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THE IMPACT OF AI-DRIVEN ACCOUNTING TECHNOLOGIES ON FINANCIAL PERFORMANCE: EVIDENCE FROM LISTED FINANCIAL COMPANIES IN JORDAN

Ibrahim AL-Radaideh[1], Mohannad Almajali[2], Almontaser Abdallah Qadorah[3], Zaid Tahat[4], Ahmad Alomari[5], Mohammad Ismail Alawamreh[5], Fawwaz Alrwabdah[7]

[1]Assistant Professor, Department of Finance, Faculty of Business, Amman Arab University, Amman, Jordan. Email: i.radaideh@aau.edu.jo
[2]Assistant Professor, Department of Finance, Faculty of Business, Amman Arab University, Amman, Jordan. Email: m.almajali@aau.edu.jo, https://orcid.org/0000-0001-6326-460X
[3]Assistant Professor, Department of Accounting, Faculty of Business, Amman Arab University, Amman, Jordan. Email: Aqadorah@aau.edu.jo, https://orcid.org/0000-0003-1295-1092
[4]Business School, University of Plymouth, UK. Email: Ztahatuk@gmail.com, https://orcid.org/0009-0007-2487-9338
[5] Department of Accounting, School of Management, Universiti Sains Malaysia, 11800 Gelugor, Penang, Malaysia. Email: ahmadalomari@student.usm.my
[6] Putra Business School, Universiti Putra Malaysia, Seri Kembangan, Malaysia. Email: Pbs22104001@grad.putrabs.edu.my
[7] Department of Accounting, School of Management, Universiti Sains Malaysia, 11800 Gelugor, Penang, Malaysia. Email: fawazrawabdeh88@yahoo.com

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Corresponding Author: Fawwaz Alrwabdah (fawazrawabdeh88@yahoo.com)

ABSTRACT

This paper investigates how the accounting technologies that are driven by artificial intelligence (AI) affect the financial performance of the financial companies that are listed in the Amman Stock Exchange (ASE) in the period of 2022-2025. With a panel sample of 96 financial companies, we examine the effects of AI use in accounting on the primary performance indicators such as return on assets (ROA), return on equity (ROE), operational efficiency, and quality in earnings. We find that AI-based accounting systems have a tremendous positive effect on financial performance, and adopters show an average ROA difference of 3.2% and ROE of 4.7% relative to non-adopters. The latter impacts are favorable to bigger organizations and those that are more prepared in digital infrastructure. We also record the changes in quality of audit, minimal accounting errors, and increased regulatory compliance among AI adopters. The research also adds to a growing body of research on the topic of digital transformation in accounting by not only providing empirical evidence on the topic of the understudied Middle East market but also has implications on how financial institutions should deal with technological disruption in emerging economies.

KEYWORDS: Artificial Intelligence, Accounting Automation, Financial Performance, Jordan, Emerging Markets.

1. INTRODUCTION

The significant progress of the artificial intelligence (AI) technologies has radically recalibrated business processes in any industry, and the accounting and financial reporting have been severely affected [1]. Machine learning algorithms, robotic process automation (RPA), natural language processing (NLP), and predictive analytics are the brightest examples of AI-based accounting systems that are going to change the usual methods of bookkeeping, financial analysis, audit operations, and compliance monitoring [2]. These technologies can provide real-time financial reporting, automation of transactions, smartness of anomalies, and better decision-making options that were once impossible with the traditional accounting information systems [3].

Although there is a current increase in the use of AI applications in accounting, there is a paucity of empirical studies that determine the actual effects of the use of these technologies on the organizational financial performance, especially in the emerging market setting [4]. Majority of the available research concentrates on developed economies, and there is a major gap of knowledge on adoption of AI, its implementation challenges, and its performance in the developing world, where the institutional structures, technological systems, and the regulatory conditions vary dramatically [5].

The application of AI in accounting is a promising topic to study, and Jordan offers an interesting case study. Being a developing nation with relatively developed financial system as a middle-income developing country, Jordan has highly sought digital transformation efforts with limited resources as it is characteristic to developing countries [6]. In 1999, an Amman Stock Exchange was created which currently has 96 financial institutions such as commercial banks, insurance companies, investment firms, and financial services providers that together constitute a large share of the national economy [7]. These organizations are under growing pressure to bring modernization in their accounting systems to comply with the international financial reporting standards (IFRS) and to improve efficiency in their operations and remain competitive in a fast-digitizing region market [8].

The current research is based on three main research questions: First, do the implementation of AI-based accounting technologies enhance the financial performance of listed financial companies in Jordan? Second, which performance aspects (profitability, efficiency, quality of earnings) are influenced the most by the implementation of AI? Third, do qualities of firms mediate AI adoption and financial performance?

Our study has a number of significant contributions. One, we present some of the initial detailed empirical studies of the AI-based accounting effects in a Middle Eastern emerging economy, which enriches the literature that is mostly Western-oriented. Second, we utilize a multi-dimensional performance framework which covers profitability, operational efficiency, and quality of earnings which provides a detailed insight into the impacts of AI on an organization. Third, we use longitudinal panel data in the period 2022-2025, the usage of which allows us to consider dynamic adoption trends and performance impact over time. Lastly, we take out major moderating variables that determine the success of AI implementation, and this offers practical implications to practitioners as well as policymakers in similar settings in the emerging economies.

The rest of this paper will be structured in the following way: Section 2 is a review of the existing literature and the development of our hypotheses. Section 3 outlines our data, variables and empirical methodology. Section 4 provides descriptive statistics and correlation analysis. In section 5 we report on our main empirical findings. Section 6 addresses implications, limitations and future research directions and Section 7 is a conclusion.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. AI-Driven Accounting Technologies: Conceptual Framework

The field of AI-driven accounting involves numerous technological tools and possibilities based on machine learning, natural language processing, computer vision, and automated decision-making to improve accounting tasks [9]. This is diverse and has applications in automated classification and recording of transactions, intelligent invoice processing, predictive cash flow analytics, fraud detection algorithms, automated financial statement preparation and AI-enhanced audit procedures [10].

The conceptual framework of appreciating the effects of AI in accounting is based on various fields. Information systems research focuses on the use of technology-organization-environment (TOE) models which articulate how technological advances generate value in terms of better information processing systems [11]. According to the agency theory, the increased surveillance and transparency provided through AI systems will decrease information asymmetry between the managers and the stakeholders [12]. The perspectives of resource-based view (RBV) place AI capabilities as strategic assets capable of creating sustainable competitive advantages in cases of their proper utilization [13].

The recent literature reports a number of ways of how AI-based accounting generates organizational value [14]. To begin with, by automating routine processes, labor costs and processing time are lowered enabling human accountants to concentrate on added value analytical processes. Second, AI algorithms enhance accuracy by reducing the error of the human during the data entry, calculations, and classification. Third, it has real-time processing facilities where decisions can be made based on the present financial data as opposed to historical data. Fourth, superior analytics reveal trends and insights that are not easily visible in the traditional means of analysis. Fifth, increased fraud controls and compliance monitoring minimises regulatory risks and related fines [15].

2.2. AI Adoption and Financial Performance

There is still a mixed and situation-specific empirical evidence on the effect of AI on the financial performance. Some of the studies show that there are positive relationships between AI adoption and profitability measures. A study on U.S. banks revealed that banks with AI-based credit scoring systems achieved a 15-20 percentage point decrease in the default rates and related net interest margin improvements [16]. An examination of European financial services companies recorded that AI implementers realized a 8-12% greater return on assets than the non- implementers in three years of execution [17].

Nonetheless, there are other studies that point to the implementation issues and conditional impacts. The multi-country study revealed that AI returns realized only following significant upfront investments and organizational restructuring and that many companies have gone through transitional periods of declining performance [18]. Studies of Asian markets indicated that institutional factors, regulatory settings and workforce competencies have a strong moderating impact on the performance of AI [19].

The connection between accounting with AI specifically and financial performance has not been considered as thoroughly. An analysis of fortune 500 firms revealed that firms that adopted automated accounting systems recorded 25 per cent faster financial close cycles and 30 per cent accounting errors [20]. A study of audit firms revealed that AI-enhanced audits increased the detection rates of material misstatements by 18 per cent and lowered the cost of the auditing by 18% [21].

Based on this literature, we propose:

H1: AI-driven accounting adoption is positively associated with financial performance among financial companies in Jordan.

2.3. Moderating Factors: Firm Size and Digital Readiness

Literature indicates that the success of AI implementation in different organizational settings is markedly different. The size of the firm is a key moderating factor because bigger firms tend to have higher financial capabilities to invest in technology, more advanced IT systems and specialized human resources to operate the more complex systems [22]. Smaller companies on the other hand might have resource limitations and implementation challenges that restrict the benefits of AI.

Stereotypical evidence demonstrates the existence of size-based disparity in technology adoption performance. Enterprise resource planning (ERP) systems studies have established that large companies achieved higher performance gains because of economies of scale and complimentary organizational strengths [23]. Research on the digitalization of the banking sector recorded that larger banks had a higher returns on technology investments than smaller banks [24].

Digital preparedness which indicates the quality of current IT infrastructure, employee digital capability, and corporate culture in relation to innovation also intermediates the success of technology adoption [25]. Companies that have established track records of digital foundation may integrate AI systems into the existing platform easier, develop and train their workforce faster and upgrade business operations easier [26].

We therefore hypothesize:

H2a: The positive relationship between AI-driven accounting adoption and financial performance is stronger for larger firms.

H2b: The positive relationship between AI-driven accounting adoption and financial performance is stronger for firms with higher digital infrastructure readiness.

2.4. AI and Operational Efficiency

In addition to profitability, AI-based accounting must result in an efficient functioning of the operation by automating the processes, minimizing the error rates, and allocating the resources more effectively [27]. Efficiency improvements are seen in the form of low operating expense ratios, expedited transaction process, reduced audit costs and asset utilization [28].

Empirical studies are supporting pieces of evidence. An analysis of the manufacturing companies revealed that automation of accounting tasks led to the decrease of the time of accounts payable processing time by 60% and accounts receivable collection time by 25% [29]. The studies of the financial institutions reported that AI-based reconciliation systems reduced the month-end close periods of 10-15 days to 3-5 days [30].

H3: AI-driven accounting adoption improves operational efficiency metrics among financial companies.

2.5. AI and Earnings Quality

The quality of earnings, which is a measure of the accuracy, reliability and informative nature of reported financial outcomes, is an important aspect of accounting system performance [31]. The AI-based systems must improve the quality of earnings by detecting anomalies better, minimizing measurement errors, and ensuring that accounting standards are more consistent [32].

The studies regarding audit technology indicate that AI devices significantly enhance the accuracy of financial statements. Researchers discovered that machine learning algorithms identify any irregularities in accounts with 85-90 percent accuracy as opposed to 6070 percent when using traditional sampling techniques [33]. Internal control systems that are powered with AI have been demonstrated to lower the frequency of restatements by about 40% [34].

H4: AI-driven accounting adoption enhances earnings quality among financial companies.

3. RESEARCH METHODOLOGY

3.1. Sample and Data Collection

The sample that we are going to use is the list of all financial firms listed on the Amman Stock Exchange (ASE) as of December 31, 2021, such as commercial banks, insurance companies, investment firms, and diversified financial services providers. Our final sample size is 96 companies, which we will observe every year between 2022 and 2025 to get 384 firm-years after removing firms that did not provide complete data or delisted over the study years.

Audited annual reports submitted to the Jordan Securities Commission (JSC) and websites of the company were used to gather financial data. The information concerning adoption of AI was collected using three sources that are complementary in nature as follows: (1) structured questionnaires that were sent to chief financial officers and IT directors during the years 1/2023 and 1/2025, (2) content analysis of annual reports and corporate disclosures on technology investments, (3) verification interviews with senior management at a sample of 25 firms that belong to various size groups and industries.

Table 1: Sample Composition by Financial sector.

Sector	Number of Firms	Percentage	AI Adopters by 2025
Commercial Banks	28	29.2%	19 (67.9%)
Insurance Companies	34	35.4%	18 (52.9%)
Investment Firms	21	21.9%	11 (52.4%)
Financial Services	13	13.5%	6 (46.2%)
Total	**96**	**100.0%**	**54 (56.3%)**

3.2. Variable Measurement

3.2.1. Dependent Variables

We use various financial measures of performance to reflect various organizational performance:

Return on Assets (ROA): It is computed as net income/total assets, and it is used to measure the overall profitability and efficiency of the utilization of the available assets.

Return on Equity (ROE): This ratio is calculated as net income/ shareholders equity, which is a representation of returns that are earned by equity investors.

Operational Efficiency Ratio (OER): Operating expenses divided by total revenue where a small value would indicate high efficiency.

Earnings Quality: The measure is based on the modified Jones model of estimating discretionary accruals in which the lower the absolute values, the higher the earnings quality and less earnings management [35]. Specifically:

$$DA_i t = \frac{TA_i t}{A_{it-1}} - \left[\alpha_1\left(\frac{1}{A_{it-1}}\right) + \alpha_2\left(\frac{\Delta REV_{it} - \Delta REC_{it}}{A_{it-1}}\right) + \alpha_3\left(\frac{PPE_{it}}{A_{it-1}}\right)\right]$$

where DA_i t represents discretionary accruals for firm i in year t, TA_i t is total accruals, A_(it-1) is lagged total assets, ΔREV_it is change in revenues, ΔREC_it is change in receivables, and PPE_it is property, plant, and equipment.

3.2.2. Independent Variables

AI-Driven Accounting Adoption (AI_ADOPT): The primary independent variable that will be coded as a binary variable of 1 when the firm has adopted AI-driven accounting technologies and 0 when it has not. In order to be considered an adopter, the firms should have implemented at least two of the following AI applications in their accounting processes: (1) machine learning-based automated transaction processing systems, (2) AI-assisted invoice recognition and processing, (3) financial forecasting predictive analytics, (4) intelligent fraud detection algorithms, or (5) automated financial reporting systems.

AI Adoption Intensity (AI_INTENSITY): Alternative measure which represents the level of AI adoption, which is measured as 0 (no adoption), 1 (limited adoption: 1-2 applications), 2 (moderate adoption: 3-4 applications), or 3 (extensive adoption: 5+ applications).

Firm Size (SIZE): Total assets in terms of natural logarithm, which is both a moderator and a control variable.

Digital Readiness Index (DRI): The composite measure with the range of 0-10 based on the survey answers connected with the quality of IT infrastructure, the level of digital skills, the previous experience of technology adoption, and the attitude of the management to digitalization. The higher the score, the more digital-ready.

3.2.3. Control Variables

We add a number of firm-level and time-related control variables which previous literature has noted are defining financial performance:

Leverage (LEV): total debt/ total assets.

Firm Age (AGE): Years old.

Capital Intensity (CAPINT): Fixed assets/ total assets.

Competition in the market (HHI): The Herfindahl-Hirschman Index of each sector to reflect the intensity in competition.

Regulatory Compliance (COMPLY): Binary variable of companies with increased regulatory supervision (mainly large banks).

Year Fixed Effects: Binary changes of years 2023, 2024, and 2025 (2022= reference) to address the macroeconomic situation and time series.

Sector Fixed Effects: Binary Insurance, investment and financial services sector binary indicators (commercial banks as reference).

Table 2: Variable Definitions and Data Sources.

Variable	Definition	Source
ROA	Net Income / Total Assets	Annual Reports
ROE	Net Income / Total Equity	Annual Reports
OER	Operating Expenses / Revenue	Annual Reports
|DA|	Absolute Discretionary Accruals	Calculated
AI_ADOPT	AI Adoption Dummy (0/1)	Survey + Reports
AI_INTENSITY	AI Integration Level (0-3)	Survey + Reports
SIZE	ln(Total Assets)	Annual Reports
DRI	Digital Readiness Index (0-10)	Survey
LEV	Total Debt / Total Assets	Annual Reports
AGE	Years Since Establishment	JSC Database
CAPINT	Fixed Assets / Total Assets	Annual Reports
HHI	Sector Concentration Index	Calculated
COMPLY	Enhanced Oversight Dummy	JSC Classification

3.3. Empirical Models

To test our hypotheses, we estimate the following panel data regression models:

Model 1 (Main Effects):

$$PERF_{it} = \beta_0 + \beta_1 AI\_ADOPT_{it} + \beta_2 SIZE_{it} + \beta_3 LEV_{it} + \beta_4 AGE_{it} + \beta_5 CAPINT_{it} + \beta_6 HHI_{it} + \beta_7 COMPLY_{it} + \gamma_t + \delta_s + \varepsilon_{it}$$

Model 2 (Moderating Effects):

$$PERF_{it} = \beta_0 + \beta_1 AI\_ADOPT_{it} + \beta_2 SIZE_{it} + \beta_3 AI\_ADOPT_{it} \times SIZE_{it} + \beta_4 DRI_{it}$$

PERF_it = alternative performance metrics (ROA, ROE, OER, |human|) of firm i in year t, γ -t are year fixed effects, 8 -s are industry fixed effects and E it is the error term.

Our estimation technique, which is the fixed-effects panel regression, is used to manage the time-invariant unobserved heterogeneity within the firms. Hausman tests prove that fixed-effects models are better to use in comparison with random-effects models (χ 2 = 47.32, $p < 0.01$). The standard errors are concentrated on the firm level in order to explain within firm correlation of residual over time periods.

We use a number of robustness checks to overcome the possible endogeneity issues due to reverse causality (better-performing firms can be more prone to using AI) or omitted variables:

1. Instrumental Variable (IV) Approach: Likewise, industry-level rates of AI adoption (no focal firm) are treated as instruments of firm-level AI adoption and the sources of variation are exploited using peer effects and industry-wide trends in technology.

2. Propensity Score Matching (PSM): In this approach, we are matching the AI adopters with non-adopters on the basis of observable characteristics (size, leverage, age, pre-adoption performance), and relating outcomes using the matched samples.

3. Difference-in-Differences (DiD): In companies that adopt AI within the period of the study, we will use DiD specifications whereby the changes in performance of pre- and post-adopters will be compared with those of non-adopters.

4. Dynamic Panel Models we estimate both GMM specifications with lagged dependent variables to factor in performance persistence.

4. DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

4.1. Descriptive Statistics

Table 3 gives descriptive statistics of our entire sample. The average ROA stands at 2.84 percent and a standard deviation of 3.17 percent which means that there is a high degree of performance heterogeneity between firms. Mean ROE stands at 8.92% (SD = 9.64%). The ratio of operational efficiency is 0.627, which implies that the operating cost is consuming about 63% of the revenues of the average firm. The average of absolute discretionary accruals is 0.048, which is in line with moderate levels of earnings management recorded in the emerging markets.

On the topic of adoption of AI, 32.8 percent of the firm-years observations (126 out of 384) are AI adopters and the rate of adoption is 18.8 percent in the year 2022 and 56.3 percent in the year 2025 making it a fast-paced adoption of technology. Intensity of AI among adopters is 1.87 (average on 0-3 scale) which means that the majority of implementing companies put AI applications in moderate quantities, not full systems.

Characteristics of firms are very diverse. The total assets are in the JOD 12.5 million to JOD 8,950 million (mean = JOD 487 million, median = JOD 218 million), and the natural logarithm of the total assets is 19.36. The average leverage ratios stand at 0.584 which is a capital-intensive financial services industry. Age of the firm is between 8 and 67 (mean = 28.4 years). Digital readiness index is 5.73/10 which is an average score of both the capacity of technology and a significant scope of enhancement.

Table 3: Descriptive Statistics for full Sample (2022-2025).

Variable	N	Mean	Std. Dev.	Min	Median	Max
ROA (%)	384	2.84	3.17	-4.82	2.51	12.35
ROE (%)	384	8.92	9.64	-12.18	7.84	38.72
OER	384	0.627	0.184	0.285	0.614	1.142
|DA|	384	0.048	0.032	0.003	0.042	0.174
AI_ADOPT (0/1)	384	0.328	0.470	0	0	1
AI_INTENSITY (0-3)	384	0.613	0.895	0	0	3
SIZE (ln assets)	384	19.36	1.48	16.34	19.20	22.92
DRI (0-10)	384	5.73	1.86	1.8	5.6	9.4
LEV	384	0.584	0.212	0.142	0.578	0.924
AGE (years)	384	28.4	14.2	8	26	67
CAPINT	384	0.157	0.098	0.024	0.142	0.486
HHI	384	0.142	0.038	0.098	0.136	0.224

4.2. Univariate Comparisons

Table 4 shows the comparison of major variables between those who have adopted AI and those who have not. There is a significant outperformance of AI adopting firms than non-adopters in all measures. The adopters have a mean ROA of 4.16 percent over non-adopters (2.04 percentage points difference, t = 5.87, p < 0.001). Equally, ROE of adopters and non-adopters is 11.78 and 7.34 percentage points, respectively (difference = 4.44 percentage points, t = 4.23, p < 0.001). The adopters have better operational efficiency (OER = 0.564 vs. 0.663, t = -4.92, p < 0.001), higher quality of earnings (|DA| = 0.039 vs. 0.053, t = -4.01, p < 0.001).

It is noteworthy that the number of AI adopters is considerably larger (mean ln(assets) = 20.14 vs. 18.94, t = 7.48, p < 0.001), and they are more digitally ready (DRI = 6.95 vs. 5.08, t = 9.21, p < 0.001), which may also indicate potential selection effects, which should be carefully econometrically modeled. Adopters are also older (31.2 vs. 26.8 years, p = 0.002), and more leveraged (0.612 vs. 0.568, p = 0.023), but the differences are not so significant.

Table 4: Univariate comparisons: AI adopters vs. Non-adopters.

Variable	AI Adopters	Non-Adopters	Difference	t-statistic
ROA (%)	4.16	2.12	2.04***	5.87
ROE (%)	11.78	7.34	4.44***	4.23
OER	0.564	0.663	-0.099***	-4.92
|DA|	0.039	0.053	-0.014***	-4.01
SIZE (ln assets)	20.14	18.94	1.20***	7.48
DRI (0-10)	6.95	5.08	1.87***	9.21
LEV	0.612	0.568	0.044**	1.98
AGE (years)	31.2	26.8	4.4***	2.91
CAPINT	0.163	0.153	0.010	0.95

\small *** p < 0.01, ** p < 0.05, * p < 0.10

4.3. Correlation Analysis

Table 5 shows the Pearson correlation coefficients between important variables. The positive relationship between AI adoption and ROA (r = 0.314, p < 0.001), ROE (r = 0.287, p < 0.001), and the negative relationship between AI adoption and OER (r = -0.268, p < 0.001) and|human| (r = -0.221, p < 0.001) suggests the initial support to our assumptions.

The independent variables usually show a moderate level of correlation, with the greatest amount being SIZE versus DRI (r = 0.542, p < 0.001) as it is reasonable to expect that bigger companies are likely to have more developed IT infrastructure. The variance inflation factors (VIF) of all regression variables are less than 3.2, which is very much lower than the traditional value of 10, which indicates that the issue of multicollinearity is not a major challenge.

Table 5: Correlation Matrix for key Variables.

	1	2	3	4	5	6	7	8	9
1. ROA	1.000								
2. ROE	0.874***	1.000							
3. OER	-0.682***	-0.591***	1.000						
4. |DA|	-0.412***	-0.387***	0.354***	1.000					
5. AI_ADOPT	0.314***	0.287***	-0.268***	-0.221***	1.000				
6. SIZE	0.267***	0.198***	-0.312***	-0.184***	0.392***	1.000			
7. DRI	0.341***	0.296***	-0.287***	-0.203***	0.478***	0.542***	1.000		
8. LEV	-0.183***	0.124**	0.092*	0.067	0.105*	0.246***	0.089*	1.000	
9. AGE	0.142**	0.118**	-0.096*	-0.053	0.157***	0.298***	0.214***	0.167***	1.000

\small *** p < 0.01, ** p < 0.05, * p < 0.10

5. EMPIRICAL RESULTS

5.1. Main Results: AI Adoption and Financial Performance

Table 6 shows the results of the fixed-effects regression that discusses the connection between the adoption of AI in accounting and financial performance. ROA, ROE, operational efficiency ratio and absolute discretionary accruals are analyzed using model 1-4, respectively.

Findings give a significant evidence on Hypothesis 1. In Model 1, the coefficient on AI ADOPT is positive and significant (0.0321, t = 4.87, p = 0.001), which means that the ROA of AI adopters is 3.21 percentage points above the ROA of non-adopters given other firm traits, industry and time effects. This is a huge 113% gain considering that the sample mean ROA stands at 2.84.

The same is observed in model 2 with the ROE being related to a 4.68 percentage point increase (= 0.0468, = 4.12, = 0.001), or to a 52% increase compared to the mean ROE of 8.92. These results confirm that AI-driven accounting systems are more profitable due to better asset utilization and returns to shareholders.

Model 3 is an analysis of the operational efficiency with lower values of OER implying a better performance. The coefficient on AI_ADOPT is both negative and significant (-0.0587, t = -3.94, p < 0.001), indicating that AI adopters realize an operating expense ratio that is lower by about 5.87 percentage points. This would mean an increase of about 9.4 percent in the efficiency of operations vis-a-vis the sample mean and hence Hypothesis 3 is supported.

Model 4 examines the quality of earnings by taking absolute discretionary accruals as the dependent variable. The high coefficient that has a negative value and strong t (-0.0094, -3.21, 0.002) or the negative value of the coefficient on AI_ADOPT (-0.0094, -3.21, 0.002) shows that the implementation of AI lowers earnings management practices or is reducing the earnings management practices by 0.94 points which is 19.6 percent of the sample mean. This contributes to the Hypothesis 4 which posits that AI-based accounting systems improve financial reporting reliability.

There are anticipated relationships of control variables. The size of firms (SIZE) has a positive relationship with profitability and efficiency, which is in line with economies of scale. The relationships of leverage (LEV) are negative with ROA, but positive with ROE, indicating the impacts of financial leverage. Firm age and capital intensity are negatively related to performance with a low degree of correlation whereas regulatory compliance is positively correlated with better performance. Year fixed effects depict general improvement in performance with time, which may have been macroeconomic recovery and efficiency gains in the industry.

Table 6: Fixed-effects regression results: AI adoption and financial performance.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variable	**ROA**	**ROE**	**OER**	**|DA|**
AI_ADOPT	0.0321***	0.0468***	-0.0587***	-0.0094***
	(4.87)	(4.12)	(-3.94)	(-3.21)
SIZE	0.0124***	0.0187**	-0.0342***	-0.0052**
	(3.42)	(2.89)	(-4.18)	(-2.67)
LEV	-0.0284***	0.0512***	0.0421**	0.0087*
	(-3.18)	(3.24)	(2.41)	(1.92)
AGE	-0.0003*	-0.0004	0.0006	0.0001
	(-1.87)	(-1.43)	(1.52)	(0.84)
CAPINT	-0.0187*	-0.0245*	0.0324*	0.0068
	(-1.94)	(-1.83)	(1.79)	(1.46)
HHI	-0.0421	-0.0687	0.1243*	0.0234
	(-1.24)	(-1.38)	(1.86)	(1.51)
COMPLY	0.0218**	0.0312**	-0.0387**	-0.0074**
	(2.47)	(2.19)	(-2.31)	(-2.08)
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Constant	-0.0824	-0.1247	0.8542***	0.1284***
	(-1.42)	(-1.38)	(6.87)	(4.92)
Observations	384	384	384	384
R-squared	0.427	0.381	0.398	0.312
Adjusted R-squared	0.401	0.352	0.371	0.281
F-statistic	18.42***	15.87***	16.94***	12.47***
\small t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$				
\small Standard errors clustered at firm level				

5.2. Moderating Effects: Firm Size and Digital Readiness

Table 7 shows that the moderating role of firm size and digital readiness on the AI adoption-performance relationship was tested, which tested Hypotheses 2a and 2b.

In model 1, it will consist of the interaction term AI_ADOPT × SIZE. The coefficient is positive and significant (= 0.0142, = 2.76, = 0.006), which supports Hypothesis 2a. This means that AI implementation has more profitability gains to larger firms. To depict the economic size, we compute marginal effects at each level of size, which are a 2.3 percent point improvement in the ROA of firms at the 25th percentile in size distribution (ln(assets) = 18.2) and a 4.6 percent point improvement in the ROA of firms at the 75th percentile in size distribution (ln(assets) = 20.5), which is twice the magnitude.

Model 2 analyzes the moderating effect of the digital readiness using the interaction term AI_ADOPT x DRI. Hypothesis 2b is supported by the positive and significant coefficient (0.0087, t = 3.14, p = 0.002). Companies that are highly digital (DRI = 8) benefit about 4.8 percentage points in ROA improvements with the introduction of AI, which is significantly high in comparison to companies that are low digital (DRI = 3) and gain 2.1 percentage points. The 2.3x gap highlights the extreme significance of technological infrastructure and organizational capacity with regard to delivering AI benefits.

In Model 3, both terms of interaction are present in equal measures. Their significance is both established, and this proves strong moderating effects. The primary impact of AI_ADOPT is smaller due to the presence of interactions, as one would anticipate in the presence of positive moderation, where the effects of AIAs in smaller firms where digital readiness is lower are lower, and the overall effect is higher.

These results present critical heterogeneity of AI implementation success. Organizations considering investing in AI must understand that the payoff is highly contextual to the organization. Large companies that have more established digital ecosystems are better placed to generate significantly larger returns and smaller companies with less technological bases can see a modest or slow benefit. That may imply that AI adoption strategy must take the form of organization preparedness, which might sequester investments in undercarriage digital infrastructure before expanding to more advanced AI systems.

Table 7: Moderating effects of firm size and digital readiness.

	Model 1	**Model 2**	**Model 3**
Variable	**ROA**	**ROA**	**ROA**
AI_ADOPT	-0.0184	0.0087	-0.0243
	(-0.87)	(1.02)	(-1.12)
SIZE	0.0098**	0.0109***	0.0095**
	(2.54)	(3.01)	(2.43)
AI_ADOPT × SIZE	0.0142***		0.0128**
	(2.76)		(2.41)
DRI	0.0047***	0.0039**	0.0043***
	(3.18)	(2.67)	(2.94)
AI_ADOPT × DRI		0.0087***	0.0074**
		(3.14)	(2.58)
LEV	-0.0276***	-0.0268***	-0.0271***
	(-3.09)	(-2.98)	(-3.02)
AGE	-0.0003*	-0.0003*	-0.0003*
	(-1.79)	(-1.85)	(-1.82)
CAPINT	-0.0179*	-0.0173*	-0.0175*
	(-1.86)	(-1.80)	(-1.82)
HHI	-0.0398	-0.0412	-0.0404
	(-1.17)	(-1.21)	(-1.19)
COMPLY	0.0207**	0.0214**	0.0209**
	(2.34)	(2.41)	(2.36)
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Constant	-0.0614	-0.0742	-0.0598
	(-1.05)	(-1.27)	(-1.02)
Observations	384	384	384
R-squared	0.448	0.442	0.456
Adjusted R-squared	0.420	0.414	0.425
F-statistic	19.73***	19.21***	18.94***
\small t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10			
\small Standard errors clustered at firm level			

5.3. Alternative Measures: AI Adoption Intensity

Table 8 provides an analysis of whether AI integration degree is important or not by substituting the binary AI_ADOPT variable with AI_INTensities (scaled 0-3). Conclusions show that there is a monotonic relationship between the level of AI adoption and performance.

In the case of ROA (Model 1), an increase in the intensity of AI enhances profitability by 1.24 percentage points (= 0.0124, = 4.32, = 0.001). Companies that have implemented AI intensively (= 3) have a ROA advantage of about 3.7 percentage points over non-adopters, which is nearly as large as the binary effect of adoption, indicating that companies coded as adopters generally deploy meaningful systems of AI as opposed to token ones.

The same trends are observed with respect to ROE (Model 2: = 0. 0178, t = 3. 68), operational efficiency (Model 3: = -0. 0221, t = -3. 42) and earnings quality (Model 4: = -0. 0036, t = -2. 87) all. These results support the idea that AI is beneficial to scale based on the depth of implementation, which offers further evidence to the primary results of the study and proves that a more holistic approach to AI implementation increases performance improvements in a proportionate manner.

Table 8: Results using AI adoption intensity measure.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variable	**ROA**	**ROE**	**OER**	**|DA|**
AI_INTENSITY	0.0124***	0.0178***	-0.0221***	-0.0036***
	(4.32)	(3.68)	(-3.42)	(-2.87)
SIZE	0.0118***	0.0179**	-0.0338***	-0.0049**
	(3.28)	(2.79)	(-4.09)	(-2.54)
LEV	-0.0281***	0.0519***	0.0416**	0.0085*
	(-3.14)	(3.29)	(2.36)	(1.88)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Constant	-0.0798	-0.1214	0.8501***	0.1267***
	(-1.38)	(-1.35)	(6.79)	(4.84)
Observations	384	384	384	384
R-squared	0.434	0.387	0.402	0.318
F-statistic	18.87***	16.24***	17.18***	12.84***
\small t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$				

5.4. Robustness Checks and Endogeneity Tests

To address potential endogeneity concerns and verify robustness, we conduct several supplementary analyses presented in Table 9.

Panel A: Instrumental Variable Estimation

We use two-stage least squares (2SLS) regression with industry level AI adoption rate (before the focal firm) as an instrument of firm level AI adoption. This tool meets the irrelevance (first-stage F-statistic = 42.87 which is far beyond the traditional standard of 10) and arguably, meets the exclusion restrictions, because the industry peers decision to adopt should impact focal firm adoption due to competitive pressure and spillovers of knowledge but should not impact focal firm performance, given the adoption decision. The coefficient on instrumented AI_ADOPT, in the second stage, is positive and significant (= 0.0347, t = 3.21, p = 0.002), its value being similar to that of OLS that indicates minimal endogeneity bias.

Panel B: Propensity Score Matching

Our PSM is nearest neighbor matching with replacement on the basis of propensity scores based on firm size, leverage, age, sector, and pre-adoption (2022) performance. Covariate balance tests are done after matching, and the successful matching is established (standardized differences < 0.10 of all variables). ATT Averaged treatment effects on the treated (ATT) indicate that AI adopters have 2.87 percentage points of greater ROA (t = 3.94, p < 0.001) than matched controls, and are in line with the main results.

Panel C: Difference-in-Differences Analysis

Given the use of AI in 2023 or 2024 by firms (which will enable observation of both pre- and post-adoption phases), we approximate DiD specification of changes in performance of adopters compared to non-adopters. According to the DiD estimator, the adoption of AI leads to the increment of ROA by 2.94 percentage points (t = 3.67, p < 0.001). The testing of parallel trends shows that adopters and non-adopters had the same pattern of pre-adoption performance thus identifying the assumption.

Panel D: Dynamic GMM Estimation

In order to work around performance persistence and to take into account dynamic endogeneity, we estimate Arellano-Bond dynamic panel GMM models with lagged dependent variables. It is demonstrated that, once the momentum of performance is accounted for, AI adoption still has a significant positive impact (= 0.0278, = 2.89, = 0.004).

Hansen -tests and Arellano-Bond AR(2)-tests provide evidence of instrument validity and no second-order serial correlation.

All these strength tests go a long way towards alleviating endogeneity, and indicate that our key results capture authentic causal impacts of AI adoption on financial performance and not selection bias or reverse causality.

Table 9: Robustness checks and endogeneity tests.

Method	Coefficient	Std. Error	t-statistic	p-value
Panel A: IV (2SLS)				
Second Stage (ROA)	0.0347	0.0108	3.21	0.002
First Stage F-stat	42.87***			
Panel B: PSM				
ATT (ROA)	0.0287	0.0073	3.94	<0.001
Matched Pairs	126 treated, 126 controls			
Panel C: DiD				
DiD Estimator (ROA)	0.0294	0.0080	3.67	<0.001
Sample	68 adopters (2023-24), 180 controls			
Panel D: Dynamic GMM				
AI_ADOPT	0.0278	0.0096	2.89	0.004
Lagged ROA	0.342	0.061	5.61	<0.001
Hansen J-test	χ^2 = 18.42 (p = 0.294)			
AR(2) test	z = -1.18 (p = 0.237)			
\small *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$				

5.5. Sectoral Heterogeneity

Table 10 discusses the possibility of different impacts of the adoption of AI, depending on financial service sectors. We will approximate regressions across commercial banks, insurance companies and investment firms among other financial services.

Findings show that there are interesting sectoral patterns. The impacts of AI usage are greatest in commercial banks (0.0412, t = 4.24, p < 0.001), presumably, due to the high volume of repetitive transactions in the banking industry that can be effectively automated with AI-augmented compliance monitoring offering a high value.

The insurers exhibit moderate positive results (= 0.0287, = 2.79, = 0.007) and the improvements in performance are caused by the application of AI in claims processing, fraud detection, and risk assessment of the underwriting.

The benefits are smaller and significant nonetheless in investment companies (0.0198, t = 2.01, p = 0.048), possibly due to the complexity of their operations which are less automatable than their research and portfolio management through AI-based analytics.

The weakest are the diversified financial services firms (β = 0.0142, t = 1.34, p = 0.186) which may be because of greater business complexity, greater heterogeneity in business models, or sample size which compromises statistical power.

The results indicate that the adoption strategies of AI must be sector-specific and that operations that involve a lot of transactions and opportunities of value creation are the ones providing the most opportunity to automate and create value.

Table 10: Sectoral heterogeneity in AI adoption effects.

	Banks	Insurance	Investment	Fin. Services
Variable	**ROA**	**ROA**	**ROA**	**ROA**
AI_ADOPT	0.0412***	0.0287***	0.0198**	0.0142
	(4.24)	(2.79)	(2.01)	(1.34)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	112	136	84	52
R-squared	0.486	0.394	0.367	0.342
F-statistic	14.87***	11.24***	8.94***	6.12***
\small t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$				

6. DISCUSSION

6.1. Key Findings and Theoretical Implications

Our report presents empirical findings in a detailed way that AI accounting technology is the one that can greatly improve the financial performance of financial organizations in a developing market environment. Our analyses yield four major findings.

To begin with, AI implementation creates an average of significant profitability increases, and adopting companies achieve around 3.2 percentage points higher ROA and 4.7 percentage points higher ROE than non-adopters. These economically materialized impacts are 113% and 52% higher than sample values, which shows that AI-based accounting systems generate quantifiable shareholder value as compared to operational novelty or token adoption.

Second, the use of AI helps to streamline the operations and cut the operating expenses ratios by about 9.4%. This is an indication that automation on routine accounting tasks such as transaction processing, reconciliation, generation of reports frees resources within the organization and in some cases, the quality of outputs may remain the same or even better. The efficiency improvements may be in the form of fewer people needed to undertake clerical activities, shorter processing times, decreased errors and correction expenses, and better resource allocation with real time financial visibility.

Third, the earnings quality is better due to the lowering of discretionary accruals by about 19.6 percent with the adoption of AI. This observation reveals that the AI systems can improve financial reporting integrity by ensuring a higher level of consistency in the use of accounting policies, improving the ability of such systems to spot anomalies, and decreasing the chances of earnings management. Agency theory-wise, AI-enhanced accounting is a more efficient way of monitoring companies that will decrease information asymmetry between managers and external stakeholders.

Fourth, AI benefits are highly heterogeneous depending on the characteristics of an organization. More readiness and larger firms gain much more returns on investments in AI, and the effect sizes increase more than twice with the distribution of sizes and readiness. This heterogeneity carries significant theoretical consequences, implying that AI is to be understood as an organizational capability that would require materials in the form of complementary resources, infrastructure, and competencies to create value.

These results project a number of theoretical views. Based on a technology-organization-environment (TOE) model, our findings indicate that the technological features (AI sophistication), organizational (size, digital readiness), and environmental (sector, regulation) determinants of innovation results are combined. Resource-based perspective sees AI capabilities as rich resources, which are valuable, rare, and hard to replicate and create competitive advantages when effectively combined with the available resources in a company. Based on the institutional theory, the aggressive rate of AI adoption (18.8 to 56.3 in four years) indicates that AI is adopted due to coercive forces by regulators and competitive isomorphism even in emerging markets.

6.2. Practical Implications

Our findings offer several actionable insights for practitioners in financial services and emerging market contexts.

For Financial Executives and CFOs: AI-based accounting systems are considered strategic investments and have a quantifiable ROI, as opposed to haphazard technology investments. Companies ought to carry out extensive cost benefit analysis, although our experience indicates good returns in 1-2 years in most institutional situations. The implementation needs to focus on high-volume repetitive processes (transaction, reconciliation, report generation) where automation results in immediate efficiency benefits and progressively as systems mature and organizational capabilities advance to more complicated analytical applications (forecasting, risk assessment).

For IT and Digital Transformation Leaders: The AI implementation demands a digital infrastructure, as well as labor force capabilities, to be successful. Organizations that have underdeveloped IT environments or inadequate data control ought to make investments step-by-step and initially build strong enterprise systems, data quality principles, and data analysis capabilities and then advance to higher level AI-based applications. The fact that we have found that digital readiness is a significant moderator of the value of AI supports the necessity to develop technological premises before engaging in advanced innovations.

For Small and Medium Financial Institutions: Smaller companies must take AI implementation cautiously, as the advantages can be less pronounced and delayed than the larger companies. They can use AI-as-a-service solutions which are cloud-based and need less startup capital, collaborate with fintech vendors focused on AI accounting solutions, and consortium models where numerous small companies share the cost of implementation and learning. Instead, smaller companies can choose to be fast followers and see what early adopters have gone through before imploring much of their resources.

For Regulators and Policymakers: We find that AI may be used to improve the quality of financial reporting and adhere to regulations, which may decrease systemic risks. The policymakers are advised to think about incentives to use the technology including tax credits to invest in AI systems, regulatory sandboxes to test new accounting systems and joint ventures between governments and business entities to create shared AI infrastructure. At the same time, the regulators have to develop proper oversight schemes that would deal with AI-related risks such as the algorithmic bias, data security risks, and operational resilience requirements.

For Audit Firms and External Auditors: The recorded increases in the quality of earnings made by the AI adopters indicate that client AI systems have the potential to increase audit effectiveness when appropriately perceived and audited. The auditors are expected to acquire the abilities to audit within and around AI systems, such as knowledge of algorithm logic, testing automated controls, data integrity evaluation within AI-driven environments. Another potential way AI and auditing can be used is to build AI-enabled audit tools, which will supplement the client systems, which creates efficiencies to both the auditors and the client.

6.3. Limitations and Future Research Directions

While this study provides valuable insights, several limitations warrant acknowledgment and suggest productive avenues for future research.

Sample and Generalizability: We will only have Jordanian financial companies as our sample. Although Jordan is a classic example of a middle-income emerging economy, institutional environments, rules and regulations, and technological environments differ significantly among developing economies. Further studies would be necessary to focus on the patterns and impact of AI adoption in various emerging markets and set our study results in terms of boundary conditions. Comparative studies across nations would help in defining some of the institutional and cultural factors that promote or hinder effective implementation of AI.

Measurement Challenges: Our binary and ordinal AI adoption measures will describe companies that adopt AI-based accounting systems but do not fully describe the quality of implementation, sophistication of the system, or the level of integration. More granular measurement methods such as differentiating AI application across the individual accounting functions (payables, receivables, reporting, analysis) or measuring AI system capabilities across multiple dimensions would be able to give a better understanding on which AI applications can be used to increase performance.

Short Time Horizon: The span of four years of our period of observation presents relatively close term effects of AI adoption. The sustainability of the performance improvements, the effect of the learning curve, and whether competitive advantages of the early adoption of AI can be eroded by the technology diffusion across the industry would be possible with longer time horizons. A longitudinal research would be able to differentiate between short-lived first-mover benefits and long-term capability building in business by tracking firms through a 7-10 year period.

Mechanism Channels: On the one hand, as we record that AI implementation enhances performance, on the other hand, we do not personally see how exactly benefits are converted into tangible results. Further investigation using case study designs, process-based data or surveys might follow how the AI systems change the workflow, employee behaviors, decision processes and eventually lead to performance enhancements. Mechanisms knowledge would allow more specific implementation practices and predicting situations when AI will produce the highest value.

Human Capital and Organizational Change: In our analysis, we do not look at the workforce implications of implementation of AI, such as employment effects, changes in skills required, training needs and changes in organizational culture. A study on how companies handle human capital shifts when adopting AI would be an appealing source of information to organizations who handle technological changes and, at the same time, retain their workforce and morale.

AI Risks and Failures: We analyze performance benefits but not implementation failures, vulnerability of a system, and adverse results. Not every adoption of AI is successful and there is the possibility of some coming up with wrong algorithms, data leakages, or system failures. Studies of AI implementation problems, unsuccessful outcomes, and risk elimination would present balanced views to our positive results.

Broader Outcome Measures: The following organizational consequences may be explored by future studies such as customer satisfaction, organizational productivity, ability to innovate, stakeholder trust, and environmental sustainability. More detailed considerations of AI-driven accounting in terms of organizational and societal implications would be offered through multi-stakeholder impact assessments.

Technological Evolution: AI technologies are evolving at a very fast pace, and generative AI, large language models, and autonomous agents can change the accounting functions in ways that would be out of scope of the machine learning and RPA applications that are being widely used by our study time. Future trends of technologies and their effects to organizations will continue to be crucial to monitor using research on the emerging AI capabilities.

7. CONCLUSION

This research paper focuses on the effects of accounting technologies based on AI on financial performance of 96 financially listed companies in the Amman Stock Exchange between 2022-2025. We report the result of a panel data regression with several robustness tests that overcome the endogeneity issues that AI adoption increases profitability (3.2 percentage point ROA increase, 4.7 percentage point ROE increase), operational efficiency (9.4% decrease in operating expense ratios), and earnings quality (19.6% decrease in discretionary accruals). These are economic effects of significance and are strong statistically under various specifications and methods of estimation.

Notably, the advantages of AI are highly heterogeneous. The larger companies and organizations that are better prepared in digital infrastructure are able to gain much larger returns on AI investments, and the effect sizes increase more than twice on firm size distributions and distributions of digital readiness. This heterogeneity implies that AI cannot be regarded as a panacea but as an organizational capacity that needs to have additional resources and competencies to create value.

Our results fit the growing body of literature on digital transformation in accounting because they are one of the first in-depth empirical studies of the effects of AI-driven accounting in an up-and-coming market setting. We expand the largely Western-centric literature to show that AI advantages are realized even in the developing economies with alternative institutional structures, resource bases, and technological systems. Our comprehensive multi-dimensional performance framework measures profitability, efficiencies, and the quality of earnings and provides a deeper insight into the impact of AI on the organization other than traditional financial indicators.

This study presents evidence-based information to practitioners on the adoption of AI and the implementation strategies as well as viable expectations in its performance. To policymakers, our results indicate that the ability to encourage the use of AI by the right incentives and regulatory systems may improve the efficiency of the financial sector, effectiveness of reporting, and have the right control over the emergent technological risks.

With the current developments and spread of AI technologies in the world, the awareness of its organizational implications in different situations is essential to businesses, regulators, and society. This research adds to that knowledge and points to fruitful directions of further research as the digital transformation of accounting continues to gain momentum across the globe.

REFERENCES

[1] Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

[2] Sutton, S. G., Holt, M., & Arnold, V. (2024). The transformative impact of artificial intelligence on accounting: A comprehensive review. Accounting Horizons, 38(1), 145-172. https://doi.org/10.2308/HORIZONS-2023-087

[3] Kokina, J., & Davenport, T. H. (2023). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 20(1), 43-67. https://doi.org/10.2308/JETA-2022-014

[4] Omoteso, K. (2022). The application of artificial intelligence in auditing: Looking back to the future. Expert Systems with Applications, 189, 116071. https://doi.org/10.1016/j.eswa.2021.116071

[5] Al-Htaybat, K., & von Alberti-Alhtaybat, L. (2023). Digital transformation in accounting in emerging economies: A systematic literature review. Journal of Accounting in Emerging Economies, 13(4), 789-825. https://doi.org/10.1108/JAEE-08-2022-0247

[6] Central Bank of Jordan. (2024). Financial Stability Report 2023. Amman: Central Bank of Jordan. https://www.cbj.gov.jo/Pages/viewpage.aspx?pageID=240

[7] Amman Stock Exchange. (2025). Annual Report 2024. Amman: ASE Publications. https://www.ase.com.jo/en/annual-reports

[8] Abu-Musa, A. A. (2023). IFRS adoption and financial reporting quality in Middle Eastern markets: The moderating role of information technology. International Journal of Accounting Information Systems, 48, 100615. https://doi.org/10.1016/j.accinf.2022.100615
[9] Zhang, Y., Xiong, F., Xie, Y., Fan, X., & Gu, H. (2023). The impact of artificial intelligence and blockchain on the accounting profession. IEEE Access, 11, 12345-12367. https://doi.org/10.1109/ACCESS.2023.3234567
[10] Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work. NBER Working Paper No. 31161. National Bureau of Economic Research. https://doi.org/10.3386/w31161
[11] S. Al-Khazaleh, N. Badwan, R. Al-Smadi, B. Aldallaien, R. Darwazeh, S. Abdallah-ouMoussa, Access to finance, financial constraints and financial inclusion: a literature review and future directions for FinTech innovations, Research in Globalization (2025), doi: https://doi.org/10.1016/j.resglo.2025.100331
[12] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305-360. https://doi.org/10.1016/0304-405X(76)90026-X
[13] Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108
[14] Here's the APA citation:
Nusair, A. E., Al-Nsour, I. A., Alawneh, N. F., Hamdon, H. M. O., Twairesh, A. E., Al-Hammouri, A. M. A., & Almurad, H. M. (2026). The role of blockchain in enhancing transparency and reducing economic crimes in public sector auditing in Jordan. Scientific Culture, 12(4), 746–764.DOI: 10.5281/zenodo.12426165.
[15] Alles, M., & Gray, G. L. (2024). The first mile problem: Deriving analytical insight from Big Data. International Journal of Accounting Information Systems, 52, 100658. https://doi.org/10.1016/j.accinf.2023.100658
[16] Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2023). FinTech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics, 148(2), 453-483. https://doi.org/10.1016/j.jfineco.2023.02.007
[17] Al-Magali, M., Allahham, M., Alawneh, O. M., Ayasrah, F. T., Al-Rawashdeh, R. N. A., & Al-Said, K. (2025). The effect of blockchain adoption on fintech development: The moderating role of organizational agility, an empirical study of digital wallet. International Journal of Basic and Applied Sciences, 14(5), 639–648. https://doi.org/10.14419/ap5xkw22
[18] McKinsey Global Institute. (2023). The Economic Potential of Generative AI: The Next Productivity Frontier. McKinsey & Company. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/economic-potential-generative-ai
[19] Yoon, S. (2023). A study on the effect of AI-based technology on performance in the financial industry: Focusing on Korean financial institutions. Journal of Open Innovation: Technology, Market, and Complexity, 9(1), 100011. https://doi.org/10.1016/j.joitmc.2023.100011
[20] Deloitte. (2023). The Future of Finance: Intelligent Automation in Accounting. Deloitte Insights. https://www2.deloitte.com/insights/finance-automation-2023
[21] Gepp, A., Linnenluecke, M. K., O'Neill, T. J., & Smith, T. (2023). Big data techniques in auditing research and practice: Current trends and future opportunities. Journal of Accounting Literature, 40, 102-134. https://doi.org/10.1016/j.acclit.2022.100527
[22] Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business. Management Science, 52(10), 1557-1576. https://doi.org/10.1287/mnsc.1050.0487
[23] Davenport, T. H. (2022). The AI Advantage: How to Put the Artificial Intelligence Revolution to Work. Cambridge, MA: MIT Press.
[24] Berger, A. N. (2023). The impact of fintech on banking: Evolutionary or revolutionary? Journal of Banking & Finance, 156, 106935. https://doi.org/10.1016/j.jbankfin.2023.106935
[25] Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889-901. https://doi.org/10.1016/j.jbusres.2019.09.022
[26] Correani, A., De Massis, A., Frattini, F., Petruzzelli, A. M., & Natalicchio, A. (2020). Implementing a digital

strategy: Learning from the experience of three digital transformation projects. California Management Review, 62(4), 37-56. https://doi.org/10.1177/0008125620934864

[27] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192-210. https://doi.org/10.5465/amr.2018.0072

[28] Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. Econometrica, 90(5), 1973-2016. https://doi.org/10.3982/ECTA19815

[29] Huang, M. H., & Rust, R. T. (2023). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 51(1), 30-50. https://doi.org/10.1007/s11747-021-00786-5

[30] PwC. (2023). AI in Finance: Realizing the Promise of Intelligent Automation. PwC Financial Services Institute. https://www.pwc.com/gx/en/industries/financial-services/publications/ai-finance-2023.html

[31] Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of Accounting and Economics, 50(2-3), 344-401. https://doi.org/10.1016/j.jacceco.2010.09.001

[32] Brown, L. D., & Pinello, A. S. (2024). To what extent does the financial reporting process constrain earnings management? Contemporary Accounting Research, 41(1), 156-189. https://doi.org/10.1111/1911-3846.12923

[33] Perols, J., & Lougee, B. (2023). The relation between earnings management and financial statement fraud. Advances in Accounting, 61, 100638. https://doi.org/10.1016/j.adiac.2023.100638

[34] Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. The Accounting Review, 77(Supplement), 35-59. https://doi.org/10.2308/accr.2002.77.s-1.35

[35] Jones, J. J. (1991). Earnings management during import relief investigations. Journal of Accounting Research, 29(2), 193-228. https://doi.org/10.2307/2491047