

The Impact of AI-Driven Risk Management on Earnings Management: Empirical Evidence from Jordan's Industrial Sector

Ayman Mansour¹, Mugheeth Amin Al-Adaileh², Hebah Alshamayleh³, Rany Abu Eitah⁴, Moayyad Al-Fawaacer⁵

¹⁻⁵ Faculty of Business, Al-Zaytoonah University of Jordan, Amman, Jordan, ayman.mansour@zuj.edu.jo, m.aladaileh@zuj.edu.jo, h.shamayleh@zuj.edu.jo, r.abueitah@zuj.edu.jo, m.alfawaacer@zuj.edu.jo

Abstract

This article analyzes the influence of AI-managed risks on employment manipulation (EM) within a Jordanian industrial firm. To guarantee comprehensive representation, 312 interviews were conducted with industry professionals possessing diverse responsibilities, organizational sizes, and demographic backgrounds via a standardized survey from March 2025 to May 2025. To validate and ensure the reliability of the findings, the research employed PLS-SEM with an adequate sample size. The results indicate that the proper integration of AI-driven risk management into operations substantially influences earnings management. The findings indicate that risk management plays a pivotal role in influencing financial reporting and discretionary accounting practices as an intermediary factor in the indirect relationship between AI deployment and earnings management outcomes. The function of AI in the regulation and implementation of earnings commodities strategies, a topic that has received less empirical focus in emerging nations like Jordan, addresses a significant gap in the literature. The findings indicate that AI improves operational efficiency, mitigates the risks of financial fraud, and strengthens regulatory compliance, impacting the three phases of planning, execution, and monitoring. These results increase the integration of theory and practice by providing distinct insights into the deployment of AI to influence earnings management, improve transparency, and ensure long-term financial sustainability in industrial firms.

Keywords: Artificial Intelligence; Risk Management; Earnings management; Industry Sector; Ethical Practices; Sustainable Operations

1 Introduction

Increased recognition of the success of technology indicates that AI has the capacity to disrupt several fields across all industries, either by supplanting existing methods or by offering innovative solutions to challenges (H. Kadhim & Al Ani, 2023; Al-Madadha, Al-Adwan, & Falahat, 2025).

2 Contextual Background and Theoretical Framework

A new industrial sector A wave of modernization is washing over Jordan's industrial sector, aided by digital technologies and new attention to corporate transparency and accountability. The opportunities of new technologies to disrupt the traditional industries and their models of operation, as well as to enhance the efficiency of their work and the quality of their financial reporting through the preservation of global management integrity and earnings quality, are provided by blockchain, artificial intelligence (AI) technologies, and big data analytics (Kadhim and Al Ani, 2023; Kang and Park, 2021). These algorithmic and computational technologies, improving the speed and accuracy of control systems, resource optimization, and financial decision-making, make organizations less likely to resort to earnings manipulation (Lee et al., 2024; Bansal, 2024). Adoption impediments remain, however, including the high cost of implementation, lack of technical knowledge, and organizational resistance to digitalization (Yaseen, Al-Adwan, Nofal, Hmoud, & Abujassar 2023). For AI to be ethically employed for detecting and preventing earnings management, data quality, model interpretability, and regulatory compliance need to be ensured (Elette et al., 2023).

There are risks and advantages when applying AI to financial information systems (FIS) in Jordanian and Middle Eastern companies. Although the adoption of the full disclosure of earnings process is getting highly popular, it is still slow due to the factors of regulatory pressure and stakeholders' limitations and other hindrances, despite the efforts to digitalize and intensify foreign investment (Kadhim & Al Ani, 2023; Horani, Al-Adwan, Al-Rahmi, & Alkhalifah 2025). The Jordanian government also has furthered the use of AI in industrial sectors by championing digital innovations and adopting financial regulations

that encourage corporate accountability in reporting (Lee et al., 2024). Vision 2025—an approach for national growth— “plans to develop institutions, ensure economic growth, and apply financial transparency and discipline in business practice” (Kadhim & Al Ani, 2023; Bansal, 2024). Jordanian firms are increasingly turning towards AI-based financial instruments that limit the space for opportunistic earnings management, notwithstanding constraints such as capital scarcity and administrative barriers (Yaseen et al., 2025) (Al-Shayea, Qeethara ,2025).

AI-based finance technology solutions in Jordan factories are altering the strategic approach towards financing and shaping projects and financial culture and response. This research applies the TOE (Technology–Organization–Environment) framework to explain how organizational readiness, technological capability, and external environmental pressures affect AI adoption as well as enhance the quality of earnings management (Bui, 2024; Kang & Park, 2021). Some of the key technologies needed for enhancing internal controls, raising stakeholders' demand for accurate financial reporting, and enhancing income transparency include blockchain, predictive analytics, and machine learning (Kadhim & Al Ani, 2023; Lee et al., 2024). As AI technologies advance, industries are also shifting towards smarter, ethical, and healthier financial management options.

This has led to criticism of traditional industrial risk management systems for not having the required ability to detect and/or prevent earnings management (Bansal, 2024). In efforts to stimulate digital innovation of financial reporting and intelligent control, AI-based tools in recent products offer superior anomaly detection and earnings manipulation prevention ability." (Lee et al., 2024). For example, blockchain and big data analytics enhance the traceability, accountability, and integrity of financial data for the purposes of project planning and spending (Bui, 2024). By the reduction of the earnings management and the increase of the truthfulness of the reported results, empirical evidence based on Partial Least Squares Structural Equation Modeling (PLS-SEM) confirms that the PM-enhanced risk management through the AI improves the performance of the project (Kang & Park, 2021; Kadhim & Al Ani, 2023). However, explanatory interpretability and weak data quality are still problematic for industrial purposes (Lee et al., 2024).

Risk management paths have an impact on operational and financial performance and industry. AI-incorporating firms show more improvement in reducing earnings manipulation (Lee et al., 2024; Bui, 2024). Firm performance and project performance, based on the overall, are between the qualitative, because it is related to the ethical use of financial resources, and the quantitative, which measures profitability and efficiency (Riady, Habibi, Mailizar, Alqahtani, Riady, & Al-Adwan 2025). By improving information quality and financial transparency and reducing the risks of misreporting and earnings management in projects, it is ensured by artificial intelligence (AI) techniques (Kadhim & Al Ani, 2023; Bui, 2024). Combined, these findings highlight the significance of AI in countering earnings management and promoting financial sustainability in firms.

The sociological and geographical aspects would moderate the performance of AI-based financial control. Unlike developed markets, emerging markets, including Jordan, face issues like the non-existence of legal structures, shortage of trained staff, and the ad hoc implementation of standards, which influence the effectiveness of AI in mitigating earnings management (Kadhim & Al Ani, 2023; Bansal, 2024). To realize the most benefit from AI in financial reporting, region-centric organizational and economic-focused solutions must be developed (Bui, 2024). AI's ability to improve internal controls and reduce discretion associated with earnings management Tile's view on the additional link between project success and financial integrity is AI. In support of this proposition, Foster, and Gupta (1994) suggest that the high cost of research development is justified if it is used to identify (Lee et al., 2024; Kang & Park, 2021).

Because adoption differs across regions and industries, it is important to understand how AI influences financial performance and organizational behavior indirectly. AI performance is also affected by financial data quality and adherence to ethical reporting requirements when managing earnings (Kadhim & Al Ani, 2023). To develop strategic AI adoption frameworks that reduce earnings manipulation and enhance financial reporting in industrial markets, researchers should investigate such associations in the future (Bansal, 2024; Bui, 2024).

More recent research is acknowledging AI's broader positive effects, for example, beyond financial performance, in terms of greater stakeholder confidence, corporate image, and investor communication (e.g., Lee et al., 2024). AI-based finance management finally leads the company toward long-term growth and market competitiveness and increases the confidence of employees and the value of a corporation (Kang & Park, 2021). AI and earnings management: AI-aided earnings management is one of the keys to ensuring sustainable Jordanian financial growth, as the industrial sector is of paramount importance to the economy (Kadhim & Al Ani, 2023; Bansal, 2024).

3 Study Hypotheses

As discussed in the above section, the present research aims to explore the AI-based risk management and EM in the Jordanian industrial companies. What we do The aims and objectives of identifying and curbing the manipulation of earnings are inseparably combined with algorithms and software of artificial intelligence used to identify, assess, and manage risks in industrial projects. This research investigation explores such issues of opportunistic EM practices and the quality of financial disclosure impacted by state-of-the-art techniques. This chapter discusses the way new technologies such as alternative risk measurement systems may completely change financial control and transparency in the industrial sector.

Previous research has revealed that the relationship between AI-based risk management and earnings management is highly complex (Kadhim & Al Ani, 2023; Kang & Park, 2021; Lee et al., 2024) and called for empirical examinations. In this context, we empirically explore how AI-enriched solutions may impact an industry, beyond technological innovation. The purpose of the present study is to examine how state-of-the-art digital tools may affect risk performance and voluntary disclosure in business corporations. In the governance of EM, this literary review indicates the intricate relationship among technology innovation, regulative context, timing, and strategy options. One of the areas that would benefit from further study is whether there are differences in the AI risk controls-EM relationship between industries and contexts (Kadhim & Al Ani, 2023).

As a study that adds to the literature on international financial regulation, the current study builds on prior research (Bui, 2024; Bansal, 2024) to explore the extent to which the uses of AI affect earnings management incentives and risk. The theory is constructed as a system of testable hypotheses for these underlying interactants with the consequence of being able to empirically test for those various base interaction phenomena that lead to it. We purely intend to lay the first stone from which the digital transformation would allow more accurate, ethical, and sustainable earnings reporting in the Jordanian manufacturing companies, using the practical application of the integration between the philosophy of risk management and the applied AI (Lee et al., 2024; Kang & Park, 2021).

3.1 Artificial Intelligence in Risk Management Frameworks

Recent theoretical models are now suggesting the dynamic relationship between AI and risk management practices in the firm of Jordanian industries. These are models that illustrate how innovation in digital, specifically risk analysis and adaptive management analysis, has established itself as an essential template in driving responsible business behavior and operational efficiency (Khalid et al., 2024; Al-Hraahi et al., 2024). AI is seen as a paradigm shift that replaces the conventional way of treating risks, but then offers a predictive and adaptive quality, which is essential in solving new risks in rapidly expanding industrial environments (Almashawreh et al., 2024; Usama et al., 2024).

It is experimentally demonstrated that AI applications may shake the risk identification, evaluation and mitigation process to the radix in the different stages of the project, including the initiation, planning and monitoring among other factors (Zekos, 2024, pp. 104-118; Zekos and Zekos, 2021). Such integration would be a proactive and risk-based form of integration founded on transparency and ethics across the organization. This places the current sensibilities of social responsibility in a headspace that is especially pertinent as emerging markets are also progressively being affected by AI through the industrial base (Abaddi, 2025; Naar, 2024).

AI risk systems, however, do not have a universal effect. Differences between sectors and countries show that the impact of AI highly depends on the readiness of the organizations, the legal environment, and the attitude of the actors (Dong & Liu, 2023; Al Shbour, 2024). From an economic perspective these systems may enhance industrial competitiveness, instill investor confidence, and generate trips to export to those markets with high alignment (Qatawneh et al., 2024; Wong et al., 2024). From a knowledge point of view, these applications add to the increasing literature concerned with responsible AI deployment, contextual risk factors, and digital management (Kulkov et al., 2024; Meitei et al., 2023).

For AI to successfully regulate responsible business conduct, regulators need to establish frameworks that foster innovation and allow ethical matching. For this equilibrium, the model of the collaboration between the government policy and the industry commitment to the AI (Khalid et al., 2024; al-Eye and Wheels, 2025) is a crucial determinant. Such cooperation would enable companies to operate risk systems that are not only cutting-edge but also locally compliant with standards of social responsibility.

These considerations lead to the formulation of the following hypotheses:

H1: The utilization of artificial intelligence (AI) has a significant effect on the adoption of risk management principles.

H1a: Employing AI during the project initiation phase significantly influences the application of risk management principles.

H1b: Employing AI during the project planning phase significantly affects the implementation of risk management principles.

H1c: The use of AI in the project's monitoring and control phase positively impacts the application of risk management principles.

3.2 The Role of Risk Management in Supporting Earnings Management (EM)

There is a shift towards focusing on the dynamism of the risk management practices and artificial intelligence (AI) interface in the theoretical models as far as Jordanian industry is concerned. The models reflect the role of digital innovations in responsible business behaviors and operational efficiency as risk analysis and adaptive management analysis have been used to make such changes (Khalid et al., 2024; Al-Hraahi et al., 2024). The adoption of AI is more a change factor, which not only encompasses the dimensions of traditional risk but also includes the predictive dimension and adaptive dimension that is required to manage the emergent threat in the context of the rapidly moving industrial environments (Almashawreh et al., 2024; Usama et al., 2024).

In fact, experimental research -h has demonstrated that project stages of initiation, planning, and monitoring accept the risk-taking process of the organization between the realization and the evaluation to the mitigation of the risks (Rahman et al., 2024; Zekos and Zekos, 2021). (2004) This sort of integration promotes the risk-taking culture that is proactive in the sense that it emphasizes openness and ethical decision-making based on the organizational structure. This fully complies with the feeling of social responsibility needed in the present times, especially in the developing world, where AI is reshaping the industry regulations (Abaddi, 2025; Naar, 2024).

However, there is another side of the story of AI-based risk systems. The sectoral and national-level variance is based on a high level of variance in the implementation of AI, and it is more dependent on the readiness of an organization, the legal framework, and the desire of the parties to the contract (Dong and Liu, 2023; Al Shbour, 2024). On the economic level, they are able to boost industrial competitiveness, trigger investor trust, and fake trips to investigate markets with high alignment potential (Qatawneh et al., 2024; Wong et al., 2024). Knowledge contribution the applications may be included in the new body of literature on responsible AI, contextual risks, and digital management (Kulkov et al., 2024; Meitei et al., 2023).

Regulatory models are needed for AI to responsibly navigate sound business practice. Attaining this balance depends on the organizational form of the coordination of industrial commitment and government policy toward AI (Khalid et al., 2024; al-Eye and Wheels, 2025). This collaboration enables firms to build advanced, yet at the same time compatible, risk systems. According to these observations, the following hypothesis is proposed:

H2: Strong implementation of risk management principles significantly enhances the realization of Earnings Management (EM).

3.3 The Role of Artificial Intelligence in Advancing Earnings Management (EM)

Both experimental and theoretical literature still postulate that well-designed risk management (RM) underpins the solution to the issue of earnings management (EM) in the Jordanian construction industry. The next state theories suggest that situational factors, strategic antecedents, and adoption of new technologies—particularly artificial intelligence (AI)—result in increased financial transparency and accountability in project-based disclosures (Kadhim & Al Ani, 2023; Bansal, 2024). This argues for increased consensus that the combination of AI-based risk approaches with earnings management thwarting schemes may result in prophylactic and adaptive regulations in a variety of construction settings.

Some scholars suggest that the adoption of a match between the pattern of contextual risk and control approaches, instead of a homogeneous control method, tends to reduce the opportunistic reporting and the management of the stakeholders' confidence that is also in a condition of riskiness and/or context volatility (Lee et al., 2024; Bui, 2024). Additionally, more general regulatory infrastructures, such as those concerning digital governance and the integrity of audits, allow for such an approach to be encouraged by looking to connect construction project management aims with national and international standards with respect to fiscal transparency and responsibility (Kadhim & Al Ani, 2023; Kang & Park, 2021).

New research also underscores the need to align short-run project performance indicators with long-run fiscal sustainability. This is the balance that is necessary to guarantee ethical reporting and disclosure obligations in the construction industry (Bansal, 2024; Lee et al., 2024). Moreover, even a perfect basis of proportioning EM methods in working capital reporting systems is already provided by universalized

application of AI-assisted financial control products (e.g., predictive analytics, digital twins, blockchain-secured audit trails) (Al, Faiza and Arisara bre & Jiraporn, 2027).

The impact to the economy is significant. Appropriately, AI risk governance will not only enhance the delivery of construction projects but also enhance responsiveness of organizations and financial disclosure credibility. It makes compliance with the terms of social responsibility and the certification of companies in the industry more convenient too, which increases the level of competitiveness and access to the capital market (Bui, 2024; Lee et al., 2024). Technical advances in AI-enabled monitoring tools already provide transparent, comprehensible, and accountable infrastructures that restrict the judgment in income recognition and are a guarantee for ethical financial practice (Kang & Park, 2021; Kadhim & Al Ani, 2023).

These results place regulatory backing as an important driver. Institutional endorsement and political support for AI-driven risk rankings may lead to greater uniformity in anti-EM enforcement and in convergence of public–private financial supervisory obligations (Lee et al., 2024; Bansal, 2024). According to these, the following hypothesis is formulated:

H3: The application of artificial intelligence (AI) significantly contributes to achieving Earnings management.

H3a: The use of AI in the initiating phase of a project significantly affects the realization of Earnings management.

H3b: The application of AI in the planning phase of a project significantly supports the achievement of Earnings management.

H3c: Utilizing AI during the monitoring and control phase of a project has a positive influence on the achievement of Earnings management.

3.4 The Mediating Role of Risk Management

Research focus has been on the impact of artificial intelligence (AI) on the mitigation of earnings management (EM) in the Jordanian construction sector. For instance, Kadhim and Al Ani (2023) show that it is possible for AI-enabled risk management to prevent manipulation in financial reporting through incorporating predictive governance into project management. Lee et al. (2024) have an illustration of using AI in detecting the anomaly in the financial data for an on-the-spot surveillance that discourages accruals and fosters transparency, so the direct proximate outcome is the curb on EM practices. Similarly, Kang and Park (2021) state that AI-based tools help to uncover irregular accounting behavior and are thus responsible for encouraging ethical financial disclosures.

ScienceDirect, Elsevier Using predictive analytics to reduce errors in financial reporting Case studies have demonstrated that predictive analytics, powered by machine intelligence, can increase the accuracy of financial reporting. For example, Kadhim and Al Ani (2023) describe the earnings quality improvement in construction companies using AI-based controls, and Bansal (2024) identifies smoothing of earnings and suppression of opportunistic behavior through transaction monitoring based on AI. They are also inspiring the EM battle by institutionalizing EM processes in organizations including transparency and responsibility in financial management. Bui (2024) and Lee et al. (2024) also assume that AI-enhanced (anomaly and financial rules) models are favourable to believable earnings outcomes.

Regarding the PM strategic effect to adequate audit quality, AI on the PM life cycle stages initiation, planning, execution, and control remains effective in maintaining the quality of earnings through increased efficiency, increased error detection, and improved adherence to financial reporting standards (Kang and Park, 2021; Bui, 2024). The implementation of AI at these steps fits the internal control structures through the encouragement of automation, human subjectivity, and manipulation of reports.

In industrial and regulatory contexts, AI impediments to industry are dissimilar, however. In EM, tooling AI, industries, however, the effect of AI in EM is not similar. These variations are influenced by data governance and audit readiness (Kadhim & Al Ani, 2023). From an economic perspective, AI adoption can create a competitive advantage by generating more confidence from financial investors while increasing access to capital markets (Bansal, 2024; Lee et al., 2024). For instance, AI-driven expense forecasting and real-time ledger analytics have permitted organizations to prevent earnings overstatements and enhance stakeholder confidence in financial reporting (Kang & Park, 2021; Bui, 2024).

Also, Lee et al. (2024) show that AI-driven financial innovation has a positive association with earnings conservatism and the effective functioning of the audit committee, crucial factors for EM reduction. The role of policy and regulation is also crucial. Bansal (2024) argues that institutions' arrangements and the regulating control of investors are the most important factors that can scale up the adoption of ethical AI in generating the financial transparency and reporting quality in the construction as well as other industries.

In this context, the study formulated the following hypotheses:

H4: Risk management serve as a mediating factor in the relationship between AI application and the achievement of Earnings management.

H4a: Risk management mediates the relationship between AI utilization in the initiating phase and the realization of Earnings management.

H4b: Risk management mediates the relationship between AI application in the planning phase and the achievement of Earnings management.

H4c: Risk management mediates the relationship between AI use during the monitoring and control phase and the achievement of Earnings management.

An illustration of the study's hypotheses is shown in Figure 1.

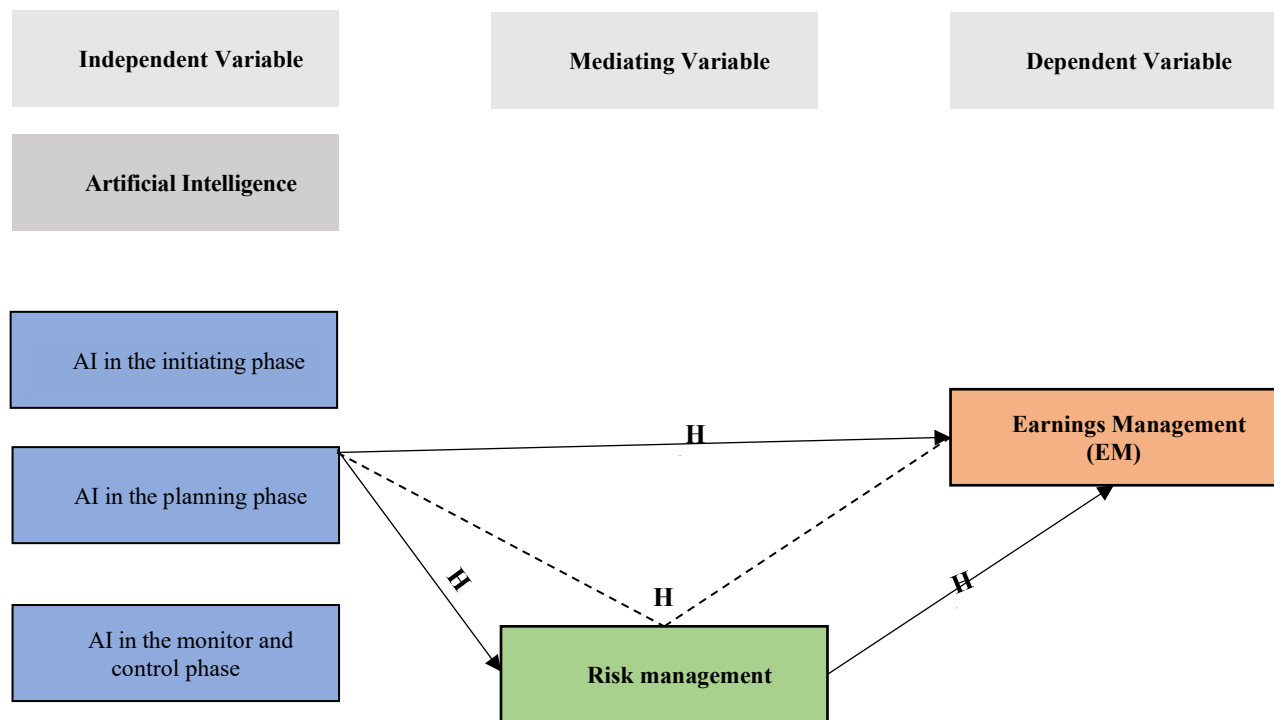


Figure 1. Study Framework with Research Hypotheses

4 Research Methodology

To generate comprehensive data, we adopted a quantitative research methodology by using an online survey as a main data collection method. It is successful in achieving high response rates and offers an organized way of gathering significant quantitative information from participants. The sampling strategy was appropriately designed for diversity to cover different engineers' roles (e.g., project managers, production engineers), companies' sizes (small, medium, large), and diverse demographic profiles in the Jordan industrial field, with good representation.

The questionnaire was intentionally designed to measure the important factors, which included artificial intelligence (AI) usage in various stages of project implementation (initiation, planning, monitoring, and control), usage of risk management practices, and how they help to reduce EM. The questions were developed with good alignment to the study purpose for the intention of gathering rich information on engineers' experiences and perceptions toward adopting AI tools for detecting and coping with the earnings-based risk. This was to allow an investigation of the effect of AI-enabled risk structures on EM reduction strategies, in line with current calls for AI-enabled financial regulation in industry.

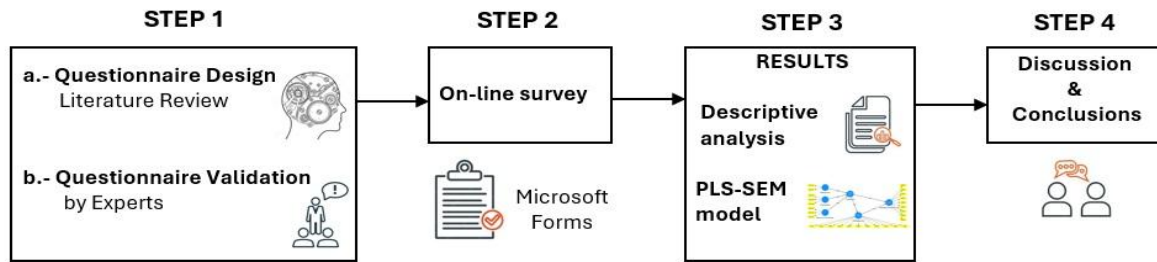


Figure 2. Workflow of Research Design

A flowchart depicting the development and validation of the questionnaire is shown in Figure 2. The instrument was prepared based on a systematic literature review and later validated by expert reviewers on clarity and accuracy. Content validity was established, and revisions were made as needed. Reliability was examined by Cronbach's alpha method and construct validity by factor analysis, and the results indicated that the instrument measured what it was intended to measure. The general definitions were "AI for Risk Management in Earnings Management," which referred to the utilization of AI devices to identify, measure, monitor, and control potential factors that may promote or inhibit the practice of earnings management (EM), and "Earnings Management" for activities that affect the time gap or the format of financial reporting.

This process of validation proved several times that it was an efficient tool that can be trusted. For generalizability, the research targeted practicing engineers that are actively involved in the delivery of industrial projects in Jordan. Specifically, the Jordanian Ministry of Trade and Industry (2024) reports that there are some 18,000 employed in the sector, with a portion of 10% (approximately 1,800) involved in associated engineering services. Based on alternative advice from Morgan (1970), a minimum sample size of 317 would be adequate. The online survey was administered in Office 365 Forms from March 14th through May 18th, 2025, and a total of 312 complete responses were received, which is sufficient to offer valid and reliable data. Furthermore, the sample consisted of engineers from different hierarchical levels and external firm sizes, which increases the generalizability of the results for the general industrial sector in Jordan.

The Jordanian sample of engineers disguised context details, and barriers and impediments of AI applications to earnings management within such a particular context may be different from other regional or industry settings. The above recommended sample size also improved the external validity of the findings, and the diversity of the sample enriched the data and facilitated an in-depth analysis of the interaction of AI applications, risk management practices, and earnings management strategies.

The survey was conducted in line with ethics especially the informed consent, data confidentiality and data use. The variables were rated through a 5-point Likert scale (strongly disagree =1; strongly agree = 5). The survey questions covered both the topics of adoption of AI, information source, regulatory climate, user experience, and perceived ease in adopting digital risk tool in the earnings reporting process.

Table 1. Variable Metrics and Reference Sources

Construct	Dimensions	Measurement Highlights	Sources
AI Application (Exogenous)	Initiating Phase	1) AI enhances feasibility assessments for industrial projects. 2) AI enables comprehensive data analysis to identify project challenges and opportunities. 3) AI automates routine tasks for project initiation.	Khalid et al. (2024), Al-Ramahi et al. (2024), Almashawreh et al. (2024)
	Planning Phase	1) AI optimizes project scheduling and resource allocation. 2) AI enhances risk modeling for mitigation strategies. 3) AI supports the development of alternative plans.	
	Monitoring and Control Phase	1) AI enhances real-time data analysis for project monitoring. 2) AI enables dynamic risk tracking and assessment. 3) AI supports predictive analytics to mitigate potential delays or disruptions.	

Earnings management (Endogenous)	Earnings Manipulation Techniques	1) AI helps identify discretionary accruals used to manipulate earnings. 2) AI detects revenue recognition timing that affects reported profits. 3) AI monitors expense deferral practices that alter earnings figures.	Kadhim & Al Ani (2023); Kang & Park (2021); Bansal (2024); Bui (2024)
	Transparency and Disclosure Quality	1) AI improves the accuracy of financial reporting and disclosures. 2) AI enhances the completeness and clarity of earnings information provided to stakeholders. 3) AI reduces errors and inconsistencies in financial statements.	
	Detection and Prediction of EM	1) AI algorithms effectively detect unusual earnings patterns. 2) AI predicts the likelihood of future earnings manipulation. 3) AI supports early warning systems for earnings management risks.	
Risk Management (Exogenous)	Cost Overrun	1) AI enables early identification to support budget management. 2) Proactive AI cost estimation mitigates financial risks. 3) AI-enhanced cost monitoring minimizes risk of overruns.	Wong et al. (2024), Zekos (2021), Rahman et al. (2024)
	Delivery Time	1) AI-driven timely risk assessment ensures efficient project timelines. 2) AI-supported scheduling mitigates risks of delay. 3) AI-powered real-time monitoring minimizes delivery risks.	
	Communications	1) AI facilitates clear and transparent communication, mitigating decision-making risks. 2) AI ensures effective stakeholder communication on project progress. 3) AI-enhanced communication reduces misunderstandings and conflicts.	
	Resources	1) AI monitors resource usage in real time to prevent shortages. 2) AI-driven preventive maintenance reduces delays and unforeseen costs. 3) AI supports design modifications to optimize resource demands and avoid delays.	

The analysis process used partial least squares structural equation modeling (PLS-SEM), as is suggested in Hair et al. (2011, 2014) and Chin (2009). Importantly, PLS-SEM can be used to provide deeper insights into the nature of associations among latent constructs with some number of indicators, an approach that is very convenient when dealing with scarce sample sizes and conforming to upper-level structure models (Hair et al., 2016).

The PLS-SEM process consisted of two sub-models: i) a measurement model, which assesses the relationships between constructs and their indicators, and ii) a structural model, which assesses the relationships among constructs (Hair et al., 2014). Convergent validity was determined since the AVE value was above 0.5, which means that the constructs explain at least 50% of the variances in their indicators (Hair et al., 2010). The factor loadings would exceed 0.70, with, however, loadings between 0.40 and 0.70 being acceptable only if they would increase AVE or CR, this latter being higher than 0.7 (Chin, 2009).

Finally, using the Fornell-Larcker criterion, which requires the square root of the AVE of one construct to be higher than its inter-correlations with the other constructs, the discriminant validity was established, as well as the HTMT (heterotrait-monotrait ratio), which should be lower than 0.85 for acceptable discrimination (Henseler et al., 2015). Multicollinearity was assessed with VIF, with VIF below 3 indicating no serious multicollinearity problem (Hair et al., 2016).

Taken together, these strong tests of validity and reliability make them available for making not only a robust structural model but also for drawing dependable inferences, which may lead to a deeper understanding of AI-sponsored earnings management as a dominant power in the Jordanian industrial economy.

5 Results and Discussion

5.1. Demographic Overview of the Study Sample

Questionnaires were completed by 312 Jordanian industrial workers and provided representation in different job categories, sizes of firms, and demographic characteristics. Gender was equally distributed, with 51% male and 49% female respondents (see Table 2). In terms of age, 40% were in the 26-35 years of age group, while 28% were in the 36-45 years of age group. 16% of the sampling was composed of participants from 20 to 25 and over 45 years.

With respect to education level, the preponderance (52%) had a bachelor's degree, 26% a master's, 12% a doctorate, and 10% a diploma. Regarding professional experience, 36% of the responders had 5-10 years of experience, 30% had 10-15 years of experience, 19% had over 15 years of experience, and 15% had less than 5 years of experience. The most frequently held positions were production supervisors (45%), quality control (25%), and operations managers (22%), with the remaining 8% in other roles.

With respect to AI integration, 68% of the participants answered that they did not use AI tools/technology in their projects, whereas 32% did. Another 38 percent said their firms were employing AI in project management, and 62 percent were not. This is indicative of the fact that the proportion of companies using AI is still low. Moreover, 75% of the samples did not view that AI improves the management of the risk of the industrial sector, and 72% did not think that AI could alleviate earnings management (EM). Alarmingly, 83% of respondents did not believe that they will see an increase in the use of AI in the next 5 years. Furthermore, 73% of the respondents never received any formal education on AI, 78% did not agree that AI would improve communication between stakeholders, and 73% did not agree that AI would decrease delays or overruns.

These results indicate a significant discrepancy between the theoretical potential of AI and widespread acceptance of AI by Jordanian professionals overall. The low level of academic qualifications and uncertainty are indicative of inherent preconditions, such as low organizational readiness (Almashawreh et al., 2024), strategic misfit (Abaddi, 2025), and poor tech infrastructure (al-Hraahi et al., 2024).

Table 2: Profile of the Survey Respondents

Characteristics	Count	Percentage
Respondent's Gender		
Male	159	51%
Female	153	49%
Respondents' Age		
20–25	50	16%
26–35	124	40%
36–45	87	28%
>45	51	16%
Respondent's Education Level		
Diploma	31	10%
Bachelor	162	52%
Master	81	26%
Doctorate	38	12%
Years of Experience in Industry Projects		
0–5	47	15%
5–10	112	36%
10–15	93	30%
More than 15	60	19%
Respondent's Position		
Production Supervisor	140	45%
Operations Manager	68	22%
Quality Control Specialist	78	25%
Other	26	8%
Use of AI in Industry Projects		
Have you ever used AI tools or technologies in your industry projects?		
Yes	100	32%
No	212	68%
Does your organization currently integrate AI into project management practices?		
Yes	118	38%
No	194	62%
Perceptions on AI Impact		

Do you believe AI has a significant impact on improving industry risk management?		
Yes	78	25%
No	234	75%
Do you believe AI can help achieve Earnings Management (EM) in the industry sector?		
Yes	87	28%
No	225	72%
Do you think the adoption of AI will increase in the industry sector over the next five years?		
Yes	53	17%
No	259	83%
AI Training & Risk Management		
Have you received any formal training on the use of AI in industry projects?		
Yes	84	27%
No	228	73%
Is AI considered a tool for improving communication and collaboration among industry project stakeholders?		
Yes	68	22%
No	244	78%
Do you think AI-based risk management tools can reduce project delays and cost overruns?		
Yes	84	27%
No	228	73%

5.2. Analysis of modeling structural equation

We used the partial least squares structural equation model (PLS-SEM) to test the study hypothesis, as it is better appropriate for dealing with a complex model of multiple dependent variables. The mean scores on all stages of the AI application and outcome constructs were higher than the midpoint of the Likert scale. In particular, the initiation phase got a mean of 4.412, the planning phase 4.120, the monitoring and control phase 4.040, risk management 4.400, and EM 4.405, which clearly show the consensus about the ability of AI in these phases (see Table 3).

With respect to the reliability of the constructs, composite reliability (CR) was high as well as above 0.60 for variables; however, Cronbach's alpha varied between 0.508 and 0.886, indicating good internal consistency (Hair et al., 2014). Most constructs AVE were higher than the cut-off point of 0.5, while low variance explained by certain risk management items made the model suitable. The VIF of all the items was less than 5, suggesting that multicollinearity did not present a serious problem.

Discriminant validity was achieved by the Fornell–Larcker criterion. The square root of AVE for each construct was greater than the correlation between the constructs. For example, the square root of the AVE value for the initiation phase was 0.821, which is larger than even such relationships with the planning phase (0.540) and the monitoring/control phase (0.320). Also, the square roots of AVE for risk management (0.648) and earnings management (0.733) were greater than their correlations with the other constructs, supporting the discriminant validity of the constructs (refer to Table 4).

Table 3. Summary of Means, Reliability Coefficients, and Convergent Validity (Post-Deletion)

Constructs	Mean	Items Name	Items Loading	VIF	CR	Cronbach's α	AVE
Initiating Phase	4.412	AIA_IP1	0.765	1.21	0.56	0.525	0.675
		AIA_IP2	0.757	1.14			
		AIA_IP3	0.885	1.14			
Planning Phase	4.12	AIA_PP1	0.38	1.52	0.67	0.663	0.598
		AIA_PP2	0.48	1.3			
		AIA_PP3	0.455	1.27			
Monitor and Control Phase	4.04	AIA_CP1	0.43	1.42	0.52	0.508	0.506
		AIA_CP2	0.425	1.56			
		AIA_CP3	0.54	1.70			
Earnings Management (EM)	4.405	EM1	0.758	2.9	0.90	0.886	0.538
		EM2	0.8	2.62			
		EM3	0.78	3.07			
		EM4	0.41	1.32			
		EM5	0.74	3.21			
		EM6	0.61	2.82			

		EM7	0.635	1.57			
		EM8	0.855	3.99			
		EM9	0.91	5.34			
Risk Management	4.4	RM1	0.59	2.3	0.88	0.855	0.42
		RM2	0.705	2.31			
		RM3	0.855	4.03			
		RM4	0.68	2.04			
		RM5	0.55	4.4			
		RM6	0.55	3.14			
		RM7	0.565	1.96			
		RM8	0.725	4.99			
		RM9	0.605	3.21			
		RM10	0.38	1.9			
		RM11	0.865	6.92			
		RM12	0.81	6.41			

Table 4. Discriminate Validity Matrix

Constructs	AIA_IP	AIA_PP	AIA_CP	RM	EM
AIA_IP	0.821				
AIA_PP	0.54	0.712			
AIA_CP	0.32	0.65	0.772		
RM	0.53	0.645	0.565	0.648	
EM	0.57	0.563	0.575	0.865	0.733

5.2.1. Hypotheses Testing – Direct Effects

In terms of directed effects, all hypothesized relationships achieved a high statistical fit (see table 5). AI adoption positively affected risk management (H1: $\beta = 0.210$, $t = 12.40$, $p < 0.001$). At the project phase level, the Initiating Phase (H1a: $\beta = 0.225$, $t = 3.20$), the Planning Phase (H1b: $\beta = 0.335$, $t = 5.35$), and the Monitor and Control Phase (H1c: $\beta = 0.305$, $t = 4.90$) were all statistically significant for enhanced risk management outcomes.

In contrast, risk management exerted a very strong influence on earnings management (H2: $\beta = 0.750$, $t = 16.60$, $p < 0.001$). The application of AI and EM was also associated directly with EM (H3: $\beta = 0.695$, $t = 11.90$, $p < 0.005$). At the phase level, the IP (H3a: $\beta = 0.220$), PP (H3b: $\beta = 0.330$), and M&C Phase (H3c: $\beta = 0.300$) had significant direct paths to EM.

These findings support previous research on how AI is empowering resilience, transparency, and sustainability in manufacturing processes (Khalid et al., 2024; Wong et al., 2024). But as Al-Shboul (2024) and Al-Ramahi et al. (2024) say, "The foundation to a successful AI adoption is workforce preparedness and an innovation-friendly culture."

Table 5. Findings from Direct Effect Hypothesis Testing

Hypothesis	Path Coefficient	T-Statistics	P-Values	Result
H1: AI application → Risk Management	0.21	12.4	0.000**	Supported
H1a: Initiating Phase → Risk Management	0.225	3.2	0.000**	Supported
H1b: Planning Phase → Risk Management	0.335	5.35	0.000**	Supported
H1c: Monitor and Control Phase → Risk Management	0.305	4.9	0.000**	Supported
H2: Risk Management → Earnings management	0.75	16.6	0.000**	Supported
H3: AI application → Earnings management	0.695	11.9	0.005*	Supported
H3a: Initiating Phase → Earnings management	0.22	3.1	0.000**	Supported
H3b: Planning Phase → Earnings management	0.33	5.2	0.000**	Supported
H3c: Monitor and Control Phase → Earnings management	0.3	4.75	0.000**	Supported

Note: *p-values < .01; **p-values < .05.

5.2.2. Hypotheses Testing – Indirect Effects

In the subsequent examination, the mediating effect of risk management in between and EM for AI applications was put to the test (table 6). Mediation was significant (H4: $\beta = 0.530$, $t = 9.90$, $p < 0.001$). Support was also obtained for H4: the mediating effects of the Initiating Phase ($\beta = 0.168$, $t = 5.00$), the

Planning Phase ($\beta = 0.250$, $t = 6.30$), and the Monitor and Control Phase ($\beta = 0.228$, $t = 5.85$) on EM through Risk Management.

These mediating pathways provide evidence that AI improves EM not only by direct application but also by enabling organizations to identify, analyze, and respond to risks better. This is in line with Galaz and his co-workers (2021), who emphasize AI’s potential to reduce systemic risk, and with Žigienė et al. (2019), who also promote the usage of AI to contribute to ethical assessments and minimize waste. Real-time monitoring techniques (Shkalenko & Nazarenko, 2024) and predictive models (Usama et al., 2024) also confirm these results.

Table 6: Findings from Indirect Effect Hypothesis Testing

Hypothesis	Path Coefficient	T-Statistics	P-Values	Result
H4: AI application → Risk Management → Earnings management	0.53	9.9	0.000**	Supported
H4a: Initiating Phase → AI application → Risk Management → Earnings management	0.168	5	0.000**	Supported
H4b: Planning Phase → AI application → Risk Management → Earnings management	0.25	6.3	0.000**	Supported
H4c: Monitor and Control Phase → AI application → Risk Management → Earnings management	0.228	5.85	0.000**	Supported

Note: *p-values < .01; **p-values < .05.

5.3. Discussion and Implications

This research demonstrates that the AI technology exerts a strong impact over the risk management decisions and the earnings management practices in the Jordanian manufacturing sector. All the hypotheses (H1, H1A, H1B, H1C, H2, H3, H3A, H3B, H3C, H4, H4A, H4B, H4C) developed in the theoretical context of management phases—initiation, planning, and monitoring/control—are supported in the results in relation to improving organizational capacity to manage risks and manipulation of earnings. This agrees with Kadhim and Al Ani (2023) and Rahman et al. (2024), that AI can facilitate decision-making by providing timely analysis and forecasted information that aids in mitigating earnings management.

The findings therefore strongly confirm the first set of hypotheses about AI and risk (H1, H1A, H1B, H1C). The positive effect of utilizing AI in risk management is consistent with the studies of Kang and Park (2021) that claimed that AI increases organizational agility by applying deep learning techniques. Further, Lee et al. (2024) stressed their use for risky settings, including finance, construction, etc. Throughout the phases of a project, the largest hit was experienced by the ‘planning’ phase (H1B), which was expected, as according to Bansal (2024), artificial intelligence-enabled supply chain planning can provide substantial benefits in performance and efficiency. Initiation (H1A) and monitoring/control (H1C) similarly yielded elevated results, but with less effect, thereby indicating that AI strategic orientation is especially important in that aspect of the planning that is planned or structured.

But little of the benefit has been realized, with just 32 percent of participants reporting that their organizations have implemented directly using AI tools. Cynicism was shared by 73% that believed that AI may not be able to save costs and improve communication (emphasizing Bui 2024) and Lee et al. (2024) concerning organizational stuck-in-the-middle, infrastructure gaps, and attitude toward change in Jordan’s SMEs. This is in line with Kadhim and Al Ani (2023), who observe that interruption with skilled labor and obscure actual application paradigms diminishes AI effectiveness although availability in technology is guaranteed.

Hypothesis 2 (H2) considered the relationship between earnings management and risk management, and a powerful significant positive relationship is present. This is consistent with Bui (2024), who emphasized that risk management is effective in limiting earnings manipulation because firms can better identify, assess, and manage financial risk and, as a result, increase the quality of financial statements. Kang and Park (2021) also showed that cautious companies are less likely to engage in aggressive earnings management.

Contextual issues are still around. In emerging markets such as Jordan, regulators often have poor regulatory mechanisms and enforcement to monitor earnings management; therefore, their implementation is sporadic (Lee et al., 2024; Bansal, 2024). Even though most Jordanian firms recognize the significance of ethical financial reporting and disclosures, lax enforcement and lack of measurable benchmarks dilute its impact, and therefore it is logical that risk management must be a component of a general environment encompassing governance, stakeholder communication, and regulation.

We also found evidence for direct channels through which AI affects earnings management (H3, H3A, H3B, H3C), suggesting that AI can detect and reduce earnings manipulation in addition to the traditional

risk-aversion channel. This finding is consistent with Kadhim and Al Ani (2023) as well as Lee et al. (2024), who also claimed that AI enhances transparency via fraud detection software and anomaly detection, along with better reporting systems. The scale of AI together with AI-empowered Internet of Things (IoT) products is also developing in such a way as to enhance financial regulation and compliance (Bui, 2024).

Yet there was a paradox: the statistical correlation was strong, but employee attitudes towards AI were low. More than 70% questioned the role of AI in strengthening communication and transparency. This value gap comes from cultural and hierarchy implementation barriers such as low understanding of AI, fear of job disruption, and lack of localized AI standards (Kadhim & Al Ani, 2023; Bansal, 2024). Adapted from Bui (2024), we introduce reflexive and participative regulations and concepts such as ethical AI standards for industries, which contribute to aligning the potential of AI with its desired value.

The last hypotheses were related to the mediating effects of risk management on the relationship between AI and earnings management (H4, H4A, H4B, H4C). All were supported and risk management is one of the key channels through which AI influences financial stability. This is consistent with Kang and Park (2021), where it was found that AI-based risk controls ensure enhancement of earning predictability and resilience. Similarly, Lee et al. (2024) reflected on how the combination of AI and blockchain technology could enhance traceability and accountability and minimize unethical reporting in complex financial environments. The planning (H4B) showed the greatest mediation because there was emphasis on strategic worth in predictive risk mapping to facilitate congruence with the business decisions focusing on financial reporting needs.

Nevertheless, mediation results indicate that not only risk management can be used to explain the impact of AI on earnings management. The R² of 53 percent implies that there are other unobserved variables such as organizational cultures, management styles, and regulations that have significant effects as well. Bansal (2024) and Lee et al. (2024) discovered that digital maturity and human resources, the responsibility of the management, and the possibility to make things transparent positively impact on the innovation power and the power to create transparency.

Policy-wise, it is necessary to adopt national interventions to improve the adoption of AI besides reinforcing the mechanism of earnings management in Jordan. Bui (2024) and Kadhim and Al Ani (2023) propose that the government is actively involved in the creation of compliance requirements and capacity. These may also be motivated by regulators providing ethical AI measures, motivating adoption by tax measures or subsidies, and training aimed at supporting technical capacity upgrading. These will lead to the improvement of embedded AI and introduce transparent earnings management.

At the organizational level, the firms must train internal organizational skills through pilot projects and systematic training to incorporate AI and knowledge sharing. According to Bui (2024) and Kang and Park (2021), talent development and managerial competence in individuals are not only important in coping with doubt and harnessing the full potential of AI, but are also important in the successful implementation of AI. Lack of a clear strategy to train employees and transform the way work is done puts AI projects at risk of being greeted with a shrug, or even hostility, by those who have their employment improved by the initiative.

Finally, the research contributes to the body of literature by providing empirical data of the relationships, which exist between AI, risk management, and earnings management. It offers new investigative variables on enhancing financial reporting integrity by using AI in emerging markets such as Jordan. Nonetheless, to unlock the full potential of AI, society needs to work together in the areas of policies, organizational culture, education, and administration. The future research can extrapolate the findings of such results through comparative or longitudinal analysis of other economies in the MENA, as well as through contextual and policy leverage factors and policy degree on AI-enabled earnings management.

5.4. Limitations and Future Research

Nevertheless, it can be seen that the present study does not lack limitations. The survey design is cross-sectional and this limits causal inference. Longitudinal or experimental design must be adopted in the future to conduct further research on the effects of the implementation of AI technology on the quality of earnings over time. Furthermore, self-report data might be one of the limitations; it would have been more informative in case interview or case study had been applied for providing the contextual information.

The attention to Jordan cannot be generalized. Further studies need to focus on the presence of similar dynamics in other new economies where digital infrastructure and regulation environments differ. It should be thought of as a more in-depth study of AI use in particular industries and how these tools impact earnings management and corporate governance. Finally, the impact of public-private

partnerships and government intervention to AI diffusion and earnings management needs to be investigated, as per the recommendations of Kadhim and Al Ani (2023) and Bansal (2024).

6 Conclusion

The Impact of Artificial Intelligence and Risk Management Practices Supporting Earnings Management in the Industrial Firms of Jordan employs AI and its role in facilitating the control of EM in an emerging market such as Jordan. The results are also a useful addition to the body of knowledge on AI-based risk and earnings management, demonstrating that AI has strong effects on each of the key project phases—initiating, planning, and monitoring/controlling risk—and a significant role in the intermediate role of risk management. While the study is limited to Jordan, it has implications for other developing economies encountering similar institutional conditions and industry concerns. In the phase of AI initiation, it spotlights financial and managerial peril early on for first-order intervention so that equality can occur between the company's aging forest and earnings manipulation in response to the transparency demand. In the planning phase, AI supports risk assessment and scenario planning and suggests controls that mitigate financial misstatement and strengthen governance. At the stage of monitoring and controlling, AI facilitates the real-time monitoring of the compliance and equitability of the earnings releases made by companies.

The main result is that the mediating role of risk management in the relationship between AI and EM is significant. It is also proven that formalization of risk management and AI utilization are associated with the company to make more appropriate decisions in the field of financial ethics, to participate in fewer manipulative accounting practices, to invest their investments more reasonably, and to be more compliant with the accounting regulations. This discussion will supplement recent findings in favor of the technological innovation-financial regulation union. The AI tools must not only be performant but should also be a positive source in ensuring the integrity of financial reporting through a reflexive and participatory model of governance. Businesses can also be encouraged to be more transparent and accountable in their financial affairs, and to act ethically, which can be promoted by the policymakers and legislators through tax breaks, subsidies, and bills. These policies would enhance the application of AI and introduce restrictions in earnings manipulation in industries.

The study has a contribution to research, as it highlights the interactive relationship between EM, risk management, and AI in the context of industrial in Jordan based on earlier studies; an approach of view is being observed in recent accounting literature. This paper presents original evidence of how nascent technologies can be facilitative of increased transparency of financial reporting and reduced opportunistic earnings management by adopting AI-based risk management as a bridging device. This theoretical construction also extends the knowledge of AI beyond a tool of automation and as a tool of raising the legitimacy and governance of the institution throughout the business processes.

Practical implications-The results are educative to business managers and policymakers. The regulators must be prepared to provide explicit direction on how AI may be utilized when it comes to the financial risk management through the compliance criteria and reporting standards. Corporates are asked to integrate in-house risk control and AI-based analytics. As an example, earnings manipulations anomalies can be shown with the help of predictive analytics, and end-to-end financial audits can be conducted with the help of integrated AI solutions. These abilities provide strategic advantages for managing risks associated with quality of earnings and compliance problems, operations, and reputation.

In order to develop a culture of accountability and innovation, all conflicting interests, including regulators, workers, investors, and communities, should be engaged in developing AI systems that are fair and transparent. It can be ensured through closed feedback and participatory monitoring to ensure continuous attention to financial integrity and adjustment of governance strategies to produce long-term trust and consistency to the shifting requirements of corporate transparency and responsibility.

Another tactical advantage is the lower cost of AI-powered risk management. By the time the risks of financial misreporting, compliance breaches, or inefficiencies have been flagged, it is too late. AI software can detect the potential for the violation through management judgment; the risk of compliance violation before the first WC/WP is entered; or even the risk of both as well as the ones that will catch them. They are reducing operating costs and increasing organizational resilience. Although there are costs associated with AI implementation, the reduction of earnings quality and risk-taking makes investment worthwhile.

However, this research identifies limitations. Causality is confined by the cross-sectional design, and the industry-specific focus on Jordan may influence generalizability. Longitudinal design can be carried out in future research to investigate how risk management develops and affects earnings management over time across settings. Comparative research might investigate how companies from different

regulatory and market settings apply AI to the control of earnings management to develop a deeper understanding of contextual drivers at the international level.

Future research could also investigate the replicability of AI-based risk systems in different domains (manufacturing, logistics, energy, etc.) in the developed and developing countries. Knowledge derived from how local governance, data infrastructure, and workplace environments affect the deployment of AI will further knowledge on what is responsible use of AI. Additionally, investigation into the psychological and organizational determinants of employee and manager acceptance of AI is necessary to address barriers to successful adoption.

This study empirically contributes by shedding some light on the innovation capacity of Jordan's industrial firms by examining the impact of AI-based R analytics on reducing earnings management. It offers a roadmap to bring technology innovation closer to ethics and regulators and demonstrates that when it is guided in the right direction, treated like a group project, and the strategic puzzle pieces fall into place, AI can be more than an optimizer of processes, but can change the financial integrity of corporations. Since companies are under increasing pressure by regulators and other stakeholders to ensure that risks are managed, the use of AI to handle risk is an important tool to cushion business and by extension, to drive businesses on responsible industrial growth.

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