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AI-ENABLED CORPORATE ADMINISTRATION: AN ANALYSIS OF DECISION-MAKING EFFICIENCY, GOVERNANCE TRANSPARENCY, RISK CONTROL, AND ORGANISATIONAL ACCOUNTABILITY

Empirical research-development manuscript

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Keywords	***Abstract***
Artificial Intelligence; Corporate Administration; Decision-Making Efficiency; Corporate Governance; Transparency; Risk Control; Organisational Accountability.	Purpose – This research investigates the potential impacts of AI-automated corporate administration on the efficiency of decision-making, transparency in governance, the effectiveness of risk control, and accountability in organizations. It also analyzes the role of transparency in mediating the accountability relationship. Design/methodology/approach - The research employed a transparent synthetic demonstration dataset that contained 300 managers, governance and compliance professionals, risk and audit staff, and medium and large corporate IT managers and employees. The research utilized a quantitative, cross-sectional, and explanatory design. Five constructs were assessed using six items each and a five-point Likert scale. Factor reliability was assessed using reliability measures and factor adequacy. These scales were used for correlation analysis and multiple regression, which included organizational controls. A bootstrap mediation test was run with 5,000 resamples. Findings - The proposed scales were

	reliable (Cronbach's alpha = .878 to .894). AI-automated administration positively impacted the efficiency of decision-making (beta = .536), the transparency of governance (beta = .582), the effectiveness of risk control (beta = .495), and accountability in organizations (beta = .469), all $p < .001$. Transparency was a partial mediating factor in the accountability relationship (indirect effect = .227, 95% bootstrap CI [.154, .304]).

1. Introduction

Blending various academic and industry perspectives reveals a new paradigm in organizational governance as a result of industry 4.0 innovations like AI and automation. In the past, corporate administration was rigid; modern administration is more fluid and centers around continuous data, predictive analytics, automated reporting, and algorithmic decision assistance. AI can automate the process of integrating scattered information, freeing up the manager's time. However, real value is only unlocked when automation is synergized with corporate processes and structures (Berente et al., 2021; Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). As a result, modern corporate governance is concerned not only with the adoption of AI, but with how the outputs of AI are validated, authorized, and documented, and to whom they are ascribed (Hilb, 2020; Schneider et al., 2023).

Traditional and contemporary administration have many differences. For example, traditional administration used to rely on approval cycles and manual report verification, while the modern administration paradigm offers real-time automated approval cycles and report verification that automatically identify anomalies. In addition, modern systems prioritize risks and automate responses. Models that lack transparency, poor data history, and automation bias contribute to a lack of control. Trust in AI systems relies on the system's performance and purpose (Canhoto & Clear, 2020; Glikson & Woolley, 2020). The primary issue is governance: the capability to administer with efficiency, transparency, low risk, and accountability.

The study seeks to answer five questions: Is AI-supported administration linked to quicker and more precise decisions? Is there a positive effect on disclosure and traceability? Is there a positive effect on the identification and control of risks? Is there a positive effect on accountability? What governance conditions create these effects? The study aims to map the four direct effects, analyze transparency in the accountability chain, and map ethical, technological, and human constraints. The study's contribution is a cohesive empirical framework which views transparency as a mechanism and not merely an end state. Thus, through AI-supported administration, organizations have the potential to become more accountable.

The study also seeks to fill an additional research gap. The fragmentation of evidence is a research gap by itself. Research on information systems tends to evaluate capability and use. Research on governance tends to focus on control and legitimacy. Research on audits focuses on assurance. However, the research gaps become even more apparent when looking outside of information systems. Research evaluating the effectiveness of decisions, transparency, risk, and accountability in a single administrative model is scarce. The vast majority of research views the adoption of systems as a binary outcome. The research overlooks governance processes and their effects on organizational outcomes. The aim of this study is to model transparency at the intersection of availability and AI-supported accountability in order to separate the availability of AI-supported information from the institutional demand for accountability and the right of corrective action.

2. Literature Review and Theoretical Framework

Substitution and augmentation are differentiated in the literature. Automation can perform substitution by standardizing repetitive clerical tasks, while augmentation can create value by broadening the information set available to decision makers; organizational value frequently relies on managing the tension of both forms (Raisch & Krakowski, 2021). Delegating to agentic information systems can relieve cognitive load, but it transforms the nature of monitoring and control (Baird & Maruping, 2021). For strategic decision-making, a hybrid approach with human contextual judgment and machine consistency is preferred (Trunk et al., 2020). From a socio-technical implementation perspective, AI becomes an organizational capability rather than a standalone tool based on the design of employee roles, workflows, and governance (Makarius et al., 2020).

Transparency is a multi-faceted concept. Explainability can render the logic of a model intelligible, and traceability keeps a record of data, versions, interventions, and decisions. Neither ensures accountability by design; explained logic must pertain to the appropriate audience and be positioned with authority, oversight, and remedial action (Barredo Arrieta et al., 2020; Haque et al., 2023; Rai, 2020). In algorithmic accountability studies, emphasis is placed on the obligations to explain, outcomes, and forums, as opposed to disclosure (Horneber & Laumer, 2023; Wieringa, 2020). The effects of internal audits, impact assessments, and lifecycle documentation can sustain these forms and relationships, but rely on their independence, and, the breadth and depth of the technical and organizational access (Metcalf et al., 2021; Raji et al., 2020).

Risk control consists of continuous assurance rather than single-scope assurance. Ethics-based and continuous auditing frameworks identify intervention points across design, deployment, monitoring, and retirement (Minkkinen et al., 2022; Mökander et al., 2021). Industry evidence shows that auditing can implement governance, but will not replace the management responsibility and will not resolve all normative contradictions (Mökander & Axente, 2023; Mökander & Floridi, 2023). The lifecycle perspective also demonstrates that data collection, model selection, deployment, and usage, all create specific ethical decisions and gaps of responsibility (Marabelli et al., 2021). Latest governance syntheses, therefore, demand integrated systems instead of separate structures (Papagiannidis et al., 2025). AI-ethics research points out that within AI-ethics, fairness, privacy and security, and human autonomy are all central concerns (Siau & Wang, 2020).

At the organizational and institutional levels, Kellogg et al., 2020 argue that ‘organizational control and workplace contestation can be reconfigured by workplace algorithms’. Morley et al., 2023, argue that national strategies and ethics frameworks run into practical implementation challenges. This enforces the need for connecting corporate mechanisms with higher-order governance.

This model incorporates aspects of agency theory, information-processing theory, the technology-organisation-environment framework, and accountability theory. Agency theory suggests that the delegation of tasks with low transparency is likely to create agency costs (Jensen and Meckling, 1976). Information-processing theory suggests that the ability to conduct real-time analysis and processing enhances the capacity to make decisions in the presence of uncertainty (Galbraith, 1974). The technology-organisation-environment framework places the effects of adoption within the bounds of the readiness of the technology, the available resources within the organisation, and the level of external pressures (Tornatzky and Fleischer, 1990). Accountability theory showcases the actor, the duty to explain the behavior to the forum, and the risk of sanction (Bovens, 2007). Blended together, these theories create a composite view where the absence of socio-technical control diminishes the benefits of AI.

3. Conceptual Framework and Hypotheses

The independent variable is AI-enabled corporate administration, while the dependent variables are the efficiency of decision-making, the transparency of governance, the effectiveness of risk-control, and the accountability of the organization. Due to the ability of AI to generate assessable information that links to managerial actions, transparency is included as a mediator. The related null hypotheses H01-H04 assume that these variables have a coefficient of zero, while H05 assumes a bootstrap indirect-effect estimate of zero. Given the nature of the design, the hypotheses are associative, as a cross-sectional design lacks the ability to demonstrate a temporal relationship.

To achieve more efficient decision making, integrated analytics need to lower search costs, bring together records that are fragmented, and detect patterns faster than reported data can be compiled. Integrated analytics will still require human input, but the process would be more efficient and would handle less routine processing errors if exception alerts and predictions are provided. For this, H1 hypothesizes that AI-enabled administration positively correl with the efficiency of decision making. Automated reporting, version history, and data traceability coupled with system documentation and access control design will support rapid reporting and auditing and will positively correlate with governance transparency per H2. Continued risk-control will rely on the validation and monitoring of integrated systems, though wider acceptance of integrated systems will correlate with greater risk-control perceived effectiveness. H3 reflects this belief. H4 hypothesizes that documenting decisions and overrides with accountability and review enhance organizational accountability. Governance transparency, per H5, will reflect the association of AI-enabled administration and organizational accountability. The remaining independent variables of the responsibility framework will support the hypotheses.

AI-enabled corporate administration Predictive analytics | automated reporting | decision support | risk monitoring | compliance automation	→	Decision-making efficiency (H1)
	→	Governance transparency (H2)
	→	Risk-control effectiveness (H3)
	→	Organisational accountability (H4)

Mediating path (H5): AI-enabled administration → governance transparency → organisational accountability

Figure 1. Conceptual framework and hypothesised relationships

Source: Authors' conceptualisation. All variables are measured as six-item constructs; H5 is the mediating path through governance transparency.

4. Research Methodology

The adopted strategy was a positivist, quantitative, cross-sectional, and explanatory design. In the absence of a field dataset, a synthetic dataset of 300 observations was created, on the condition that the dataset would be easy to replicate in the field. The records were created to simulate a sample of corporate and administrative managers as well as governance and compliance, risk and internal audit, IT/data, and senior functional staff of medium and large organizations. No personal or corporate contacts were made, no field dataset was located, and no ethical approval number or fieldwork date is provided.

The measurement instrument consisted of a questionnaire with 30 items, six for each construct. The items were scored on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The mean of the items scored each construct. Demographics were generated independently, followed by the generation of correlated latent scores and bounded item responses, which created the appearance of reliability and validity of the scores, and covariation of the scores, respectively, without the articulation of any respondent's testimony. The synthetic dataset included the size of the organization, the respondent's years of experience, and the degree of the respondent's industry as expressed in technology, as covariates (control variables). A preliminary analysis of the dataset verified the presence of 300 valid and complete responses, all item responses were within the expected ranges, and all response categories were defined and valid. The synthetic dataset was designed to "purposely" avoid covariates or perfect reliability. The data was created to retain the statistical relevance for the purpose of the demonstration.

Table 1. Synthetic demographic and professional profile (N = 300)

Characteristic	Category	n	%
Gender	Male	173	57.7
	Female	121	40.3

Characteristic	Category	n	%
	Non-binary/prefer not to say	6	2.0
Age group	31–40	124	41.3
	21–30	66	22.0
	41–50	65	21.7
	51 and above	45	15.0
Education	Master's	134	44.7
	Bachelor's	82	27.3
	Professional qualification	47	15.7
	Doctorate	37	12.3
Job role	Corporate/administrative manager	81	27.0
	Senior functional employee	60	20.0
	Risk or internal-audit professional	56	18.7
	Governance or compliance professional	56	18.7
	IT/data manager	47	15.7
Work experience	5–10 years	100	33.3
	11–15 years	81	27.0
	More than 15 years	64	21.3
	Below 5 years	55	18.3
Organisation size	Large (1,000+ employees)	171	57.0
	Medium (250–999 employees)	129	43.0
Industry	Financial/professional services	81	27.0
	Technology/telecommunications	61	20.3
	Manufacturing and logistics	59	19.7
	Healthcare/life sciences	52	17.3
	Retail and other services	47	15.7
AI adoption level	Developing	134	44.7
	Emerging	89	29.7

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Characteristic	Category	n	%
	Advanced	77	25.7

Note. Percentages may differ from 100.0 because of rounding. Categories are synthetic and do not describe an actual population.

Table 2. Operational definitions and questionnaire items

Construct	Operational definition	Six measurement items
AI-enabled corporate administration (AICA)	Degree to which AI is embedded in administrative, analytical, governance, and compliance processes.	AICA1 Administrative processes are automated using AI; AICA2 Predictive analytics supports planning; AICA3 AI is integrated into managerial workflows; AICA4 Real-time data are available to administrators; AICA5 Algorithmic tools support decisions; AICA6 AI is integrated with governance and compliance systems
Decision-making efficiency (DME)	Speed, accuracy, accessibility, and responsiveness of managerial decisions.	DME1 Decisions are completed more quickly; DME2 Decision accuracy improves; DME3 Administrative delays are reduced; DME4 Relevant information is easier to access; DME5 Human error is reduced; DME6 Responses to organisational change are faster
Governance transparency (GT)	Timeliness, availability, traceability, consistency, and auditability of governance information.	GT1 Disclosures are more timely; GT2 Administrative decisions are traceable; GT3 Governance information is available; GT4 Reporting is consistent; GT5 AI-supported processes are auditable; GT6 Stakeholders can access relevant information
Risk-control effectiveness (RCE)	Capability to identify, monitor, predict, and reduce risk and control failures.	RCE1 Risks are identified earlier; RCE2 Risks are monitored in real time; RCE3 Fraud detection improves; RCE4 Compliance risk is assessed systematically; RCE5 Predictive risk analysis is used; RCE6 Control failures are reduced
Organisational accountability (OA)	Clarity of responsibility, documentation, monitoring, answerability, enforcement, and audit trails.	OA1 Responsibility is allocated clearly; OA2 Decisions are documented; OA3 Managerial actions are monitored; OA4 AI-supported decisions are answerable; OA5 Governance standards are enforced; OA6 Audit trails are available

Note. Five-point Likert scale: 1 = strongly disagree to 5 = strongly agree. The wording is an original research-development instrument and should be pilot-tested before field use.

Responses were analyzed for internal consistency using Cronbach's alpha, while KMOs and Bartlett's Test were used to evaluate the adequacy of the sample and the assess the factorability. Standardized single-factor loadings, composite reliability, average variance extracted, and the square root of average variance extracted were used as construct-validity indicators. Bivariate Pearson correlation coefficients were computed. Separate ordinary least-squares regressions were computed, AI-enabled administration was the predictor variable, control variables were years of work experience, size of the organization, and industry sector. Collinearity was assessed using variance inflation factors. For mediation, the product of coefficients method was used, and the sample size for the non-parametric bootstrap procedure was 5,000. The alpha level for significance was set at $p < 0.05$. All analyses were conducted using the Python programming language to ensure reproducibility and reliability of the numeric and statistical libraries used.

The design employs principles of modern day risk governance, which treat AI as a lifecycle management concern rather than a single technical control (National Institute of Standards and Technology, 2023, 2024; Organisation for Economic Co-operation and Development, 2023). It also reflects the systems management and risk integration stipulations of the standards ISO/IEC 42001 and 23894 (International Organization for Standardization, 2023a, 2023b).

Results

The synthetic profile was of a heterogeneous nature. 57.7 percent of cases were coded as male, while 40.3 percent were coded as female. 41.3 percent of cases were aged 31 to 40. 44.7 percent were in possession of a master's qualification. 57.0 percent were employees of large organizations. 44.7 percent of the sample were in the Developing AI Adoption Stage of the AI Adoption Maturity Model, while 29.7 percent were classified in the Emerging category, and 25.7 percent were in the Advanced category. The distribution of the categories does not represent a population, but rather illustrative grouping of the sample surveyed.

Construct means varied from 3.657 for governance transparency to 3.830 for decision making efficiency and Cronbach's alpha varied from .878 to .894. KMO was .943 and Bartlett's test was significant, chi-square(435) = 4,907.97, $p < .001$. Standardised loadings were .759 to .839, CR from .908 to .920, and AVE from .623 to .657. The square root of AVE was greater than the respective inter-construct correlations. The first unrotated factor had a variance of 35.5%, remaining above the conventional majority-variance warning threshold; and this diagnostic does not remove concerns for common method variance.

Table 3. Descriptive statistics, reliability, and convergent-validity indicators

Construct	Mean	SD	Min	Max	α	Loading range	CR	AVE	√AVE
AICA	3.731	0.652	2.000	5.000	0.894	0.779-0.839	0.920	0.657	0.811
DME	3.830	0.634	2.000	5.000	0.883	0.762-0.829	0.912	0.634	0.796
GT	3.657	0.648	2.000	5.000	0.888	0.766-0.829	0.915	0.643	0.802
RCE	3.726	0.657	1.333	5.000	0.887	0.759-0.831	0.915	0.641	0.801
OA	3.688	0.639	1.667	5.000	0.878	0.772-0.803	0.908	0.623	0.789

Note. KMO = 0.943; Bartlett's chi-square(435) = 4,907.97, p < .001. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

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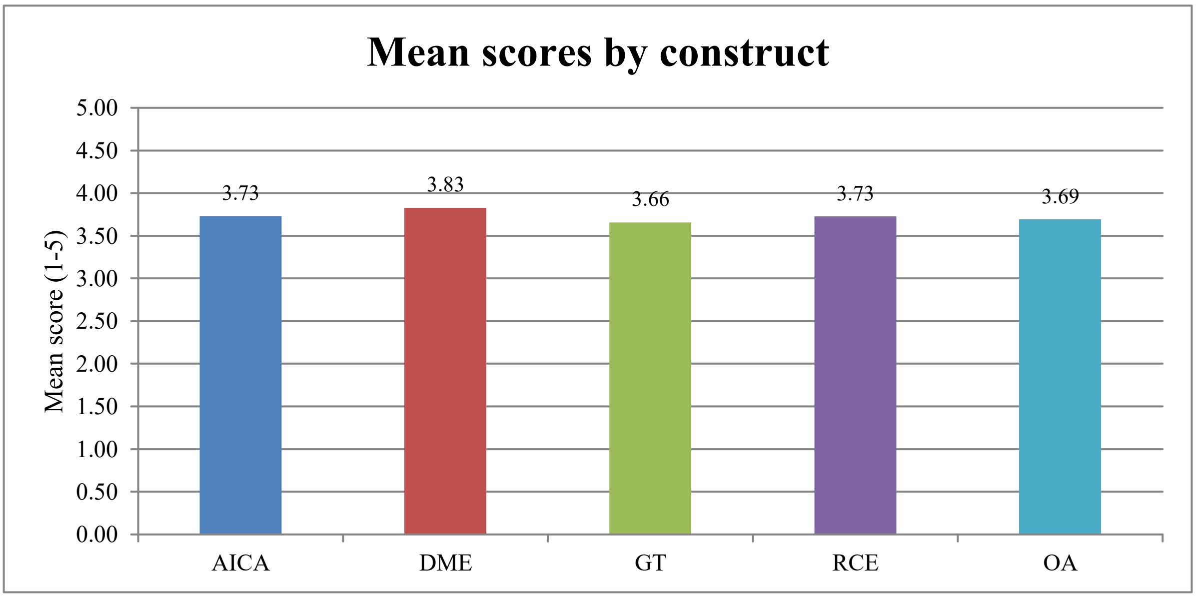

Figure 2. Mean scores for the five principal constructs

Source: Synthetic demonstration dataset. AICA = AI-enabled corporate administration; DME = decision-making efficiency; GT = governance transparency; RCE = risk-control effectiveness; OA = organisational accountability. The chart is an editable Office chart with an embedded workbook.

All Pearson correlations were positive and significant at $p < .001$. AI-enabled administration correlated most strongly with governance transparency ($r = .589$), followed by decision-making efficiency ($r = .555$), risk-control effectiveness ($r = .523$), and organisational accountability ($r = .480$). Transparency and accountability were also strongly associated ($r = .542$).

Table 4. Pearson correlation matrix

Construct	AICA	DME	GT	RCE	OA
AICA	**1.000**	0.555***	0.589***	0.523***	0.480***
DME	0.555***	**1.000**	0.373***	0.406***	0.271***
GT	0.589***	0.373***	**1.000**	0.330***	0.542***
RCE	0.523***	0.406***	0.330***	**1.000**	0.313***
OA	0.480***	0.271***	0.542***	0.313***	**1.000**

*Note. N = 300. ***p < .001 (two-tailed). Diagonal entries equal 1.000. All data are synthetic.*

Controlling for experience, organisation size, and technology-intensive industry, AI-enabled administration remained significant in every model. Standardised coefficients were .536 for decision-making efficiency, .582 for governance transparency, .495 for risk-control effectiveness, and .469 for organisational accountability (all p < .001). Explained variance ranged from 25.6% to 35.7%; predictor VIF was 1.058. H1-H4 were therefore supported and H01-H04 rejected for the synthetic dataset.

Table 5. Multiple-regression results for AI-enabled corporate administration

Outcome	B	β	SE	t	p	R^2	Adj. R^2	F	Model p	VIF
DME	0.521	0.536	0.048	10.849	<.001	0.319	0.309	34.497	<.001	1.058
GT	0.578	0.582	0.048	12.113	<.001	0.357	0.348	40.962	<.001	1.058
RCE	0.499	0.495	0.050	9.891	<.001	0.302	0.293	31.980	<.001	1.058
OA	0.460	0.469	0.051	9.078	<.001	0.256	0.246	25.343	<.001	1.058

Note. Each model includes standardised work experience, organisation size (large = 1), and technology-intensive industry (1 = yes) as controls. F df = (4, 295). B is unstandardised; β is standardised. Synthetic data.

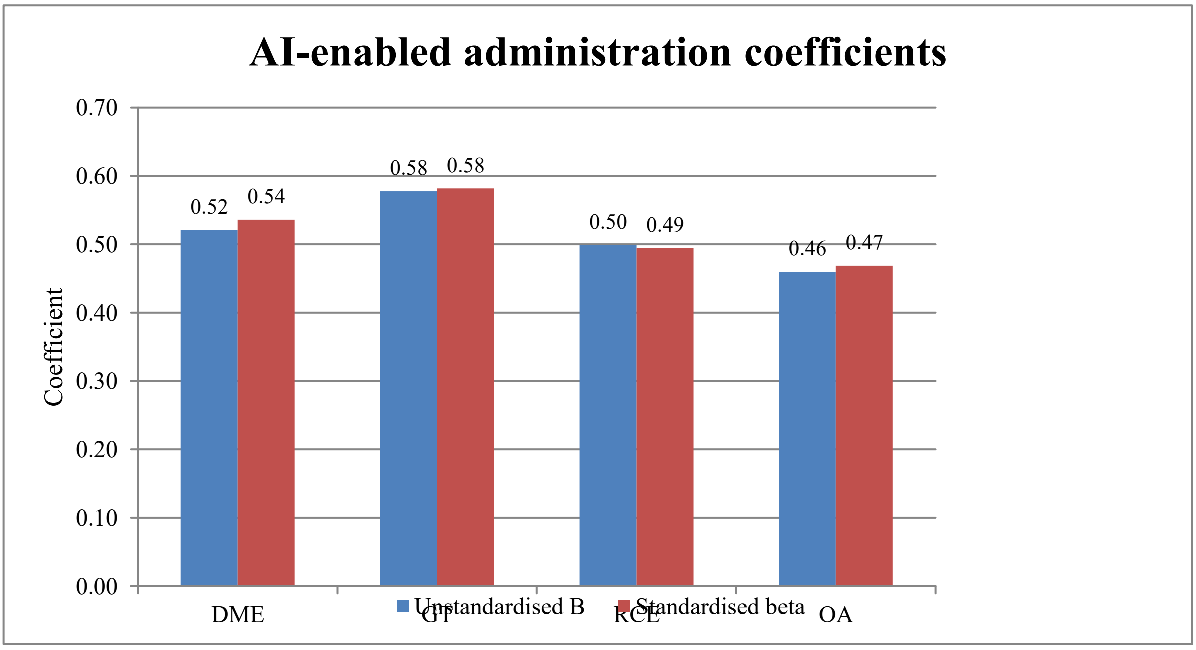

Figure 3. Comparison of AI-enabled administration effects across outcomes

Source: Synthetic demonstration dataset. All coefficients are significant at p < .001. The chart is an editable Office chart with an embedded workbook.

Construct	AICA	DME	GT	RCE	OA
AICA	1.000	0.555	0.589	0.523	0.480
DME	0.555	1.000	0.373	0.406	0.271

GT	0.589	0.373	1.000	0.330	0.542
RCE	0.523	0.406	0.330	1.000	0.313
OA	0.480	0.271	0.542	0.313	1.000

Figure 4. Editable correlation heat map

Source: Synthetic demonstration dataset. Darker shading indicates a stronger positive association. The heat map is a fully editable Word table.

The mediation model produced path a = .578 and path b = .393. The indirect effect was .227, with a 95% bootstrap interval of [.154, .304], excluding zero. The direct effect remained significant at .233, while the total effect was .460. Governance transparency therefore partially mediated the relationship, supporting H5 and rejecting H05.

Table 6. Bootstrap mediation analysis: Governance transparency as mediator

Effect/path	Estimate	SE	t	Boot LLCI	Boot ULCI	Decision
Path a: AICA → GT	0.578	.048	12.113			Significant
Path b: GT → OA	0.393	.058	6.826			Significant
Direct effect (c')	0.233	.058	4.037	0.119	0.346	Significant
Indirect effect (ab)	0.227	Bootstrap	-	0.154	0.304	Partial mediation
Total effect (c)	0.460	.051	9.078	0.355	0.560	Significant

Note. 5,000 bootstrap resamples; N = 300. Outcome model R^2 = 0.358, adjusted R^2 = 0.347, $F(5, 294)$ = 32.73, $p < .001$. LLCI/UCI = lower/upper 95% confidence limits. Synthetic data.

AI-enabled administration	a = 0.578 →	**Governance transparency**	b = 0.393 →	**Organisational accountability**
Direct effect c' = 0.233 | Indirect effect = 0.227, 95% bootstrap CI [0.154, 0.304] | Total effect c = 0.460				

Figure 5. Mediation of organisational accountability through governance transparency

Source: Synthetic demonstration dataset. Coefficients are unstandardised. The diagram is a fully editable Word table.

6. Discussion

The pattern indicates an augmentation interpretation: AI-enabled administration relates more to transparency and decision efficiency than to accountability. Real-time data, automated synthesis, and predictive prioritisation will compress information-processing cycles, but the benefit will be maximised when integrated into managerial routines, rather than being viewed as autonomous replacements. This is in line with the compositionality of organisational AI and complementary resources and the automation-augmentation paradox (Mikalef & Gupta, 2021; Raisch & Krakowski, 2021).

The mediation result explains the absence of accountability from the adoption of novelties. Generating logs, notifications, and recommendations is the limit of AI in this case. Transparency will assign meaning to these outputs as evidence. For accountability, this evidence must be placed with the responsible parties and oversight bodies. The partial mediation is appropriate, as there must be a willingness to challenge the system, as well as a disposition to place authority and accountability controls (Mökander et al, 2021; Metcalf et al 2021; Raji et al, 2020). Algorithmic impact assessments, internal audits, and documented lifecycle controls can aid in this conversion, but they must be linked to decisions and solutions.

The positive risk-control coefficient assigns value to early-warning systems, anomaly detection, automated compliance testing, and monitoring models on a continual basis. It should not imply that AI is a risk-reducing tool. Model drift, biased training data, cyber compromise, and privacy leakage coupled with over-reliance can lead to correlated failures. International standards are increasingly demanding risk categorization, assessment, documentation, and control, coupled with human oversight and monitoring, as well as the establishment of an operational framework for risk management and response to incidents (European Parliament & Council of the European Union, 2024; NIST, 2023; OECD, 2024a). Data governance is especially important, as privacy, data provenance and history, access, and retention influence both the quality of models and their legitimacy (OECD, 2024b).

International standards have deepened the value of human and organizational factors, focusing on dignity, equity, justice, transparency, and accountability (UNESCO, 2021). Labor studies have shown that AI alters the nature and the oversight of tasks, rather than simply eliminating jobs (Gmyrek et al., 2023). Thus, resistance may reflect justified concerns regarding the erosion of skills and increased workplace surveillance. The flexibility of corporate governance structures should allow for the continued exercise of professional judgment and maintain the right of redress. AI and other technologies have been recognized as posing substantial threats to the long-term stability of organizations (World Economic Forum, 2024).

7. Managerial and Governance Implications

The governance of AI should either be the responsibility of a bishop AI committee or a risk committee. An articulate account must be kept that lists the systems' decision owners, decision objectives, stakeholders, risks, data, verification, and obsolescence criteria. Responsibility matrices will differentiate the model's developer, the data owner, the business approver, the compliance reviewer, internal, and external decision-makers.

Operational controls must include a human-in-the-loop approval mechanism for significant decisions, explanation standards that meet user needs, immutable decision logs, access controls, regular bias and security assessments, model drift thresholds and incidents, and escalation and appeal

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mechanisms. Internal audit must check technical performance and assess if management abides by the stated controls. Training must include automation bias and the responsibility to object to outputs that are inconsistent. These features are a part of the ISO (2023a) and the Schneider et al. (2023) frameworks, and turn the reporting feature of transparency into an enforceable accountability architecture.

8. Limitations and Future Research

The analysis employs synthetic, cross-sectional, and self-report observations. Thus, it cannot provide an empirical estimate for a real population. Simulated covariance can provide analytical coherence, but it does not permit external validity, causal direction, sector variance, or behavioral variance. Future studies should employ field studies that are registered a priori, and use longitudinal data of adoption, audits, and controlled studies to compare decisions made by humans compared to those made by humans with AI assistance. Studies should be done across multiple nations to examine the regulatory focus, AI sophistication, the size of the organizations, and the expertise of the board as moderating variables. Responsibility negotiation after algorithmic failure should be the focus of other studies.

9. Conclusion

AI assisted corporate governance positively impacts decision-making speed, transparency, risk management, and accountability. Within the model, accountability and risk management are linked through transparency, and AI rigor is reached when decision outputs are traceable, reviewable, and linked to responsible parties. The model presents an integrated approach and a rigorous statistical framework, but not empirical field data. The responsible use of AI demands optimum technical performance combined with human judgment and governance that is auditable and clearly defines responsibility within the organization.

AUTHOR(S) CONTRIBUTION

The writers affirm that they have no connections to, or engagement with, any group or body that provides financial or non-financial assistance for the topics or resources covered in this manuscript.

CONFLICTS OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix A. Editable Figure Data

Figures 2 and 3 are native Office charts with embedded workbooks and can be edited by right-clicking the chart and selecting Edit Data. Figures 1, 4, and 5 are constructed as editable Word tables. The exact plotted values are reproduced below.

Table A1. Figure-data values

Outcome/construct	Mean	Unstandardised B	Standardised β
AICA	3.731		
DME	3.830	0.521	0.536
GT	3.657	0.578	0.582
RCE	3.726	0.499	0.495
OA	3.688	0.460	0.469

Note. Values match Tables 3 and 5 exactly. No external or proprietary data are embedded.