Likert 1–5)	**AI_Tool_Complexity** (Likert 1–5)	**AI_Cost_Barrier** (Likert 1–5)	**AI_Reduces_Human_Auditors** (Likert 1–5)	**AI_Integration_Challenge**	**AI_Essential_Next_5_Years** (Likert 1–5)	**AI_Benefits_Outweigh_Drawbacks** (Likert 1–5)	**AI_Creates_New_Roles** (Likert 1–5)	**AI_Requires_Continuous_Learning** (Likert 1–5)	**Optimism_AI_Public_Auditing** (Likert 1–5)	**AI_Impact_Public_Auditing**
		Total	N	14	14	14	14	14	14	14	14	14	14	14	14
			Mean	3.071	3.143	4.429	3.929	3.929	2.643	4.000	3.500	3.714	3.929	4.071	3.929
			Std. Deviation	1.0716	.6630	.7559	.8287	.8287	.7449	.6794	1.0190	.6112	.6157	.4746	.8287
		Total	N	16	16	16	16	16	16	16	16	16	16	16	16
			Mean	3.813	3.938	4.625	3.438	3.375	3.375	3.250	2.938	3.125	2.938	3.875	3.125
			Std. Deviation	.8342	.9287	.7188	1.0935	1.2042	1.5438	1.2383	.9287	.8851	.9287	.8062	.8851

		Total	N	9	9	9	9	9	9	9	9	9	9	9	9
			Mean	4.000	3.222	4.000	3.333	3.222	2.667	4.111	3.111	3.556	3.333	4.444	3.667
			Std. Deviation	1.0000	.4410	1.0000	.7071	.9718	1.3229	1.3642	1.1667	.5270	.5000	.5270	1.0000
		Total	N	9	9	9	9	9	9	9	9	9	9	9	9
			Mean	3.111	3.111	4.333	4.000	3.111	2.556	3.333	3.667	3.333	3.889	4.111	4.000
			Std. Deviation	.3333	.6009	.8660	1.0000	.9280	1.1304	.8660	.8660	.8660	.7817	.6009	.8660
	Total	N		48	48	48	48	48	48	48	48	48	48	48	48
		Mean		3.500	3.417	4.396	3.667	3.458	2.875	3.646	3.271	3.417	3.479	4.083	3.625
		Std. Deviation		.9453	.7945	.8184	.9528	1.0306	1.2484	1.1011	1.0051	.7672	.8503	.6469	.9368

Appendix 4: Survey: The Role of Accounting Information and AI in Public Sector Internal Auditing

Section 1: General Characteristics of Respondents

1. Job Title
    - [Open Text]
2. Years of Experience in Internal Auditing
    - Less than 2 years
    - 2–5 years
    - 6–10 years
    - More than 10 years
3. Educational Background
    - Accounting
    - Auditing
    - Finance
    - IT
    - Other (please specify): _______
4. Organization Type
    - Local government
    - National government
    - Government agency
    - State-owned enterprise
    - Other (please specify): _______

Section 2: Use of Accounting Information in Auditing

5. How frequently do you use accounting information in your internal audit work? (1 = Never, 5 = Always)
6. To what extent do you agree with the following statements? (1 = Strongly Disagree, 5 = Strongly Agree)
    - Accounting information is essential for assessing financial health in public sector audits.
    - Accounting information helps improve accountability and transparency in my audit work.
    - My audit reports rely heavily on accounting information for evidence-based findings.
    - I receive adequate training in interpreting accounting data for audits.
    - Accounting information provided by my organization is accurate and reliable.
    - Access to relevant accounting information is sufficient for my auditing needs.

Section 3: Perception and Use of Artificial Intelligence in Auditing

7. How familiar are you with AI tools in auditing? (1 = Not familiar, 5 = Very familiar)
8. How often do you use AI tools (e.g., data analytics, anomaly detection) in your auditing work? (1 = Never, 5 = Always)
9. To what extent do you agree with the following statements about AI in auditing? (1 = Strongly Disagree, 5 = Strongly Agree)
    - AI tools improve the accuracy of audit findings.
    - AI helps in detecting anomalies and fraud more effectively than traditional methods.
    - AI increases the efficiency of the audit process.
    - AI reduces the workload of internal auditors.
    - I am confident in my ability to use AI tools in audits.
    - My organization provides adequate resources for AI tools in auditing.
    - I receive sufficient training on how to apply AI in my audit work.
10. Which AI tools do you currently use in auditing? (Select all that apply)
    - Data analytics
    - Machine learning
    - Predictive modeling
    - Anomaly detection
    - Process automation

  - None
  - Other (please specify): ________

Section 4: Benefits of AI in Internal Auditing

11. How beneficial do you find AI in each of the following aspects of auditing? (1 = Not Beneficial, 5 = Highly Beneficial)
    - Increasing audit efficiency
    - Improving data accuracy and reliability
    - Enhancing fraud detection
    - Supporting evidence-based decision-making
    - Reducing human error
    - Assisting with complex data analysis
12. To what extent has AI transformed your approach to accounting information in auditing? (1 = Not at All, 5 = Completely)

Section 5: Challenges and Concerns with AI in Auditing

13. To what extent do you agree with the following statements about challenges with AI in auditing? (1 = Strongly Disagree, 5 = Strongly Agree)
    - I am concerned about data privacy and security when using AI tools.
    - The use of AI may compromise ethical standards in auditing.
    - There are insufficient guidelines for AI use in public sector auditing.
    - AI tools are too complex for effective use without extensive training.
    - The cost of AI technology is a barrier for its implementation in auditing.
    - AI might eventually reduce the role of human auditors.
14. How challenging do you find it to integrate AI into your audit practices? (1= Not challenging, 5= Extremely challenging)
15. What are the main barriers to AI implementation in your work? (Select all that apply)
    - Lack of training
    - High cost
    - Data privacy concerns
    - Complexity of AI tools
    - Resistance to change
    - Lack of support from management
    - Other (please specify): ________

Section 6: Future Perspectives on AI in Public Sector Auditing

16. To what extent do you agree with the following statements about the future of AI in auditing? (1 = Strongly Disagree, 5 = Strongly Agree)
    - AI will become essential in public sector auditing within the next five years.
    - The benefits of AI in auditing outweigh its potential drawbacks.
    - AI will create new roles and responsibilities for internal auditors.
    - AI will require continuous learning and adaptation by auditors.
    - I am optimistic about the role of AI in improving public sector auditing practices.
17. In your opinion, how likely is it that AI will significantly change the public sector auditing profession? (1 = Very unlikely, 5 = Very likely)
18. What additional support or resources would you find helpful for integrating AI into your auditing work?
    - [Open Text]

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