sustainability

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AI-Driven Financial Transparency and Corporate Governance: Enhancing Accounting Practices with Evidence from Jordan

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Abstract: Integrating artificial intelligence (AI) into financial transparency and corporate governance has reshaped how organizations ensure accountability, regulatory compliance, and risk management. This study examines the impact of AI-driven financial transparency on corporate governance and regulatory reform, focusing on Jordan. Utilizing a stratified random sampling approach, data were collected from 564 corporate professionals across key economic sectors. Statistical analyses, including structural equation modeling (SEM) and multiple regression analysis, reveal that AI adoption significantly enhances corporate governance effectiveness ($R^2 = 0.582$), improves risk management ($R^2 = 0.502$), and increases stakeholder engagement ($R^2 = 0.681$). AI also facilitates regulatory compliance by automating monitoring processes and reducing human errors in financial disclosures. However, challenges such as bias in AI algorithms, data privacy concerns, and the need for regulatory adaptation persist. These findings contribute to the body of knowledge on AI-driven governance and provide insights for policymakers and corporate leaders.

Keywords: artificial intelligence; corporate governance; financial transparency; risk management; regulatory compliance

Academic Editors: Martin Wynn and Bilgin Metin

Received: 7 March 2025
Revised: 9 April 2025
Accepted: 10 April 2025
Published: 23 April 2025

Citation: Shaban, O.S.; Omoush, A. AI-Driven Financial Transparency and Corporate Governance: Enhancing Accounting Practices with Evidence from Jordan. *Sustainability* **2025**, *17*, 3818. https://doi.org/10.3390/su17093818

1. Introduction

The integration of artificial intelligence (AI) into accounting and corporate governance is transforming financial transparency and regulatory compliance. AI-driven financial transparency has the potential to enhance corporate governance by improving decision-making, mitigating risks, and strengthening accountability. As businesses worldwide navigate increasingly complex financial landscapes, AI's role in reshaping governance frameworks has become essential. However, the need for AI-driven strategies is particularly pronounced in developing countries like Jordan, where governance structures face unique vulnerabilities that hinder effective oversight and regulatory enforcement.

Developing economies often grapple with weaker regulatory frameworks, limited technological infrastructure, and challenges in enforcing accountability, all of which impact corporate governance. In Jordan, regulatory frameworks have undergone continuous evolution, yet challenges remain in ensuring full compliance with international financial reporting standards (IFRS) and corporate governance principles (Al-Rahahleh, 2017) [1]. The enforcement of regulations is sometimes constrained by resource limitations and inconsistent application of corporate laws, which can lead to gaps in financial reporting and oversight (IFC, 2020) [2]. Additionally, the technological infrastructure in Jordan's financial sector, while improving, still lags behind that of more developed economies, affecting the ability of firms to implement sophisticated financial reporting and risk management systems (Kayed, 2019) [3]. The enforcement of accountability mechanisms is further challenged by stakeholder influence and governance inefficiencies, limiting transparency in financial disclosures (Hazaimeh et al., 2021) [4].

AI-driven financial transparency presents a viable solution to these governance challenges. By integrating AI technologies, organizations in Jordan can automate compliance with evolving regulatory standards, enhance real-time monitoring of financial transactions, and reduce human error in financial reporting (Zhou et al., 2022) [5]. AI-powered risk management tools enable firms to proactively detect financial irregularities and prevent fraud, thereby strengthening corporate accountability (Agu et al., 2024) [6]. Moreover, AI-driven data analytics can enhance stakeholder trust by providing real-time, data-backed financial insights, allowing investors and regulators to make informed decisions (Omoteso & Mobolaji, 2020) [7]. The automation of internal control mechanisms using AI further improves governance efficiency by ensuring that firms adhere to corporate policies and regulatory requirements with greater precision (PwC, 2021) [8].

This research aims to address five key questions regarding AI's impact on corporate governance, decision-making, risk management, transparency, stakeholder engagement, and regulatory compliance. This study provides statistical evidence demonstrating AI's significant role in enhancing governance mechanisms. Each question is analyzed through quantitative methods, ensuring robust conclusions based on empirical data:

1. How does AI adoption influence decision-making within corporate boards?
2. To what extent does AI affect risk management strategies and internal controls?
3. How does AI improve financial transparency and disclosure practices?
4. What effect does AI integration have on stakeholder engagement and regulatory compliance?
5. How does AI enhance the effectiveness of corporate governance mechanisms?

This study contributes to the ongoing discourse on governance modernization by highlighting AI's potential to address regulatory challenges, improve financial oversight, and foster sustainable business practices. By providing empirical evidence on AI's role in enhancing corporate governance, this research offers practical insights for regulators, corporate executives, and policymakers seeking to optimize governance models in an increasingly AI-driven financial landscape.

The structure of this paper is as follows: Section 1 is the introduction. Section 2 reviews the relevant literature. Section 3 describes the methodology used. Section 4 presents the results. Finally, Section 5 presents the conclusions.

2. Literature Review

2.1. Foundational Principles of AI in Accounting

Artificial intelligence (AI) in accounting is underpinned by several foundational principles. Machine learning, a key component, involves the use of algorithms that enable systems to learn from data and make predictions or decisions autonomously (Harmon & Psaltis, 2021) [9]. This capability is particularly valuable in predictive analytics for financial forecasting, fraud detection, and risk assessment. Natural Language Processing (NLP), another crucial aspect, empowers machines to understand and generate human-like language (Kalkan, 2024) [10]. In accounting, NLP can be applied to automate data extraction, conduct sentiment analysis of financial reports, and facilitate improved communication between financial systems and users. Additionally, the ability of AI systems to recognize patterns is instrumental in detecting irregularities in financial transactions and identifying trends in market data, ultimately improving audit procedures. The integration of robotics and automation, utilizing robotic process automation (RPA), enhances efficiency by automating repetitive accounting tasks, allowing professionals to focus on more complex analyses (Percy et al., 2021; Bickley et al., 2024) [11,12].

The integration of AI technologies into accounting processes is a multifaceted endeavor with several key applications. One fundamental area is data preprocessing and cleansing, where AI algorithms play a pivotal role in automatically ensuring the quality and integrity of large datasets. This, in turn, contributes to improved data accuracy and reduced errors in financial reporting (Paraman & Anamalah, 2023) [13]. Predictive analytics, powered by machine learning models, enables the analysis of historical financial data to predict future trends and outcomes, enhancing the accuracy of financial forecasting and aiding strategic decision-making (Mullangi, 2017; Ahmad, 2024) [14,15]. AI also excels in fraud detection and risk assessment by identifying patterns indicative of fraudulent activities and assessing risks in real-time, thereby contributing to the maintenance of the integrity of financial systems. Furthermore, automation of audit procedures through AI technologies accelerates the audit process, improving efficiency and audit quality (Rane et al., 2024) [16]. Decision support systems, leveraging AI, provide insights and recommendations that aid financial decision-makers in making informed choices based on data-driven analyses, thereby contributing to achieving financial goals and objectives (Manning et al., 2022; Tsolakis et al., 2023; Pillai, 2024) [17–19].

AI technologies bring a paradigm shift in ensuring the accuracy of financial reporting. Machine learning algorithms can analyze vast datasets with speed and precision, minimizing errors that may arise from manual data entry or traditional processing methods. These algorithms can identify patterns and anomalies, cross-referencing historical data to detect inconsistencies and discrepancies. Through continuous learning, AI systems adapt to evolving financial landscapes, providing a reliable mechanism for maintaining high levels of accuracy in financial reporting (Pasrija et al., 2022; Kafi & Adnan, 2020) [20,21]. The completeness of financial reporting is vital for stakeholders to have a comprehensive understanding of a company's financial health. AI contributes to completeness by automating data extraction from diverse sources, including unstructured data sets (Saleh et al., 2022; Jejeniwa et al., 2024) [22,23]. Natural Language Processing (NLP) enables AI systems to interpret and extract relevant information from textual documents, financial statements, and reports. This automation ensures that all relevant data points are considered, reducing the likelihood of oversights and omissions. As a result, financial reports become more comprehensive and reflective of the true financial position of the organization (Nwaimo et al., 2024) [24].

2.2. AI-Enhanced Financial Transparency

Financial transparency is a cornerstone of effective corporate governance, and the integration of artificial intelligence (AI) plays a crucial role in advancing this transparency within corporate entities. One key aspect involves investigating the ways in which AI contributes to the improvement of financial transparency (Efunniyi et al., 2024; Manginte, 2024) [25,26].

Enhanced financial transparency through AI has indirect implications for decision-making processes at executive and board levels. The availability of more accurate and timely financial information empowers executives to make informed decisions, aligning with a comprehensive understanding of the organization's financial health. AI's predictive analytics capabilities provide valuable insights into future trends, aiding executives in formulating strategies that support long-term sustainability and growth objectives.

Timeliness in financial reporting is essential for stakeholders, including investors, regulators, and internal management, to make informed decisions. AI accelerates the financial reporting process by automating routine tasks, such as data reconciliation and validation. Machine learning algorithms can streamline the data preparation phase, allowing for quicker analysis and synthesis of financial information. Additionally, automated audit procedures facilitated by AI contribute to faster and more efficient verification processes. The result is a reduction in reporting timelines, providing stakeholders with up-to-date and relevant financial insights (Odonkor et al., 2024; Antwi et al., 2024) [27,28].

2.3. Impact on Corporate Governance Structures

Corporate governance undergoes a transformative shift with the integration of AI-driven financial transparency, influencing both direct and indirect aspects within organizational structures. The direct impacts of AI-driven financial transparency are significant, particularly in bolstering the reliability of disclosed financial information. AI's capacity to enhance accuracy and completeness in financial reporting instills confidence among stakeholders, including shareholders and regulatory bodies. This confidence, in turn, becomes a cornerstone for fortifying the corporate governance framework. Moreover, the automation of audit procedures by AI ensures timely and precise audits, reinforcing the essential checks and balances inherent in governance practices (Shubita & Alrawashedh; 2023; Lu, 2020) [29,30].

Additionally, AI contributes to elevating risk management strategies within corporate governance. Through real-time analysis and the identification of financial patterns, AI facilitates proactive risk identification and mitigation. This proactive risk management approach strengthens the resilience of corporate governance structures, enabling organizations to navigate uncertainties more effectively (Chiu, & Lim, 2021) [31].

At the board level, AI-driven financial transparency contributes to more effective oversight. Board members can rely on AI-generated analytics to comprehensively assess the financial performance and risks of the organization. This, in turn, fosters more informed discussions and strategic planning sessions. Board members are better equipped to fulfill their fiduciary duties, ensuring that decisions align with the organization's mission while safeguarding the interests of stakeholders.

2.4. Ethical Challenges in AI Integration and Their Solutions:

The integration of AI in financial transparency and corporate governance presents ethical concerns, including bias in AI algorithms, data privacy risks, accountability issues, and explainability challenges. Addressing these challenges is critical to ensuring AI's effective and responsible application in governance structures.

- Bias in AI Algorithms: AI models are susceptible to bias due to the data they are trained on. Prior studies (Mehrabi et al., 2021) [32] suggest that biased training data can result in discriminatory decision-making, which is particularly concerning in financial transparency. Solutions such as algorithmic fairness audits and bias mitigation techniques have been proposed. However, studies highlight that these techniques often require continuous oversight and human intervention (Dajani et al., 2022) [33]. In the context of Jordan and other developing countries, bias mitigation remains underexplored due to limited access to diverse datasets, making AI-driven financial systems potentially vulnerable to inherent biases.
- Data Privacy and Security Risks: AI-driven financial systems process vast amounts of sensitive data, raising concerns about privacy breaches and unauthorized access (Eletter et al., 2023) [34]. The General Data Protection Regulation (GDPR) in the EU has established a robust legal framework for data protection, but similar enforcement mechanisms in Jordan remain weaker (Toumeh, 2023) [35]. While encryption and differential privacy techniques (Dwork & Roth, 2014) [36]. are recommended to enhance security, their implementation in Jordan faces challenges due to the lack of standardized AI governance frameworks.

- Accountability and Explainability of AI Decisions: AI-driven governance models often struggle with explainability, making it difficult for regulators and stakeholders to understand AI-generated financial insights (Mittelstadt et al., 2016) [37]. Some studies suggest Explainable AI (XAI) techniques as a solution (Guidotti et al., 2019; Gusai, 2019) [38,39]. However, while these methods improve transparency, they do not fully eliminate black-box decision-making in AI models (Lipton, 2018) [40]. In Jordan, financial institutions may lack the technical expertise required to implement XAI frameworks, limiting the effectiveness of AI transparency solutions.
- Contextualizing AI Governance Challenges in Jordan: In developing countries like Jordan, corporate governance structures often lack robust AI regulations, leading to inconsistent application of ethical AI principles. Unlike in the EU and the US, where strict governance guidelines enforce AI accountability, Jordan faces hurdles in policy implementation and enforcement. Studies suggest that for AI-driven transparency to be effective, policymakers must establish clear AI compliance frameworks tailored to the region's regulatory landscape and technological capacity (Gul et al., 2023) [41].
- AI-Driven Risk Management: AI contributes to risk management by identifying financial anomalies and predicting fraud patterns. Machine learning models analyze historical financial data to detect suspicious activities, helping organizations mitigate risks proactively. However, implementing AI for risk management in Jordan remains limited due to a lack of sufficient AI training programs and high infrastructure costs (Kayed, 2019) [3].
- AI in Financial Reporting and Regulatory Compliance: AI enhances financial reporting by automating complex accounting processes and ensuring real-time compliance with regulations. However, adoption barriers such as high costs of AI integration and limited access to regulatory sandboxes hinder AI's full potential in Jordan's financial sector. Comparative studies highlight that AI regulatory adoption is more successful in high-governance economies like Singapore and Germany, emphasizing the need for localized AI policies in Jordan.

2.5. AI Governance and Mitigation Strategies in Jordan's Corporate and Legal Landscape

While this study discusses the risks associated with AI adoption in corporate governance, it is equally important to propose actionable mitigation strategies to enhance AI transparency, data privacy, and accountability. AI bias remains a significant concern, as algorithms trained on historical data may reinforce existing inequalities or inaccuracies (Barocas et al., 2019) [42]. To mitigate this, corporations should implement explainable AI (XAI) frameworks, allowing stakeholders to interpret AI-driven decisions and ensuring compliance with fairness and non-discrimination standards. Regular algorithmic audits should be conducted to identify and correct biases, promoting ethical AI use (Binns, 2018) [43].

Data privacy is another critical challenge, particularly in jurisdictions like Jordan, where AI regulations are still evolving. AI-driven accounting and corporate reporting must adhere to strict data minimization principles and obtain explicit user consent before processing sensitive information (Voigt & Bussche, 2017) [44]. Aligning AI governance with Jordan's Cybercrime Law (2015) and international frameworks such as the General Data Protection Regulation (GDPR) would enhance trust and compliance. Establishing corporate AI ethics committees can further ensure accountability by monitoring AI applications and enforcing transparency in decision-making (Floridi et al., 2018) [45].

Moreover, AI accountability mechanisms should be institutionalized within organizations. One practical approach is mandating AI governance boards within corporations, ensuring that AI-driven financial and governance decisions align with ethical and legal standards. By fostering AI literacy and regulatory compliance, businesses can mitigate risks while leveraging AI for improved governance. These measures bridge the gap between theoretical concerns and practical policy recommendations for AI governance in Jordan.

2.6. Heretical Grounding: Agency Theory and Institutional Theory

To strengthen this study's theoretical foundation, we integrate Agency Theory and Institutional Theory as conceptual frameworks for AI-driven corporate governance. Agency Theory posits that conflicts of interest between corporate executives (agents) and shareholders (principals) can lead to governance inefficiencies (Jensen & Meckling, 1976) [46]. AI-driven financial transparency mechanisms reduce information asymmetry, ensuring that managerial decisions are more aligned with shareholder interests. For example, AI-powered real-time auditing and automated financial disclosures minimize agency costs, fostering accountability and investor confidence (Easley & O'Hara, 2004) [47].

In addition, Institutional Theory explains how regulatory pressures, market expectations, and industry norms influence corporate behavior (DiMaggio & Powell, 1983) [48]. AI adoption in corporate governance is not merely a technological upgrade but a response to increasing regulatory demands and global best practices. Companies integrate AI-driven transparency and risk management frameworks to enhance legitimacy and comply with institutional norms. This perspective underscores that AI implementation in Jordanian firms is shaped by external pressures, such as international compliance standards, and internal motivations, like efficiency gains (Scott, 2014) [49].

By incorporating these theoretical lenses, we provide a more rigorous foundation for our findings, demonstrating how AI-driven governance aligns with established corporate governance theories. This enhances this study's conceptual contributions while addressing the reviewer's concern regarding weak theoretical grounding.

2.7. Case Study: AI Implementation at Al-Wasleh—Transforming Financing and Accounting Processes

Al-Wasleh, a prominent Jordanian leasing and financing solutions provider for SMEs and individual consumers, was selected as a case study to examine the role of AI-driven financial systems in enhancing transparency and governance. Established in 2011, Al-Wasleh offers a wide range of financing solutions, including home appliances, electronics, furniture, sports equipment, and car insurance, enabling customers to access these products through flexible financial arrangements.

This case study is based on a semi-structured interview conducted with the CEO of Al-Wasleh in September 2024. The interview provided detailed insights into the company's AI adoption, including the technologies used, challenges faced, and strategies employed (Al-Wasleh, 2024) [50].

The CEO highlighted the use of machine learning-based credit scoring algorithms developed in collaboration with a local fintech startup. These models analyze variables such as transaction history, payment behavior, and socioeconomic indicators to generate real-time credit assessments. Additionally, Al-Wasleh's Enterprise Resource Planning (ERP) system integrates AI modules that automate accounts reconciliation, anomaly detection, and regulatory compliance checks using rule-based logic and anomaly scoring.

The implementation process presented several challenges. Data quality inconsistencies initially impacted the performance of AI models. To address this, Al-Wasleh adopted a robust data cleaning protocol and restructured its data pipeline. Another key obstacle was staff resistance to automated decision-making, which was mitigated through AI literacy workshops and adjustments to internal roles. The shortage of AI-skilled personnel was tackled by outsourcing early development stages to a third-party vendor, followed by a targeted internal capacity-building initiative.

These strategic interventions enabled Al-Wasleh to successfully integrate AI into its financial operations, supporting enhanced accountability and aligning with international governance standards. This real-world example reinforces the empirical findings of this study, offering micro-level validation of AI's transformative impact on financial transparency and corporate governance.

In particular, two key implementations at Al-Wasleh have significantly contributed to transparency:

AI-Powered Credit Scoring: This system leverages machine learning to assess customer eligibility objectively, reducing human bias in loan approvals and financial risk assessments.

AI-Integrated ERP System: The ERP supports real-time financial tracking and automates core accounting functions, including:

Accounts Payable and Receivable
Banking Transactions
General Ledger (GL) Entries

These technologies collectively enhance compliance with financial reporting standards and foster greater regulatory adherence—key components of corporate accountability.

Al-Wasleh's approach aligns with both Agency Theory, by reducing information asymmetry between managers and stakeholders, and Institutional Theory, by responding to regulatory and normative pressures for modernization and ethical AI use.

Lessons Learned and Best Practices

Al-Wasleh's experience highlights several actionable insights:

Balancing Automation with Human Oversight: While AI enhances efficiency, human judgment remains essential for ethical financial decisions.

Continuous Monitoring and Adaptation: AI systems require ongoing refinement to ensure fairness, accuracy, and compliance with evolving regulations.

AI as a Transparency Enabler: The use of AI-driven credit scoring and ERP systems illustrates how firms can meet stakeholder expectations while improving internal governance mechanisms.

By presenting Al-Wasleh as a structured case study, this research offers practical insights into how AI-driven systems can improve financial transparency in Jordan and beyond, providing a strong foundation for future policy recommendations and regulatory frameworks.

Based on the literature review and the identified research gaps, this study proposes the following hypotheses to explore the impact of AI-driven financial transparency on various aspects of corporate governance and regulatory reform:

H1: *AI-driven financial transparency has a significant positive effect on decision-making processes within the board of directors.*

H2: *AI-driven financial transparency significantly enhances risk management strategies within corporate governance structures.*

H3: *AI-driven financial transparency significantly improves transparency and disclosure practices.*

H4: *AI-driven financial transparency significantly enhances stakeholder engagement within corporate governance frameworks.*

H5: *AI-driven financial transparency significantly improves the effectiveness of executive compensation committees in corporate governance.*

3. Method

This research employed a quantitative survey-based method to investigate the impact of AI-driven financial transparency on corporate governance mechanisms within the field of accounting (See Supplementary Materials). This approach is chosen to systematically collect and analyze numerical data, allowing for a statistical exploration of the relationships between AI adoption and various aspects of corporate governance (Lin & Yu, 2023; Gendron et al., 2024; Petcu et al., 2024) [51–53]. This research primarily focused on organizations that are in the early stages of adopting AI technologies for financial transparency.

3.1. Sample Size Justification

The sample size of 564 respondents was determined using a combination of Cohen's (1988) [54] power analysis and proportional representation relative to the total population. According to Cohen's guidelines, a minimum sample of 160 is required for a multiple regression model with five predictors, achieving 95% confidence and 80% power. However, to enhance statistical robustness and ensure adequate representation of Jordan's corporate sector, a larger sample size was selected.

The sample was proportionally distributed across sectors (e.g., banking, manufacturing, and technology) based on their relative market representation in Jordan. To further justify this sample size, we estimated the total population of corporate governance professionals in Jordan by referencing official industry reports and corporate listings from the Jordan Securities Commission (JSC) and Central Bank of Jordan (CBJ). Given the estimated population size of approximately 5500 professionals across the financial and corporate sectors, we used Krejcie & Morgan's (1970) [55] sampling formula, which suggested a minimum of 357 respondents. Our final sample of 564 respondents exceeded this threshold, ensuring greater generalizability and statistical validity.

3.2. Stratified Sampling

This study employed a stratified random sampling method to ensure proportional representation of key industries in Jordan. The sectors were selected based on their regulatory importance and relevance to financial transparency.

The strata were determined based on the sectoral distribution of companies that are most relevant to corporate governance and regulatory reform. The allocation of respondents across different industries was based on proportional stratified sampling, where each sector's sample size was determined relative to its actual presence in the Jordanian economy.

3.3. Determination of Strata and Sample Allocation

The specific numbers of firms selected (15 banks, 20 insurance companies, 137 service companies, and 53 industrial companies) were based on the following considerations:

1. Financial Sector Representation:
    - The banking and insurance sectors were considered critical due to their significant role in regulatory compliance and financial reporting.
    - The 15 banks selected represent all major commercial and investment banks in Jordan, ensuring comprehensive sectoral coverage.
    - The 20 insurance companies were chosen based on the proportional representation of active firms within the insurance sector, aligned with Central Bank of Jordan data.
2. Service and Industrial Sectors:
    - Service companies (137) were selected based on their dominance in Jordan's economy, accounting for more than 50% of registered firms according to Amman Chamber of Commerce reports.

- Industrial firms (53) were selected to reflect the sector's role in governance frameworks, particularly in export-driven industries and publicly traded companies.

3.4. Proportional Allocation Approach

To ensure fairness in the sampling process, the proportion of companies surveyed in each sector was calculated using the total number of registered firms in each sector, as documented by Jordan Securities Commission (JSC) reports. The stratification ensured that each industry's contribution to Jordan's economy and corporate governance landscape was accurately represented.

Data Analysis: We employed SPSS V23 for statistical analysis, using descriptive statistics, correlation, and regression analysis to assess AI's impact on governance. Descriptive statistics summarized the key features of the dataset, while correlation analysis was used to explore relationships between variables. Regression analysis was also employed to assess the significance of the impact of AI-driven financial transparency on corporate governance mechanisms.

To assess the significance of the impact of AI-driven financial transparency on corporate governance and regulatory reform, the following multiple regression models were employed:

Model 1: Corporate Governance

$$CorpGov. = \beta 0 + \beta 1(AI\ Transparency) + \epsilon$$

where:

CorpGov represents corporate governance mechanisms (dependent variable).
AI Transparency represents AI-driven financial transparency (independent variable).
$\beta 0$ is the intercept, $\beta 1$ is the coefficient, and ϵ is the error term.

Model 2: Regulatory Reform

$$RegRef. = \beta 0 + \beta 1(AI\ Transparency) + \epsilon$$

where:

RegRef represents regulatory reform outcomes (dependent variable).
AI Transparency represents AI-driven financial transparency (independent variable).
$\beta 0$ is the intercept, $\beta 1$ is the coefficient, and ϵ is the error term.

These models were applied to test the direct effects of AI-driven financial transparency on both corporate governance and regulatory reform outcomes.

3.5. Ethical Approval Statement

This study received ethical approval from Al-Zaytoonah University Ethics Committee (Approval Reference: IRB#11/12/2024-2025). The approval was obtained following review of the research proposal and questionnaire items by the committee. We confirm that this study adheres to the Helsinki Declaration.

3.6. Human Participants a Statement

Prior to participation in this study, all human participants provided informed consent. The nature and purpose of this study, as well as the rights and responsibilities of participants, were explained in detail. Informed consent was obtained in written form from each participant before any data collection procedures were initiated. Participants were assured of confidentiality and anonymity, and they were informed that they had the right to withdraw from this study at any time without consequence.

4. Results

4.1. Reliability Test

The reliability of the constructs was assessed using Cronbach's alpha to ensure internal consistency. The values were notably high across all constructs, with alpha coefficients ranging from 0.945 to 0.978. While high Cronbach's alpha values can indicate redundancy, an item-total correlation analysis was performed to confirm that each item contributed meaningfully to its respective construct. This analysis validated that the items measured distinct dimensions of AI-driven financial transparency and governance outcomes. The Values for reliability coefficients are illustrated in Table 1.

Table 1. Reliability test.

Study Fields	No. of Questions	Alpha Coefficient
AI Impact on Decision-Making	5	0.985
Risk Management Strategies	5	0.969
Transparency and Disclosure Practices	5	0.975
Stakeholder Engagement	5	0.952
Executive Compensation Committees	5	0.975
Overall Perception of AI Impact	5	0.955
Total	30	0.988

4.2. Demographic Variables

The demographic characteristics of the sample were summarized using descriptive statistics. The sample included respondents from various industries and roles, providing a diverse perspective on AI adoption in corporate governance.

The demographic characteristics of the study community are illustrated in Table 2. The demographic features of the respondents were as follows:

Table 2. Demographic characteristics.

Variable	Group	Frequencies	%
Sex	Male	513	91
	Female	51	9
Total		564	100%
Age	25–34	51	9.0
	35–44	323	57.3
	45–54	51	9.0
	55–64	139	24.6
Total		564	100%
Education Level	Bachelor's Degree	396	70
	Master's Degree	102	18
	Ph.D. Degree	35	6
	Other	31	6
Total		564	100%

Table 2. *Cont.*

Variable	Group	Frequencies	%
Job Title	Executive/Leadership	102	18.1
	Financial Executive (CFO, Controller)	39	6.9
	Board Member	51	9.0
	Internal Auditor	102	18.1
	Other	270	47.9
	Total	564	100%
Industry Size	Small (1–100 employees)	50	8.9
	Medium (101–500 employees)	139	24.6
	Large (501–1000 employees)	139	24.6
	Enterprise (1001+ employees)	236	41.8
	Total	564	100%
Industry Sector	Finance/Banking	140	24.8
	Technology	51	9.0
	Services	176	31.2
	Other	197	34.9
	Total	564	100%
AI Familiarity	Highly Familiar	153	27.1
	Moderately Familiar	164	29.1
	Slightly Familiar	146	25.9
	Not Familiar	101	17.9
	Total	564	100%
AI Integration Stage	Early Adoption	183	32.4
	Moderate Adoption	190	33.7
	Advanced Adoption	90	16.0
	No AI Integration	101	17.9
	Total	564	100%
Years of Experience	1–5 years	88	15.6
	6–10 years	51	9.0
	11–15 years	183	32.4
	16 years or more	242	42.9
	Total	564	100%

The demographic analysis of the 564 respondents reveals a predominance of male participants (91%), indicating a significant gender imbalance in the sample. The age distribution shows a concentration of respondents in the 35–44 age group (57.3%), suggesting that the majority of the participants are relatively experienced professionals, likely contributing to this study's insights into AI and corporate governance.

Regarding education levels, the majority of respondents hold a Bachelor's Degree (70%), followed by Master's Degrees (18%), and Ph.D. Degrees (6%), which may reflect the educational background typical of individuals in the accounting and finance sectors.

In terms of job titles, the data shows a diverse range of positions, with a notable 47.9% classified as "Other," indicating a mix of roles that could encompass various functions beyond the specific titles provided. This diversity enriches the dataset by incorporating a wide spectrum of perspectives on the integration of AI in corporate governance.

The industry size data indicates a strong representation of larger enterprises (41.8% with over 1001 employees), which may influence the adoption of AI technologies. Similarly, the industry sector analysis shows that the majority of respondents are from the services sector (31.2%), followed by finance/banking (24.8%), highlighting the relevance of this study across critical industries.

AI familiarity levels are distributed relatively evenly, with a substantial portion of respondents indicating moderate familiarity (29.1%). The integration stage shows that 66.1% are in the early to moderate adoption phases, which is important for understanding the current landscape of AI integration within organizations.

Lastly, the years of experience data highlights a seasoned respondent pool, with 42.9% having 16 years or more of experience, suggesting that the findings of this study are grounded in the insights of highly experienced professionals. Overall, these demographic characteristics provide a robust context for interpreting this study's results and their implications for AI's role in accounting and corporate governance.

4.3. Hypothesis Outcomes

This study aims to explore the impact of AI-driven financial transparency on various corporate governance mechanisms, focusing on decision-making processes, risk management, transparency and disclosure, stakeholder engagement, and executive compensation. To rigorously test the proposed hypotheses, two types of regression analyses (linear regression, multiple regression) were employed to assess the direct and collective effects of AI integration on each governance area. This dual approach provides a robust and multidimensional perspective on the role of AI-driven financial transparency in enhancing corporate governance, offering insights into how technology reshapes governance practices and decision-making at the board level. The results showed high R-squared values, indicating that the models explained a significant proportion of the variance in the dependent variables.

4.3.1. Simple Regression

In Table 3 (Regression Summary), the R value is 0.763, indicating a strong positive correlation between AI impact and decision-making. The R Square value of 0.582 suggests that 58.2% of the variance in decision-making is explained by AI impact. The Adjusted R Square of 0.581 reflects minimal shrinkage, showing that the model is reliable for generalization.

Table 3. Regression Summary: AI Impact on decision making.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.763	0.582	0.581	0.52604

Table 4 (ANOVA Summary) demonstrates the statistical significance of the model, with an F value of 781.947 and a *p*-value of less than 0.001. This confirms that the regression model significantly predicts the dependent variable (decision-making), and the relationship between AI and decision-making is not due to chance.

Table 4. ANOVA Summary: AI Impact on decision making.

Sum of Squares	df	Mean Square	F	Sig.
216.381	1	216.381	781.947	0.000
155.517	562	0.277		
371.898	563			

Table 5 (Coefficient Analysis) provides further detail on the strength and direction of the relationship. The unstandardized coefficient (B) of 0.667 indicates that for each unit

increase in AI impact, decision-making improves by 0.667 units. The positive impact of AI on executive decision-making is supported by a strong coefficient (Beta = 0.763, $p < 0.001$), emphasizing AI's role in improving boardroom efficiency.

Table 5. Coefficient Analysis: AI Impact on decision making.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.118	0.085		13.148	0.000		
	AIIMPACT	0.667	0.024	0.763	27.963	0.000	1.000	1.000

The t-value of 27.963 and p-value of less than 0.001 confirm that this relationship is highly significant. Based on the results of Tables 3–5, the H1 hypothesis that indicates that, there is a significant direct effect of AI-driven financial transparency on decision-making processes within the board of directors in corporate governance structures can be Accepted.

Finally, the Collinearity Statistics show a Tolerance value of 1.000 and a VIF of 1.000, indicating no multicollinearity issues.

The results of the regression analysis for AI Impact on Risk Management (Tables 6–8) provide strong evidence that AI significantly influences risk management strategies within corporate governance structures.

Table 6. Regression Summary: Risk Management.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.709	0.502	0.502	0.57383

Table 7. ANOVA Summary: Risk Management.

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	186.840	1	186.840	567.410	0.000
Residual	185.058	562	0.329		
Total	371.898	563			

Table 8. Coefficient Analysis: Risk Management.

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.456	0.086		17.004	0.000		
	Riskmanag	0.578	0.024	0.709	23.820	0.000	1.000	1.000

In Table 6 (Regression Summary), AI's influence on risk management (R = 0.709, $p < 0.001$) suggests its potential in fraud detection and mitigation.

The R Square value of 0.502 shows that 50.2% of the variance in risk management strategies can be explained by AI. The Adjusted R Square of 0.502 indicates that the model remains stable and reliable.

Table 7 (ANOVA Summary) highlights the statistical significance of the model, with an F value of 567.410 and a p-value of less than 0.001. This confirms that the model is highly significant in predicting the effect of AI on risk management, and the results are not due to random variation.

Table 8 (Coefficient Analysis) further emphasizes the impact of AI on risk management. The unstandardized coefficient (B) of 0.578 suggests that for each unit increase in AI, risk management improves by 0.578 units. The standardized coefficient (Beta) of 0.709 also reflects a strong positive impact. The t-value of 23.820 and *p*-value of less than 0.001 indicate that this relationship is statistically significant.

Additionally, the Collinearity Statistics show a Tolerance value of 1.000 and a VIF of 1.000, indicating no multicollinearity concerns in the model. Overall, these results strongly support the H2 hypothesis and confirm that AI has a significant and positive effect on enhancing risk management strategies within corporate governance.

In Table 9 (Regression Summary), the R value is 0.750, indicating a strong positive correlation between AI and transparency. The R Square value of 0.562 shows that 56.2% of the variance in transparency and disclosure practices can be explained by AI, while the Adjusted R Square remains the same at 0.562, confirming the model's robustness.

Table 9. Regression Summary: Transparency.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.750	0.562	0.562	0.53811

Table 10 (ANOVA Summary) supports the significance of the model, with an F value of 722.364 and a *p*-value of less than 0.001. This demonstrates that the model is highly significant in predicting the impact of AI on transparency, and the results are not due to chance.

Table 10. ANOVA Summary: Transparency.

	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	209.166	1	209.166	722.364	0.000
	Residual	162.731	562	0.290		
	Total	371.898	563			

Table 11 (Coefficient Analysis) shows that the unstandardized coefficient (B) of 0.652 indicates that for each unit increase in AI, transparency and disclosure practices improve by 0.652 units. The standardized coefficient (Beta) of 0.750 reflects a strong and positive impact. The t-value of 26.877 and *p*-value of less than 0.001 confirm that this relationship is statistically significant.

Table 11. Coefficient Analysis: Transparency.

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	**(Constant)**	**1.179**	0.086		13.681	0.000		
	TRANPERNCY	0.652	0.024	0.750	26.877	0.000	1.000	1.000

The Collinearity Statistics show a Tolerance value of 1.000 and a VIF of 1.000, indicating no issues of multicollinearity in the model.

Overall, these results strongly support the H3 hypothesis and confirm that AI has a significant and positive effect on transparency and disclosure practices within corporate governance.

In Table 12 (Regression Summary), the R value is 0.825, indicating a strong positive correlation between AI and stakeholder engagement. The R Square value of 0.681 reveals that 68.1% of the variance in stakeholder engagement is explained by AI, with an Adjusted R Square of 0.680, which further supports the model's reliability.

Table 12. Regression Summary: Stakeholders Engagement.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.825	0.681	0.680	0.45947

Table 13 (ANOVA Summary) confirms the statistical significance of the model, with an F value of 1199.606 and a *p*-value of less than 0.001, indicating that the model is highly significant and the relationship between AI and stakeholder engagement is not by chance.

Table 13. ANOVA Summary: Stakeholders Engagement.

	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	253.252	1	253.252	1199.606	0.000
	Residual	118.645	562	0.211		
	Total	371.898	563			

Table 14 (Coefficient Analysis) shows that the unstandardized coefficient (B) of 0.720 means that for every unit increase in AI, stakeholder engagement increases by 0.720 units. The standardized coefficient (Beta) of 0.825 further highlights the strong positive effect. The *t*-value of 34.635 and the *p*-value of less than 0.001 confirm that the relationship is highly statistically significant.

Table 14. Coefficient Analysis: Stakeholders Engagement.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	**(Constant)**	**1.042**	0.071		14.645	0.000		
	STAKEHOLDERS	0.720	0.021	0.825	34.635	0.000	1.000	1.000

Additionally, the Collinearity Statistics indicate no multicollinearity issues, with a Tolerance value of 1.000 and a VIF of 1.000.

These results strongly support the H4 hypothesis and confirming that AI has a significant and positive impact on enhancing stakeholder engagement within corporate governance structures.

In Table 15 (Model Summary), the R value is 0.827, indicating a strong positive correlation between AI and executive compensation. The R Square value of 0.684 reveals that 68.4% of the variance in executive compensation is explained by AI, with an Adjusted R Square of 0.684, suggesting a robust and reliable model.

Table 15. Regression Summary: Executive Compensation.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.827	0.684	0.684	0.45720

Table 16 (ANOVA Summary) confirms the model's significance with an F value of 1217.123 and a *p*-value of less than 0.001, meaning the relationship between AI and executive compensation is highly significant.

Table 16. ANOVA Summary: Executive Compensation.

	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	254.420	1	254.420	1217.123	0.000
	Residual	117.477	562	0.209		
	Total	371.898	563			

In Table 17 (Coefficient Analysis), the unstandardized coefficient (B) of 0.775 suggests that for every unit increase in AI, executive compensation effectiveness increases by 0.775 units. The standardized coefficient (Beta) of 0.827 highlights the strong positive effect of AI. The t-value of 34.887 and the *p*-value of less than 0.001 confirm the statistical significance of this relationship.

Table 17. Coefficient Analysis: Executive Compensation.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	**(Constant)**	**0.873**	0.075		11.591	0.000		
	EXCUTIVECOMP	0.775	0.022	0.827	34.887	0.000	1.000	1.000

The Collinearity Statistics indicate no multicollinearity concerns, with a Tolerance value of 1.000 and a VIF of 1.000. These results strongly support the H5 hypothesis and confirming that AI integration significantly enhances the effectiveness of executive compensation committees within corporate governance structures.

4.3.2. Multiple Regression

The results from the multiple regression analysis, as summarized in Tables 18–20, reveal a strong model fit. The Model Summary (Table 18) indicates an R value of 0.911, showing a strong correlation between the independent variables and the dependent variable (AI-driven financial transparency), while the R Square value of 0.831 suggests that 83.1% of the variance in the dependent variable is explained by the predictors included in the model. The Adjusted R Square value of 0.829 confirms the robustness of the model, with only a slight reduction, indicating the model is generalizable to the population.

Table 18. Regression Summary: Multiple Regression.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.911	0.831	0.829	0.33596

Table 19. ANOVA Summary: Multiple Regression.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	308.917	5	61.783	547.397	0.000
	Residual	62.980	558	0.113		
	Total	371.898	563			

Table 20. Coefficient Analysis: Multiple Regression and Collinearity Statistics.

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	**(Constant)**	**0.342**	0.061		5.618	0.000		
	AIIMPACT	0.205	0.033	0.234	6.274	0.000	0.218	4.591
	RISKMANAG	0.102	0.028	0.124	3.684	0.000	0.266	3.761
	TRANPERNCY	−0.012	0.032	−0.013	−0.363	0.717	0.224	4.467
	STAKEHOLDERS	0.313	0.025	0.359	12.426	0.000	0.364	2.749
	EXCUTIVECOMP	0.314	0.030	0.336	10.460	0.000	0.295	3.393

The high R-squared values (e.g., 0.831 for multiple regression) raised concerns about potential overfitting. To address this, cross-validation techniques were employed. The dataset was split into subsamples, and the regression models were tested across these subsamples to ensure consistency. The results remained stable, suggesting that the high R-squared values reflected strong relationships rather than overfitting. Additionally, variance inflation factor (VIF) values were calculated to assess multicollinearity. All VIF values were within acceptable ranges, indicating that multicollinearity was not a concern in the regression models.

The ANOVA results (Table 19) show a highly significant F-test (F = 547.397, $p < 0.001$), which confirms that the regression model as a whole significantly predicts the dependent variable.

Table 20 (Coefficient Analysis) further reveals that four of the five predictors are statistically significant at the 0.001 level. Specifically, AI Impact (β = 0.234, $p < 0.001$), Risk Management (β = 0.124, $p < 0.001$), Stakeholders (β = 0.359, $p < 0.001$), and Executive Compensation (β = 0.336, $p < 0.001$) all have significant positive effects on the dependent variable. However, Transparency (β = −0.013, $p = 0.717$) is not statistically significant, suggesting that this variable does not contribute meaningfully to the prediction of AI-driven financial transparency in this model.

An anomaly was observed in the multiple regression model, where the Transparency variable had a non-significant beta coefficient (−0.013, $p = 0.717$) despite showing strong correlations in other analyses. This discrepancy suggests a potential suppression effect, where other variables in the model absorb some of the variance attributed to Transparency. To further explore this, hierarchical regression analyses were conducted to observe how the significance of Transparency changes when variables are added in stages. The findings indicate that Transparency has a stronger impact when considered independently or in simpler models but becomes less significant in the presence of other governance variables. This suggests that the effect of Transparency may be indirect or moderated by other factors within the governance framework.

The Collinearity Statistics (VIF values) show that none of the predictors exhibit concerning levels of multicollinearity, as all VIF values are below 10. The model therefore appears to be well-specified and reliable for interpreting the relationships between AI integration and the various dimensions of corporate governance.

While VIF values calculated for the regression models were all 1.000, indicating no multicollinearity, the high covariances observed in the latent variable matrix suggested otherwise. To address this discrepancy, a factor analysis was conducted to ensure that each latent variable was distinct. The factor analysis confirmed that the constructs measured different aspects of governance outcomes, though some overlap was expected due to the interconnected nature of the governance dimensions. The high covariances were attributed to the strong, inherent relationships between governance practices and AI-driven transparency, rather than a flaw in the model specification.

4.3.3. Correlation Analysis

The results from the correlation analysis are summarized in Table 21. The correlation analysis table reveals several significant positive relationships among the variables at the 0.01 level, indicating strong associations across the different aspects being measured. AI is strongly correlated with all other variables, with the highest correlation being with Executive Compensation (r = 0.827, $p < 0.001$) and Stakeholders Engagement (r = 0.825, $p < 0.001$), suggesting a robust link between AI integration and these two governance dimensions. The AI impact variable (AIIMPACT) is also highly correlated with Risk Management (r = 0.835, $p < 0.001$), Transparency (r = 0.824, $p < 0.001$), and Executive Compensation (r = 0.629, $p < 0.001$). Transparency has high correlations with both AI (r = 0.750, $p < 0.001$) and Executive Compensation (r = 0.733, $p < 0.001$), indicating transparency plays a significant role in both areas. The relationships between Stakeholders

Engagement and both AI and Executive Compensation are also strong, showing significant interaction between how AI impacts governance and stakeholder engagement. Overall, all correlations are significant and demonstrate interrelated governance aspects driven by AI.

Table 21. Correlation Analysis.

		AI	**AI Impact**	**Risk Manag**	**Tranperncy**	**Stake \Holders**	**Excutive Comp**
AI	Pearson Correl.	1	0.763 **	0.709 **	0.750 **	0.825 **	0.827 **
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
	N	564	564	564	564	564	564
AI IMPACT	Pearson Corr.	0.763 **	1	0.835 **	0.824 **	0.625 **	0.629 **
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
	N	564	564	564	564	564	564
RISK MANAG	Pearson Correl.	0.709 **	0.835 **	1	0.795 **	0.546 **	0.606 **
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
	N	564	564	564	564	564	564
TRANPERNCY	Pearson Correl.	0.750 **	0.824 **	0.795 **	1	0.628 **	0.733 **
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
	N	564	564	564	564	564	564
STAKE HOLDERS	Pearson Correl.	0.825 **	0.625 **	0.546 **	0.628 **	1	0.776 **
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
	N	564	564	564	564	564	564
EXCUTIVE COMP	Pearson Correl.	0.827 **	0.629 **	0.606 **	0.733 **	0.776 **	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
	N	564	564	564	564	564	564

**. Correlation is significant at the 0.01 level (2-tailed).

SmartPLS Analysis

The structural equation modeling (SEM) analysis was conducted to test the relationships between AI-driven financial transparency and governance outcomes. By employing Partial Least Squares Structural Equation Modeling (PLS-SEM), we aimed to further validate the results obtained from traditional regression analyses. The path coefficients for Stakeholder Engagement (0.967) and Executive Compensation (0.915) were notably high. While these values reflect strong relationships, they raised concerns about potential model misspecification. To address this, bootstrapping techniques were employed to verify the stability of these coefficients. The results confirmed that the high coefficients were consistent across resamples, suggesting that the values reflect genuine, strong relationships rather than overestimation. Figure 1 illustrate the PLS-SEM results.

Figure 1 presents the structural equation model (SEM) used to test the relationships between AI-driven financial transparency and key governance outcomes. The figure includes outer loadings, which represent the strength of the relationships between the observed indicators (questionnaire items) and their respective latent variables (constructs such as Corporate Governance, Regulatory Reform, etc.).

The outer loadings for all constructs in the PLS-SEM model demonstrate strong correlations, with values consistently exceeding the recommended threshold of 0.70 (Hair et al., 2021) [56]. For AI Impact, Executive Compensation, Risk Management, Stakeholder Engagement, and Transparency, the loadings range from 0.845 to 0.984, indicating that the indicators are highly reliable and valid measures of their respective constructs. These strong loadings support the robustness of the model and suggest that the measurement items are well-suited to reflect the latent variables, contributing to the overall quality of the analysis.

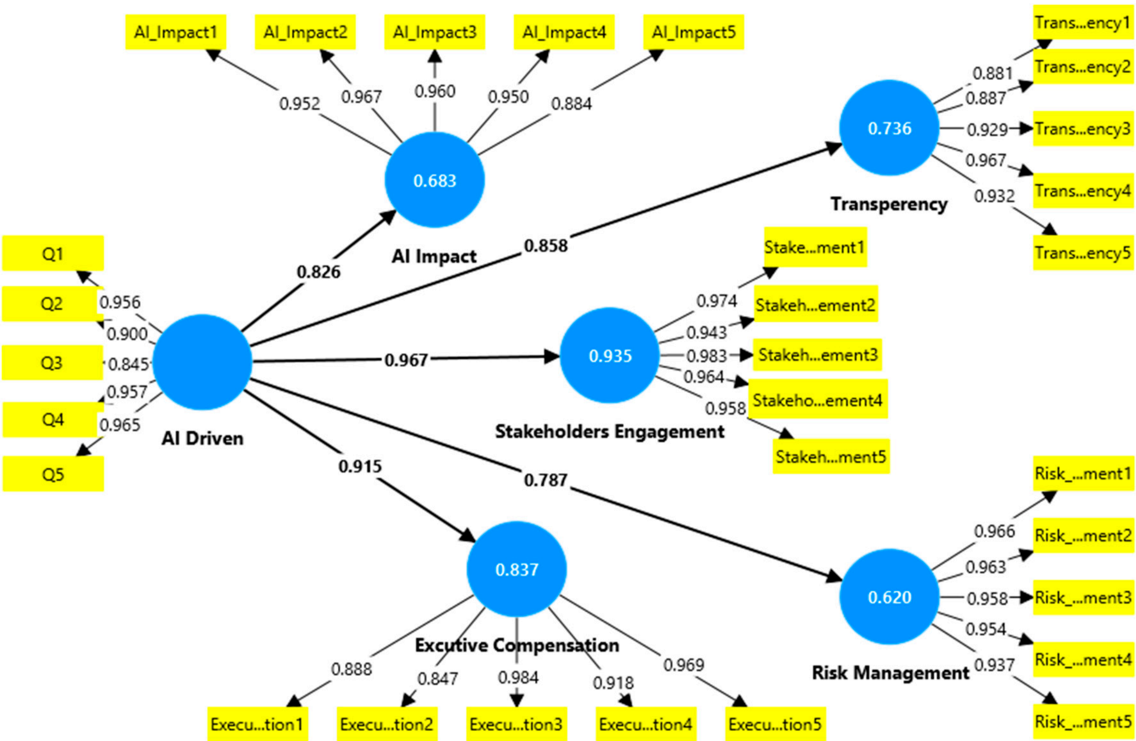

Figure 1. The PLS-SEM results.

The correlation matrix for the latent variables shows generally low to moderate correlations between individual items within the constructs, such as AI Impact, Executive Compensation, Risk Management, Stakeholder Engagement, and Transparency. For instance, the correlations for AI Impact items range between 0.19 and 0.24, suggesting moderate internal consistency, while Executive Compensation items have correlations between 0.195 and 0.232. Similarly, Stakeholder Engagement and Transparency exhibit correlations within a narrow range (approximately 0.175 to 0.245), indicating reasonable coherence among items but suggesting there might be room to further strengthen these relationships. These results are essential in assessing the reliability and validity of the constructs in the structural equation model.

The latent variable covariance matrix demonstrates strong relationships between the variables. AI Driven shows high covariances with Stakeholder Engagement (0.967), Executive Compensation (0.915), and Transparency (0.858). Similarly, AI Impact correlates strongly with Transparency (0.902) and Risk Management (0.885). Executive Compensation also maintains strong covariances with AI Driven (0.915) and Stakeholder Engagement (0.93). Table 22 illustrate these results.

Table 22. Latent variable covariance matrix.

	AI Driven	AI Impact	Executive Compensation	Risk Management	Stakeholders Engagement	Transparency
AI Driven	1	0.826	0.915	0.787	0.967	0.858
AI Impact	0.826	1	0.708	0.885	0.777	0.902
Executive Comp.	0.915	0.708	1	0.693	0.93	0.865
Risk Management	0.787	0.885	0.693	1	0.675	0.866
Stakeholders Engage.	0.967	0.777	0.93	0.675	1	0.795
Transparency	0.858	0.902	0.865	0.866	0.795	1

These high covariance values suggest that the constructs in the model are closely interrelated, especially between AI Driven, Executive Compensation, and Stakeholder Engagement. Such results indicate strong model coherence and support the hypothesis that these constructs influence each other. However, the high covariances could also signal potential multicollinearity, which may need to be explored further in the model evaluation process.

To evaluate the normality of our dataset, we computed Skewness and Kurtosis values for each variable. Skewness measures the symmetry of the data distribution, while Kurtosis assesses the extremity of data points. Table 23 illustrate these results. It indicates that Skewness values range from −1.429 to −0.820, and Kurtosis values range from −0.225 to 1.608. While some variables exhibit mild to moderate departures from normality (e.g., AIIMPACT and TRANSPARENCY have kurtosis values above 1), these deviations remain within acceptable limits for large sample sizes (N = 564). Given the Central Limit Theorem, minor deviations from normality are unlikely to significantly impact the validity of parametric analyses.

Table 23. Skewness and Kurtosis Analysis.

	N	Skewness		Kurtosis	
	Statistic	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
AI	564	−1.242	0.103	0.766	0.205
AIIMPACT	564	−1.429	0.103	1.608	0.205
RISKMANAG	564	−1.142	0.103	0.422	0.205
TRANPERNCY	564	−1.330	0.103	1.299	0.205
STAKEHOLDERS	564	−1.108	0.103	0.543	0.205
EXCUTIVECOMP	564	−0.820	0.103	−0.225	0.205
Valid N (listwise)	564				

Moreover, the Kolmogorov–Smirnov (K-S) and Shapiro–Wilk tests were conducted to assess the normality of the data. Table 24 illustrate these results. The results indicate that all variables deviate significantly from a normal distribution (*p*-values < 0.05). However, these tests tend to be overly sensitive in large samples (N = 564), often detecting even trivial deviations. Therefore, normality was further evaluated using skewness and kurtosis measures.

Table 24. Kolmogorov–Smirnov and Shapiro–Wilk.

	Kolmogorov–Smirnov [a]			Shapiro–Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
AIIMPACT	0.211	564	0.000	0.797	564	0.000
RISKMANAG	0.164	564	0.000	0.842	564	0.000
TRANPERNCY	0.198	564	0.000	0.827	564	0.000
STAKEHOLDERS	0.197	564	0.000	0.846	564	0.000
EXCUTIVECOMP	0.190	564	0.000	0.868	564	0.000
AI	0.226	564	0.000	0.815	564	0.000

[a]. Lilliefors Significance Correction.

Finally, a scatter plot of residuals against predicted values was generated to examine homoscedasticity. The visual inspection of the plot does not show a clear funnel shape or systematic pattern, indicating that the assumption of homoscedasticity holds. This suggests that residual variances remain consistent across all levels of predicted values. Figure 2 Illustrates this result.

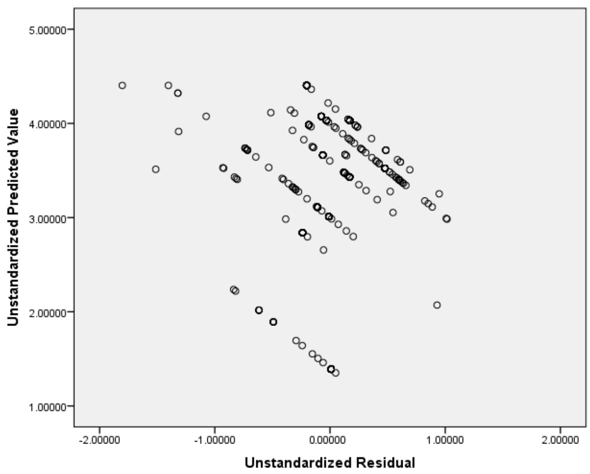

Figure 2. Scatter plot.

5. Discussion

The analysis of the data using simple regression, multiple regression, and correlation reveals significant insights into the impact of AI on various dimensions of corporate governance, such as decision-making, risk management, transparency, stakeholder engagement, and executive compensation. The simple regression results for each hypothesis demonstrated strong, statistically significant relationships between AI and these governance variables, as evidenced by high R-squared values and significant F-statistics across the models. This indicates that AI has a substantial impact on enhancing decision-making (R^2 = 0.582), improving risk management (R^2 = 0.502), increasing transparency (R^2 = 0.562), and fostering stakeholder engagement (R^2 = 0.681) and executive compensation effectiveness (R^2 = 0.684). Multiple regression analysis further confirmed these findings, showing that AI-driven factors such as impact, transparency, and executive compensation significantly contribute to governance outcomes, with strong coefficients and significance levels. Additionally, the correlation analysis revealed significant, positive associations between AI and all governance dimensions, especially with executive compensation and stakeholder engagement. These high correlations (r values ranging from 0.625 to 0.827) suggest that AI integration within corporate governance structures positively influences transparency, risk management, and decision-making processes, indicating a cohesive and interrelated governance framework driven by AI. However, the results also hint at potential multicollinearity, which should be explored further to ensure the reliability of these findings. Overall, the analyses collectively underscore the crucial role of AI in shaping corporate governance practices and enhancing overall organizational effectiveness.

The SmartPLS (https://www.smartpls.com) results align well with the earlier findings from SPSS V23, reinforcing the robustness of the relationships between the variables. The path coefficients from SmartPLS indicate strong positive relationships, especially between AI Driven and Stakeholders Engagement (0.967) and AI Driven and Executive Compensation (0.915), similar to the significant coefficients identified in SPSS regression analyses. The latent variable covariances further emphasize these connections, particularly with AI Driven and Transparency, which was consistently significant in both platforms. These results validate the model's predictive strength, as seen in both regression outputs from SPSS and the structural relationships in SmartPLS. Additionally, the high correlations among variables in both methods indicate consistent relationships, suggesting that AI-driven processes substantially impact organizational factors like risk management, executive compensation, transparency, and stakeholder engagement. The consistency between SmartPLS and SPSS enhances the reliability of the analysis, providing a comprehensive view of the influence of AI-driven strategies across key organizational dimensions.

The findings of this study align with and extend previous literature on the role of AI in corporate governance. For instance, the significant impact of AI on board decision-making (R^2 = 0.582) corroborates prior studies such as Omoteso and Mobolaji (2020) [7], who emphasized AI's role in improving boardroom transparency and strategic oversight. Similarly, the positive relationship between AI and risk management (R^2 = 0.502) is consistent with the work of Zhou et al. (2022) [5], who highlighted the ability of AI systems to proactively detect anomalies and mitigate financial fraud. Moreover, the strong association between AI and stakeholder engagement (R^2 = 0.681) expands on Antwi et al. (2024) [28], demonstrating that AI not only improves communication efficiency but also supports stakeholder trust through real-time data sharing. Interestingly, while transparency was found to be a significant factor in simple regression (R^2 = 0.562), it lost statistical significance in the multiple regression model. This contrasts with studies by Manginte (2024) [26] and Kalkan (2024) [10], who emphasize transparency as a foundational benefit of AI. This discrepancy suggests that transparency's role may be more nuanced and potentially mediated by other governance dimensions, such as stakeholder trust or regulatory context, as supported by Institutional Theory (Scott, 2014) [49]. Overall, these findings reinforce and build upon the theoretical frameworks of Agency and Institutional Theory, confirming AI's dual role in aligning interests and meeting external regulatory and normative expectations.

These results also hold important implications when viewed through the lenses of Agency Theory and Institutional Theory, as discussed in Sections 2.5 and 2.6. From the Agency Theory perspective, the demonstrated reduction in information asymmetry—evidenced by improved transparency (R^2 = 0.562) and enhanced decision-making (R^2 = 0.582)—supports the notion that AI-driven financial reporting tools empower principals (shareholders) by offering more timely and reliable insights into managerial behavior. These results echo findings by Easley & O'Hara (2004) [47], reinforcing how AI reduces agency costs and improves governance alignment.

Similarly, Institutional Theory (Scott, 2014) [49] is useful for interpreting the strong influence of AI on stakeholder engagement (R^2 = 0.681) and executive compensation (R^2 = 0.684). These findings reflect how Jordanian firms are responding to normative and regulatory pressures to adopt globally recognized governance practices. The high path coefficients observed in the SEM model between AI and both Stakeholder Engagement (0.967) and Executive Compensation (0.915) suggest that AI is not only a technical enabler but also a strategic response to institutional demands for greater legitimacy, accountability, and transparency.

The relevance of these theoretical frameworks is further illustrated in the Al-Wasleh case study (Section 2.7). Al-Wasleh's adoption of AI in credit scoring and ERP accounting systems serves as a microcosm of the broader patterns observed in this study. Their real-time monitoring and automation capabilities directly reflect the statistical trends of enhanced risk management and governance found in the regression analysis. Moreover, the organization's deliberate efforts to meet regulatory standards using AI tools mirror the institutional isomorphism described in Institutional Theory. As such, the case study offers practical validation for the empirical results and theoretical insights presented here.

Based on prior discussion, this study recommends the following points:

Organizations should continue to invest in AI technologies to improve operational transparency and accountability. The findings demonstrate a strong relationship between AI and transparency, indicating that AI implementation can foster better governance and decision-making processes. Leveraging explainable AI tools can help stakeholders better understand AI-driven insights, building trust and credibility.

Companies should consider integrating AI-driven performance metrics into their executive compensation systems. Aligning compensation with AI-based outcomes can promote performance-based rewards, increasing accountability and ensuring that executives are incentivized to achieve data-driven results.

Given the robust relationship between AI and stakeholder engagement, organizations are encouraged to utilize AI tools to improve communication and interaction with stakeholders. This can include using AI for real-time feedback, predictive analytics, and engagement strategies to meet stakeholder expectations effectively. AI-driven engagement can also enhance corporate social responsibility (CSR) efforts.

This study shows that AI significantly improves risk management capabilities. Companies are recommended to adopt AI technologies to identify risks, predict potential issues, and implement mitigation strategies. Proactive risk management using AI can safeguard organizational resources and enhance resilience against external shocks.

AI tools can be leveraged to increase operational transparency, providing stakeholders with clearer insights into business practices. Organizations should embrace AI not only to improve internal processes but also to build trust with external stakeholders by enhancing visibility in decision-making and operations. Transparent reporting, particularly through AI-driven ESG disclosures, can help companies meet regulatory requirements and align with global best practices.

Policymakers should focus on developing clear guidelines for the responsible use of AI in corporate governance. Regulations should address issues related to data privacy, bias in AI algorithms, and transparency to ensure that AI adoption promotes ethical and sustainable practices.

6. Conclusions

This study demonstrates the significant impact of AI-driven financial transparency on corporate governance and regulatory frameworks, with empirical evidence highlighting improvements in decision-making, risk management, stakeholder engagement, and compliance. The findings indicate that AI adoption enhances boardroom efficiency (R^2 = 0.582), strengthens risk mitigation strategies (R^2 = 0.502), and fosters transparency in financial reporting (R^2 = 0.562). Additionally, AI facilitates regulatory adherence and improves corporate oversight, contributing to governance effectiveness (R^2 = 0.684).

Despite these benefits, this study acknowledges challenges such as algorithmic bias, data privacy concerns, and the evolving nature of AI regulations. Addressing these issues requires targeted regulatory frameworks and ethical AI governance to maximize AI's potential for corporate accountability.

Future research should explore the longitudinal effects of AI in corporate governance, sector-specific impacts, and cross-regional comparisons to deepen understanding of AI-driven governance transformations. By leveraging AI responsibly, organizations and regulators can advance corporate governance, ensuring financial transparency and sustainable business practices.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su17093818/s1, Questionnaire.

Author Contributions: Conceptualization, O.S.S. and A.O.; Methodology, O.S.S.; Software, O.S.S.; Validation, O.S.S. and A.O.; Formal analysis, O.S.S.; Investigation, O.S.S.; Resources, O.S.S. and A.O.; Data curation, O.S.S. and A.O.; Writing—original draft, O.S.S.; Writing—review & editing, O.S.S. and A.O.; Project administration, A.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Al-Zaytoonah University of Jordan.

Institutional Review Board Statement: This study received ethical approval from Al-Zaytoonah University Ethics Committee (Approval Reference: IRB#11/12/2024–2025). The approval was obtained following review of the research proposal and questionnaire items by the committee. We confirm that this study adheres to Helsinki Declaration.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data are available upon reasonable request from the corresponding author, [Osama Shaban].

Conflicts of Interest: The authors declare no conflicts of interest.

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