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ARTIFICIAL INTELLIGENCE ADOPTION IN ACCOUNTING INFORMATION SYSTEMS: DRIVERS, STRATEGIC IMPLICATIONS, AND ORGANIZATIONAL AGILITY

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ABSTRACT

The objective of the study to explores the adoption of Artificial Intelligence (AI) in Accounting Information Systems (AIS), focusing on its drivers, strategic implications, and impact on organizational agility. The study employs a quantitative approach with a sample of 250 professionals from different sectors, and the Technology–Organization–Environment (TOE) framework helps to investigate the ways in which internal assistance, external pressures, and technical preparedness affect the integration of AI. The findings reveal th growth of AI especially in fields like automated processes, predictive analytics, and fraud detection in organisations. Agility, flexibility, and innovation are greater in organizations with a robust IT infrastructure. The research also highlights the way AI is becoming more widely accepted for its potential to improve efficiency, decision-making, and change accounting procedures. The study tried to provide in depth understanding how AI-enabled AIS may function as an essential resource in the rapidly evolving business.

KEYWORDS: Accounting Information Systems, Accounting Information Systems, Technology–Organization–Environment (TOE) framework, AI adoption.

1. INTRODUCTION

The way businesses gather and use data to aid in decision-making has changed as a result of the use of Artificial intelligence (AI), in Planning, both financial and strategic decisions (Burström et al., 2021). BI solutions used commercial databases structured data to ddemonstration insights through static reports and pre examined dashboards (Spiess-Knafl, 2022). However, these traditional methods were not capable of real-time data processing and making advance dissection (Raoofi & Yasar, 2023). By using complicated analytics and machine learning, AI-powered BI systems have become a decisive facilitator for data-driven decision-making as firms function in more dynamic contexts (Kahreh et al., 2014). Businesses can gain a deeper understanding of their financial and strategic operations with the help of AI-driven tools which offer features like real-time data examination, identifying patterns, and self governing decision support system (Cheng et al., 2020).

The ability of AI is to combine both organized and unorganized data from diverse sources, including financial transactions, customer interactions, and external market reports (Zdravković et al., 2021). The unstructured data is arduous for traditional BI systems, which run on pre-formulated queries, to handle, which restricts to provide useful insights (Shahzad et al., 2023). On the other hand, AI-driven BI solutions use machine learning methods like the processing of natural languages (NLP), and reinforcement learning to help businesses find undiscovered trends and patterns in their statistics (Kahreh et al., 2014). These AI-based models ameliorate their prediction powers and help firms make better financial and strategic choices by continually learning and updating from both past and current information (Cheng et al., 2020).

Artificial intelligence (AI) technologies such as machine learning, natural language processing, had a considerable influence on the accounting industry (P et al., 2021). The growing interest of AI for financial reporting between accounting professionals and accounting firms indicates its influence (Saxena, 2022). Both small and larger organizations are embracing AI (Rawashdeh, 2023). The use of AI in finance is a revolutionary development that is changing the accounting industry rapdliy (Zhu et al., 2022). Artificial intelligence (AI) changing the context of accounting work, automating procedures, and reducing the burden on accountants to concentrate more on managerial and creative duties (Kariana Rosi & Mahyuni, 2021). Accounting professionals' and students' roles and responsibilities are being impacted by this shift to AI-based accounting, which is making the future of the field more real (Leitner-Hanetseder et al., 2021). Additionally, the growing use of AI in accounting is driving the creation of creative teaching strategies in universities to generate accounting professionals with AI expertise (Cai, 2022). The use of AI in the accounting sector presents both potential and problems as it develops further (Chouhan, 2020).

Accounting experts have different opinions on the convenient application of AI-based accounting techniquesand it resulted in the development of both new problems and solutions for pre-existing ones(Hohma et al., 2023). Concern about the moral and responsible use of AI in accounting is developing, and suggestions are being made to guarantee moral behavior when using AI in financial reporting, auditing, and accounting (Dara et al., 2022). The Objectives of the study are

* To identify the drivers that influence the aacquisition of Artificial Intelligence in Accounting Information Systems (AIS).
* To examine the extent of AI adoption and integration within Accounting Information Systems.
* To analyze the impression of AI adoption in AIS on organizational agility, including adaptability and innovation

2. LITERATURE REVIEW

Artificial intelligence (AI) has revolutionized the accounting industry by offering accomplished solutions for managing huge dataset, improving accuracy, and automating job performance (Rao & Shahbaz, 2021). Artificial intelligence (AI) is a branch of computer science which focuses on developing machine capacity to enlarge cognitive functions of the human brain, including comprehending information, tackling issues, and choice-making. AI is increasingly being incorporated into all areas of accounting, auditing, accounting for financial transactions, management accounting, and taxation (Wang et al., 2022). Together, these technologies renovate financial analysis capabilities, risk assessment operations, and fraud detection operations while speeding up data processing while maintaining compliance (Abdullah & Almaqtari, 2024 , Acemoglu & Restrepo, 2019). Financial report compilation, transaction reconciliation, and compliance supervision tasks are made easier by AI systems (Wach et al., 2023). By integrating automated technology and AI systems, organizations may provide bona fide financial reports while reducing human mistakes rates.

This, in turn, leads to improved cost management and external financial reporting (Tilahun, 2019). By amplify internal controls, facilitating performance evaluation, business transactions, improving the process of making decisions, (Onaolapo & Odetayo, 2013). The benefits of AIS include helping managers predict the future, improving company management, increasing economic and social benefits (Soudani, 2012). Furthermore, AIS aids in the production of non-financial as well as financial information that support performance assessment, supervision, evaluation, and resource allocation (Napitupulu, 2018). User satisfaction, top management support, and the system alignment with organizational activities are some of the factors that affect an effective implementation of AIS (Mkonya et al., 2018 ; Nguyen Thanh et al., 2020). Applying AIS successfully entails using the system for a variety of managerial tasks and making sure users are happy with the information that is produced (Hertatietal., 2021). Through effective utilization of AIS and alignment with organizational objectives and activities, businesses can optimize their operations and attain long-term growth. Innovation is the creation, and use of new concepts, procedures, goods, or services (Baregheh e tal., 2014). According to Damanpour et al. (2009), there are multifarious types of innovation, such as service, technological, administrative, product, process, business, and organizational innovations. These forms of innovation can be interdependent, meaning that choosing one type may influence choosing another (Bareghehetal., 2014). Innovation is a agglomerative process that involves several organizational decision-making stages rather than a one-time event. Several factors, including the degree of novelty, how novel it is, and to whom it is novel, must be taken into account when measuring innovation (Ellonen et al., 2008). Innovation extends beyond product and process innovation to include areas such as supply chain, marketing, services, organizational, and business model innovation (Baunsgaard & Clegg, 2015). Economic, environmental, political, social, and technological factors are some of the elements that can impact the success of innovation (Repo & Matschoss, 2019). Additionally, innovation is an elaborate process that involves gathering, analyzing, and producing knowledge (Filippi & Barattin, 2015).

2.1. Organizational Agility and AI-enabled AIS

Since the pandemic, the consideration of organizational fickleness have been more significant. This is because organizations demand new approaches to promote employee engagement, grow skills, and reform organizational performance in order to sustain competitiveness and execute on their plan (Appelbaum et al., 2017). Among the other pressures are the growing use and integration of technology, the application of artificial intelligence, and the employment of ienhanced levels of customer satisfaction, increased levels of consumer requirements, and increased investments in technology are all expected (Gerald et al., 2020). Another factor that has contributed to the need for higher organizational and strategic agility is the presence of market emulation, as well as legislative, political, and economic pressures. What is meant by the term "organizational agility" is "the capability to rapidly sense and conditioning to external and internal changes in order to produce episodic results in a profitable and cost-effective manner" (Yu & Guo, 2014). There is a strong connection between it and the implementation of the strategy of an organization. One of the advantages is that it assent for more flexibility in the assembly of resources, knowledge, processes, and skills, which in turn speeds up the learning process inside an organization so that it can keep up with increasing environmental change (Pallathadka et al., 2021).

2.2. Technology–organization–environment framework

The technology-organization-environment (TOE) framework is a framework that explains how technology is adopted in organizations and the way technological, organizational, and environmental contexts all affect the method of embracing and executing technological innovations. The Technology-Organization-Environment (TOE) framework was used , the organizational context in which it is used, and the adventitious environment in which the organization operates, affect the adoption and use of new technologies (Awa et al., 2017). It also concentrate on the specific behaviors of people inside the company, the framework emphasizes more fundamental characteristics, such as the organizational, technical, and environmental settings (Picoto et al., 2021). Psychological models like the technology acceptance model, the theory of reasoned action, and the theory of planned behavior should be used to comprehend technology adoption at the person level (Malik et al., 2021). Although the difference between person and organization level theories is widely acknowledged, it also makes it challenging to look into the higher level characteristics. Since material is only available from people working for the target organization, it is unavoidably skewed by the opinions of those people.

(Baker, 2011). Although the TOE framework has been utilized extensively, there hasn't been much theoretical advancement since its inception. Because the TOE framework is "too generic" and provides a great deal of flexibility in changing elements and metrics, there is no need to modify the theory itself, which explains why there hasn't been much progress (Gangwar et al., 2014). The idea does not provide competing reasons and fits in "too well" with other theories of technological adoption (Min et al., 2024).

Proposed Framework

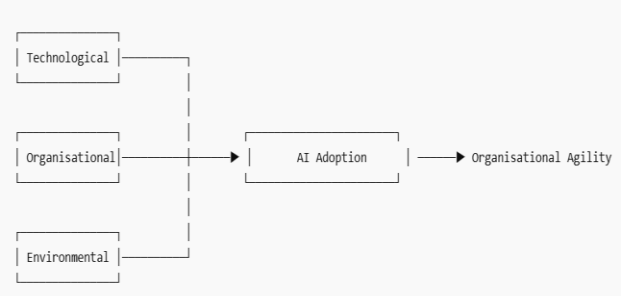

Figure 1: Proposed Framework.

3. METHODOLOGY

The study equipped quantitative approach to analyse the drivers of AIS and its impact on adoption of AI into businesses. The survey conducted through a structured questionnaire administered to accounting professionals, auditors, and IT managers working in different organizations that have implemented AI-enabled AIS. The survey instrument has three main constructs: key drivers of adoption (technological readiness, organizational support, and environmental pressures), the extent of AI integration into AIS (automation, predictive analytics, and real-time reporting), and organizational agility outcomes (adaptability, innovation, and competitive advantage). Sstratified random sampling method was employed to ensure representation from small, medium, and large enterprises, with a targeted sample size of 250 respondents. The questionnaire was used a 5-point Likert scale, and prior to distribution, it validated through expert review and pilot testing of 60 samples. Collected data was analyzed using SPSS where descriptive statistics will summarize the demographic profile and adoption levels, while inferential techniques such as correlation analysis and multiple regression will test the relationships between drivers, AI adoption, and organizational agility. Reliability will be assessed using Cronbach's alpha, and validity will be ensured through factor analysis. Ethical standards will be maintained by ensuring voluntary participation, confidentiality, and informed consent.

4. DATA ANALYSIS AND RESULTS

4.1. Demographic Analysis

Table 1. highlights the demographic profile of the survey across industries and roles. IT and service-based organizations lead the way, showing a strong inclination toward tech-driven transformation. Medium-sized firms dominate the sample, suggesting that mid-tier companies are actively exploring AI integration. Managers and accountants make up the majority of respondents, highlighting both strategic and operational interest in AI adoption. Interestingly, the experience level is well-balanced—40% of participants have over a decade of experience, while another 40% fall in the 5–10 year range. This mix of seasoned professionals and emerging talent adds depth to the insights. The presence of IT specialists also signals a growing technical readiness. Overall, the demographic spread reflects a healthy cross-section of organizations that are either preparing for or already engaging with AI in accounting, making the findings both relevant and representative of current industry dynamics.

Table 1: Demographic Analysis.

Demographic Category	Options	Count	Percentage
Organization Type	Manufacturing	50	20%
	Services	62	25%
	IT	75	30%
	Finance	50	20%
	Other	13	5%
Organization Size	Small	75	30%
	Medium	112	45%
	Large	63	25%
Respondent Role	Manager	88	35%
	Accountant	75	30%
	IT Specialist	63	25%
	Other	24	10%
Years of Experience	Less than 5	50	20%
	5–10	100	40%
	More than 10	100	40%

4.2. General AI Awareness

Table 2 shows the general awareness of AI among respondents is impressively high. Nearly 80% have heard about AI applications in accounting, and over 85% believe it can enhance efficiency—a clear sign that AI is no longer just a buzzword but a recognized tool for transformation. While 62% of organizations currently use AI tools, a notable 70% have considered adoption in the past two years, indicating growing strategic interest. The most striking insight is that 88% of respondents feel AI is essential for future competitiveness. This reflects a strong belief in AI's potential to reshape accounting processes, improve accuracy, and drive smarter decision-making.

However, the gap between awareness and actual implementation suggests that while the enthusiasm is there, some organizations may still be navigating barriers like cost, training, or infrastructure. Overall, the data reveals a forward-looking mindset and a readiness to embrace AI as a key driver of innovation in accounting.

Table 2. General Awareness

Question	Yes (Count)	No (Count)	Yes (%)	No (%)
Have you heard about AI applications in accounting?	195	55	78%	22%
Does your organization currently use any AI-based tools?	155	95	62%	38%
Do you believe AI can improve efficiency in accounting processes?	213	37	85%	15%
Has your organization considered AI adoption in the last 2 years?	175	75	70%	30%
Do you feel AI adoption in accounting is necessary for future competitiveness?	220	30	88%	12%

4.3. Descriptive Analysis

Table 3. Descriptive Analysis

Variables	Question	Mean	Standard deviaion
Technological Drivers	Sufficient IT infrastructure	2.96	1.45
	Reliable accounting data	2.93	1.39
	System compatibility with AI	2.84	1.4
	AI tools user-friendly	2.91	1.39
Organizational Drivers	Top management support	3	1.4
	Adequate financial resources	3.02	1.41
	Employees trained	3.02	1.39
	Culture promotes innovation	2.89	1.42
Environmental Drivers	Regulatory requirements	3.09	1.42
	Industry competition	3.03	1.38
	Client expectations	2.95	1.37
	Market trends influence adoption	3.04	1.41
AI Adoption	AI for data analysis	3.12	1.42
	AI for fraud detection	2.94	1.34
	AI for forecasting	2.71	1.41
	Automation increased	2.93	1.41
	Employees skilled in AI	2.96	1.34
Organizational Agility	Quick response to environment changes	3.02	1.42
	Better resource reallocation	2.98	1.42
	More innovative	3.09	1.31
	Stronger competitive advantage	3.02	1.42
	Improved adaptability	3	1.49

Table 3 demonstrate the descriptive analysis of the AI adoption survey reveals insightful patterns across five key dimensions: technological, organizational, environmental, adoption, and agility. Respondents rated their technological readiness moderately, with "Sufficient IT infrastructure" (mean = 2.96) and "AI tools user-friendly" (2.91) suggesting a fair level of preparedness, though "System compatibility with AI" scored slightly lower (2.84), indicating room for improvement. Organizational factors such as "Top management support" (3.00) and "Employees trained" (3.02) reflect a supportive internal environment, while "Culture promotes innovation" (2.89) hints at variability in fostering change. Environmental drivers like "Regulatory requirements" (3.09) and "Market trends" (3.04) show that external pressures are acknowledged, though "Client expectations" (2.95) suggest mixed perceptions. In terms of AI adoption, "AI for data analysis" leads with a mean of 3.12, showing strong engagement, while "AI for forecasting" lags at 2.71, possibly due to complexity or limited exposure. Organizational agility indicators are encouraging, with "More innovative" (3.09) and "Quick response to environment changes" (3.02) reflecting adaptability. Standard deviations across items range from 1.31 to 1.49, indicating moderate variability in responses. Overall, the data suggests that while organizations are aware of AI's potential and are making strides in adoption, there are disparities in infrastructure, culture, and strategic alignment that may influence the pace and success of implementation.

Reliability Analysis

Table 4: Reliability Analysis.

Section	Cronbach's Alpha	Interpretation
Technological Drivers	0.81	Good reliability
Organizational Drivers	0.78	Acceptable reliability
Environmental Drivers	0.74	Acceptable reliability
AI Adoption	0.83	Good reliability
Organizational Agility	0.85	Excellent reliability

Table 4 the reliability analysis of AI adoption survey reveals a strong foundation for measuring key constructs. Cronbach's Alpha, a widely accepted metric for internal consistency, shows that each section of your survey is performing well. Technological Drivers scored 0.81, indicating that respondents consistently interpreted questions about IT infrastructure, system compatibility, and user-friendliness. Organizational Drivers followed closely

with 0.78, suggesting that items related to leadership support, financial resources, and training are aligned and coherent. Environmental Drivers, with an alpha of 0.74, show acceptable reliability—respondents had a shared understanding of external pressures like regulations and market trends. AI Adoption scored 0.83, reflecting a solid internal consistency in how participants rated their use of AI for tasks like forecasting and fraud detection. Most impressively, Organizational Agility reached 0.85, demonstrating excellent reliability. This means that items measuring adaptability, innovation, and responsiveness are tightly interrelated. Overall, these scores confirm that your survey sections are well-constructed and reliable. They provide confidence that the data collected truly reflects the underlying dimensions of AI readiness and impact in accounting environments.

4.4. Correlation Analysis

Table 5: Correlation Analysis.

	Tech_Score	Org_Score	Env_Score	AI_Score	Agility_Score
Tech_Score	1	-0.001	0.031	-0.102	-0.005
Org_Score	-0.001	1	0.052	0.055	-0.011
Env_Score	0.031	0.052	1	-0.03	-0.136
AI_Score	-0.102	0.055	-0.03	1	-0.03
Agility_Score	-0.005	-0.011	-0.136	-0.03	1

Table 5. highlights the correlation between the variables and provides detailed insights into how different drivers related to organizational agility in the context of AI adoption. The range of correlation ranges between two variables from -1 (perfect negative) to +1 (perfect positive). In this matrix, most correlations are weak, suggesting limited direct associations. For instance, Technological Drivers and Organizational Drivers show virtually less correlation (-0.001), indicating that having strong IT infrastructure doesn't necessarily align with internal support systems. Environmental Drivers have a negative correlation with Organizational Agility (-0.136), implying that external pressures like regulations or market trends may hinder agility rather than enhance it. AI Adoption also shows a weak negative correlation with agility (-0.030), which could suggest that simply using AI tools doesn't automatically translate into more adaptive organizations. As none of the drivers show strong positive relationships with agility, highlighting a potential gap between technology implementation and strategic responsiveness.

5. LIMITATIONS AND FUTURE RESEARCH DIRECTION

The study tried to cover all the aspects but still there are some limitations. First, the findings may not be as broadly applicable as they may be since the evidence was gathered from a specific nation and industrial environment. Using unidentified surveys raises the possibility of bias since participants can have different interpretations related to AI. Ffuture study can explore to broadening its application to include assessments across different industries and nations. Furthermore it could comprise case studies and interviews to understand the deepness of topic. Llongitudinal research can also be perform to check the long-term effects regarding competence and agility, be performed to get the better results in long term. Iinvestigating certain AI technologies—such as automated robot processes or natural language processing—and how they bring value to accounting duties can be done.

6. CONCLUSION

A digital transformation in businesses how they handle financial data, discriminate irregularities, and adapt artificial intelligent machines into accounting information systems. This research demonstrates that organizational factors, technical proficiency as well as external factors all influence the adoption of AI. Businesses are better equipped to use AI technologies for automated processes, identifying fraud, and prediction when they have better access to AI. The findings also demonstration how important it is to match AI projects with more general business goals in order to improve competitiveness, agility, and creativity in the business. The difference between knowledge and use of AI indicates that many businesses are still overcoming obstacle like cost, instructional materials, and network integration. As AI develops further, its use in administration is probably going to go below operational effectiveness and encompass real-time analytics and strategic decision patronage. In the end, a comprehensive strategy that incorporates software with social norms, authority, and a long-term aim is needed for effective adoption. Through achieving this, businesses can take full advantage of AI-powered AIS and set business up for sustainable achievement in an economy that is becoming more and more centered around data.

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APPENDIX

Demographics

(Please tick the appropriate option)

Organization Type:	☐ Manufacturing ☐ Services ☐ IT ☐ Finance ☐ Other
Organization Size:	☐ Small ☐ Medium ☐ Large
Respondent Role:	☐ Manager ☐ Accountant ☐ IT Specialist ☐ Other
Years of Experience:	☐ Less than 5 ☐ 5–10 ☐ More than 10

General AI Awareness (Yes/No Questions)

(Please circle one option for each)
Have you heard about Artificial Intelligence (AI) applications in accounting? Yes / No
Does your organization currently use any AI-based tools (in any department)? Yes / No
Do you believe AI can improve efficiency in accounting processes? Yes / No
Has your organization considered AI adoption in the last 2 years? Yes / No
Do you feel AI adoption in accounting is necessary for future competitiveness? Yes / No

A) Technological Drivers

1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Our organization has sufficient IT infrastructure to support AI-based accounting systems.	☐1 ☐2 ☐3 ☐4 ☐5
High-quality and reliable accounting data is available for AI applications.	☐1 ☐2 ☐3 ☐4 ☐5
Existing accounting systems are compatible with AI integration.	☐1 ☐2 ☐3 ☐4 ☐5
AI tools for accounting are perceived as user-friendly and effective.	☐1 ☐2 ☐3 ☐4 ☐5

B) Organizational Drivers

Top management strongly supports AI adoption in accounting.	☐1 ☐2 ☐3 ☐4 ☐5
Our organization allocates adequate financial resources for AI projects.	☐1 ☐2 ☐3 ☐4 ☐5
Employees are trained to use AI in accounting processes.	☐1 ☐2 ☐3 ☐4 ☐5
Our organizational culture promotes innovation and acceptance of new technologies.	☐1 ☐2 ☐3 ☐4 ☐5

C) Environmental Drivers

Regulatory requirements encourage AI adoption in accounting.	☐1 ☐2 ☐3 ☐4 ☐5
Industry competition motivates us to adopt AI tools in accounting.	☐1 ☐2 ☐3 ☐4 ☐5
Client expectations push us to adopt AI-enabled accounting systems.	☐1 ☐2 ☐3 ☐4 ☐5
Market trends and technological advancements influence our AI adoption decisions.	☐1 ☐2 ☐3 ☐4 ☐5

D) AI Adoption

AI is integrated into our accounting systems for data analysis and reporting.	☐1 ☐2 ☐3 ☐4 ☐5
Our organization uses AI tools for fraud detection and risk management.	☐1 ☐2 ☐3 ☐4 ☐5
AI applications are utilized for forecasting and decision support in accounting.	☐1 ☐2 ☐3 ☐4 ☐5
The level of automation in accounting processes has increased due to AI.	☐1 ☐2 ☐3 ☐4 ☐5
Our employees are trained and skilled in using AI-based accounting systems.	☐1 ☐2 ☐3 ☐4 ☐5

E) Organizational Agility

Our organization can quickly respond to changes in the business environment due to AI-enabled accounting systems.	☐1 ☐2 ☐3 ☐4 ☐5
AI adoption has improved our ability to reallocate resources effectively.	☐1 ☐2 ☐3 ☐4 ☐5
Our organization is more innovative due to AI integration in AIS.	☐1 ☐2 ☐3 ☐4 ☐5
AI adoption has strengthened our competitive advantage in the market.	☐1 ☐2 ☐3 ☐4 ☐5
Overall, AI adoption in AIS has enhanced our organizational adaptability.	☐1 ☐2 ☐3 ☐4 ☐5