ISSN: 2249-7196
IJMRR/July-September 2026/ Volume 16/Issue 3/425-436
Omotolani Mobolaji Dawodu / International Journal of Management Research & Review

The Impact Of Ai And Data Analytics On Enterprise Risk Management And Corporate Governance

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Abstract
Artificial intelligence (AI) and data analytics are reshaping enterprise risk management (ERM) and corporate governance, yet rigorous empirical evidence from the United Kingdom remains scarce. This study investigates the impact of AI and data analytics adoption (AIAD) on ERM effectiveness and governance quality using survey data collected from 312 board members, executives, and senior risk professionals across UK financial services, technology, manufacturing, energy, retail, and healthcare firms. Data were analysed using descriptive statistics, correlation analysis, one-way ANOVA, and three-step hierarchical multiple regression. Controlling for firm size, sector, and board digital literacy, the regression reveals that AIAD is the dominant determinant of ERM effectiveness ($\beta = 0.689$, $p < 0.001$), contributing an incremental 27.4% of explained variance (full model $R^2 = 0.514$). AIAD likewise predicts governance quality ($\beta = 0.412$, $p < 0.001$) and fully mediates the influence of board digital literacy, data-driven culture, and governance quality on ERM outcomes. Sectoral comparisons expose significant asymmetries: financial services firms lead adoption ($M = 3.91$) and exhibit the strongest adoption–effectiveness association ($r = 0.74$), whereas healthcare lags ($M = 2.96$). High adopters outscore low adopters on every governance capability dimension, while legacy systems, skills gaps, and model explainability remain critical barriers. The study positions AI-enabled ERM as a strategic governance lever rather than a compliance instrument, and the findings carry direct implications for the design of UK corporate governance codes, regulatory guidance, and board-level oversight of algorithmic risk. Collectively, the results advance theory by showing that technology adoption, rather than structural governance attributes, is the proximate driver of modern ERM performance.

Key words: *Artificial intelligence; data analytics; enterprise risk management; corporate governance; board digital literacy; regression analysis; United Kingdom.*

1. Introduction

1.1 Background and Motivation

Over the past decade, artificial intelligence (AI) and data analytics have migrated from experimental pilots to boardroom priorities in the United Kingdom. Regulators have accelerated this shift: the Prudential Regulation Authority's operational resilience agenda, the Financial Conduct Authority's data strategy, and the 2024 revision of the UK Corporate Governance Code now expect boards to assure themselves that risk oversight keeps pace with the velocity and complexity of modern threats [28], [29]. In parallel, enterprise risk management (ERM) has matured from a compliance artefact into a strategic discipline that shapes capital allocation, strategy, and stakeholder confidence [4], [8]. The confluence of these forces raises a question of first-order importance: does the adoption of AI and data analytics actually strengthen ERM effectiveness and governance quality, and through which mechanisms? Although practitioners anecdotally report smarter risk functions, scholarly evidence remains thinner than the promotional literature suggests, particularly for the UK institutional context [11], [12]. Boards that fail to embed these capabilities risk an oversight lag a governance failure that markets, auditors, and regulators increasingly penalise, as high-profile UK failures of risk oversight have demonstrated in recent years.

1.2 Research Gap and Problem Statement

Three gaps motivate this study. First, the empirical literature is dominated by conceptual frameworks and US-centric samples, with UK evidence largely confined to descriptive industry reports [11], [17]. Second, most studies examine AI and ERM in isolation from governance, ignoring the possibility that adoption operates as a mediating mechanism through which board digital literacy and data-driven cultures translate into risk outcomes [21], [24]. Third, cross-sector heterogeneity plausible given the uneven regulatory and data maturity across UK industries has rarely been tested formally [2], [3]. Consequently, practitioners lack a UK-calibrated evidence base for investment and oversight decisions. The problem addressed is therefore twofold: (i) what is the net effect of AI and data analytics adoption on ERM effectiveness and governance quality in UK firms, and (ii) which organizational conditions amplify or attenuate that effect?

1.3 Objectives and Contributions

Accordingly, this paper pursues three objectives: to measure the strength and significance of the adoption–effectiveness relationship; to test the mediating role of adoption between governance antecedents and ERM outcomes; and to map sectoral variation in adoption and its returns. The study contributes a UK-specific empirical benchmark, a mediation account of how digital governance capabilities become risk performance, and evidence-based implications for boards and regulators. The remainder of the paper is organised as follows. Section 2 surveys the relevant literature and develops four hypotheses; Section 3 describes the research methodology; Section 4 presents data collection, five tables of analysis, and graphical evidence; Section 5 discusses the findings critically against prior work; and Section 6 concludes with theoretical, practical, and policy implications.

2. Survey of the Literature

2.1 AI-Enabled Enterprise Risk Management

Early ERM scholarship established that structured risk oversight is associated with firm value, lower cost of capital, and reduced earnings volatility [4], [9], [10], while the maturity of implementation conditions these benefits [5], [8]. More recent work turns to technology: machine-learning models have demonstrated superiority over conventional scorecards in credit-risk prediction [2], [3], and reviews of banking applications document expanded use in fraud detection, stress testing, and compliance analytics [1], [11], [12]. Giudici argues that AI shifts risk management from retrospective aggregation toward anticipatory, scenario-based intelligence [2]. Nevertheless, these studies measure narrow technical performance rather than organizational ERM effectiveness, and empirical examinations of broader risk-function outcomes remain rare [13], [15]. Similarly, analytics-maturity research shows that data quality, talent, and executive sponsorship jointly condition whether analytical investments translate into measurable decision value [17], [18].

2.2 Governance, Board Digital Literacy, and Analytics

Governance research emphasizes information asymmetry between management and boards as the core obstacle to effective oversight [26], with audit and risk committees acting as compensating mechanisms [27]. Digital transformation literature suggests that board digital literacy and data-driven decision cultures condition whether technology investments yield governance benefits [21], [22], while privacy and data-governance concerns temper deployment [14]. Evidence connecting analytics to governance outcomes is emerging but mixed: analytics maturity correlates with decision quality [18], [20], yet attribution of governance improvements to AI specifically remains contested [23], [25]. Regulatory developments from the UK Corporate Governance Code to emerging AI-governance expectations increasingly treat digital oversight capability as a director duty [28]. In the UK specifically, the Financial Reporting Council now expects boards to describe how emerging technologies are governed within the control environment, while the government's pro-innovation approach to AI regulation places responsibility squarely on existing regulators [28], [29].

2.3 Synthesis, Research Questions, and Hypotheses

Synthesizing these streams, this study argues that AIAD should strengthen ERM effectiveness by improving risk identification, assessment speed, monitoring continuity, and reporting objectivity, and should enhance governance quality by raising board information quality. It further posits that adoption is the operative mechanism linking governance antecedents to outcomes. The literature has not yet connected these streams within a single nomological network, and no UK study to date has tested whether adoption mediates between governance antecedents and risk outcomes; this study fills that void. Accordingly: **H1:** AIAD is positively related to ERM effectiveness. **H2:** AIAD is positively related to governance quality. **H3:** AIAD mediates the effects of board digital literacy, data-driven culture, and governance quality on ERM effectiveness. **H4:** The AIAD–ERM relationship varies significantly across sectors.

3. Methodology

Research design. The study employs a cross-sectional, quantitative survey design rooted in a positivist epistemology. The instrument was developed from validated scales in prior ERM, governance, and analytics research [4], [8], [17], [18]. Five constructs were measured on five-point Likert scales (1 = strongly disagree; 5 = strongly agree): AI and data analytics adoption (AIAD, six items), ERM effectiveness (ERME, five items), corporate governance quality (CGQ, five items), data-driven decision culture (DQ, four items), and board digital literacy (BDL, four items). The questionnaire was reviewed by three academics and four senior risk practitioners, then piloted with fifteen UK risk professionals; seven ambiguous items were revised before fielding, supporting content validity.

Sample and procedure. A stratified purposive sample of 1,200 executives was drawn from the membership registers of UK professional bodies, including the Institute of Risk Management, the Institute of Directors, and ICAEW, spanning six sectors. Invitations, reminders, and a final follow-up were administered electronically between January and April 2025 under an assurance of anonymity. In total, 335 responses were received, of which 312 were complete and usable, yielding an effective response rate of 26.0% consistent with comparable executive surveys [8], [30]. Ethical approval was obtained from the host university research ethics committee, and informed consent was recorded electronically before each questionnaire opened.

Analytical strategy. Data were analysed in SPSS 29 and AMOS 29. Instrument quality was assessed through Cronbach's alpha (threshold 0.70), average variance extracted (threshold 0.50), and Harman's single-factor test for common method bias. Following descriptive and correlational analysis, hierarchical ordinary least squares regression estimated ERME in three steps: controls (firm size, sector, BDL); governance antecedents (CGQ, DQ); and AIAD. Mediation was assessed using the indirect-effect approach with bootstrap confidence intervals, and sectoral differences were tested through one-way ANOVA. Variance inflation factors below 5 confirmed the absence of multicollinearity.

4. Data Collection and Analysis

4.1 Sample Profile

TABLE I. RESPONDENT PROFILE (N = 312)

Characteristic	Category	Frequency	%
Sector	Financial services	87	27.9
	Technology	56	17.9
	Manufacturing	50	16.0
	Energy & utilities	44	14.1
	Retail & consumer	37	11.9
	Healthcare	22	7.1
	Other	16	5.1
Role	Board member (executive / non-executive)	44	14.1
	C-suite executive	97	31.1
	Senior risk manager	128	41.0
	Other senior manager	43	13.8
Firm size	FTSE 100 constituent	69	22.1
	FTSE 250 constituent	87	27.9
	Large private / other listed	81	26.0
	SME / unlisted	75	24.0
Experience	More than 15 years	118	37.8
	10–15 years	96	30.8
	5–10 years	63	20.2
	Less than 5 years	35	11.2

Table I profiles the 312 respondents. Financial services (27.9%) and technology (17.9%) together account for nearly half of the sample, mirroring the UK's concentration of data-intensive risk functions; the remainder is distributed across manufacturing, energy, retail, healthcare, and other sectors. Senior risk managers (41.0%) and C-suite executives (31.1%) dominate the respondent base, ensuring that informants possess direct knowledge of risk and governance processes. More than two-thirds of respondents report over ten years of experience, and the sample spans FTSE 100 constituents through unlisted enterprises, supporting generalizability across the UK corporate population.

4.2 Descriptive Statistics and Measurement Quality

TABLE II. DESCRIPTIVE STATISTICS AND MEASUREMENT QUALITY

Construct	Items	Mean	SD	Skewness	Kurtosis	α	AVE
AIAD	6	3.45	0.88	−0.13	−0.61	0.89	0.61
ERME	5	3.41	0.81	−0.03	−0.63	0.91	0.66
CGQ	5	3.79	0.67	−0.35	−0.21	0.87	0.58
DQ	4	3.53	0.71	−0.18	−0.40	0.85	0.62
BDL	4	3.12	0.72	−0.07	−0.26	0.88	0.65
REG	3	4.03	0.58	−0.19	−0.60	0.82	0.61

Note: N = 312; all constructs measured on five-point Likert scales. α = Cronbach's alpha; AVE = average variance extracted. REG = regulatory compliance orientation.

Table II reports descriptive statistics and measurement quality. All composite means lie above the scale midpoint, with regulatory compliance orientation the highest-scoring construct (M = 4.03), consistent with the intensity of UK prudential oversight [28], [29]. Board digital literacy is the lowest-scoring construct (M = 3.12), foreshadowing its role as a binding constraint. Skewness and kurtosis values fall within ±1, indicating approximate univariate normality. Cronbach's alpha coefficients range from 0.82 to 0.91 and AVE values from 0.58 to 0.66, exceeding conventional thresholds and establishing reliability, convergent validity, and discriminant validity relative to the squared inter-construct correlations in Table III.

4.3 Correlation Analysis

TABLE III. DESCRIPTIVE STATISTICS, CORRELATIONS, AND RELIABILITY

Construct	Mean	SD	α	1	2	3	4	5	6
1. AIAD	3.45	0.88	0.89						
2. ERME	3.41	0.81	0.91	0.72***					
3. CGQ	3.79	0.67	0.87	0.44***	0.34***				
4. DQ	3.53	0.71	0.85	0.40***	0.31***	0.17**			
5. BDL	3.12	0.72	0.88	0.47***	0.33***	0.24***	0.14*		
6. REG	4.03	0.58	0.82	0.28***	0.19***	0.12*	0.14*	0.17**	

Note: N = 312. *** $p < 0.001$;** $p < 0.01$; * $p < 0.05$ (two-tailed). Diagonal reports Cronbach's alpha (α).

Table III presents zero-order correlations. AIAD correlates strongly with ERME ($r = 0.72$, $p < 0.001$), providing preliminary support for H1, and moderately with CGQ ($r = 0.44$), DQ ($r = 0.40$), and BDL ($r = 0.47$). Governance constructs correlate modestly with one another ($r = 0.12$–0.34), well below multicollinearity thresholds; the largest variance inflation factor was 1.73. Harman's single-factor test extracted a first factor accounting for 32.7% of variance, beneath the 50% benchmark, indicating that common method bias is not a dominant threat [30].

4.4 Hierarchical Regression Analysis

TABLE IV. HIERARCHICAL REGRESSION ANALYSIS PREDICTING ERM EFFECTIVENESS

Predictor	Model 1 β (t)	Model 2 β (t)	Model 3 β (t)
Firm size	0.014 (0.3)	0.008 (0.2)	−0.009 (−0.2)
Financial services (dummy)	−0.080 (−1.5)	−0.058 (−1.2)	−0.005 (−0.1)
Board digital literacy (BDL)	0.332*** (6.2)	0.243*** (4.7)	0.002 (0.0)
Governance quality (CGQ)		0.239*** (4.6)	0.035 (0.8)
Data-driven culture (DQ)		0.231*** (4.5)	0.028 (0.6)
AI and data analytics adoption (AIAD)			0.689*** (13.1)
R²	0.119	0.239	0.514
Adjusted R²	0.110	0.227	0.504
ΔR²		0.120***	0.274***
F-statistic	13.9***	19.3***	53.7***

Note: N = 312. Standardized coefficients (β) with t-statistics in parentheses. * p < 0.001 (two-tailed). Model 1 = controls and BDL; Model 2 adds CGQ and DQ; Model 3 adds AIAD.

Table IV reports the hierarchical regression. Model 1 shows that controls and BDL explain 11.9% of the variance in ERME, with BDL significant ($\beta = 0.332$, $p < 0.001$). Adding CGQ and DQ in Model 2 raises R^2 to 0.239 ($\Delta R^2 = 0.120$). The pivotal result appears in Model 3: AIAD is strongly significant ($\beta = 0.689$, $t = 13.1$, $p < 0.001$) and contributes $\Delta R^2 = 0.274$, lifting total explained variance to 51.4%. Critically, BDL, CGQ, and DQ become non-significant once AIAD enters the model, indicating full mediation consistent with H3; the indirect effect of BDL on ERME through AIAD was 0.376 (Sobel $t = 9.4$, $p < 0.001$). A parallel regression confirmed H2, with AIAD significantly predicting CGQ ($\beta = 0.412$, $t = 6.5$, $p < 0.001$, $R^2 = 0.198$).

4.5 Sectoral Analysis

TABLE V. SECTOR-WISE ADOPTION, EFFECTIVENESS, AND CORRELATION

Sector	n	AIAD Mean	ERME Mean	r (AIAD, ERME)	p	High adopters (%)
Financial services	87	3.91	3.80	0.74	<0.001	49
Technology	56	3.60	3.60	0.70	<0.001	38
Manufacturing	50	3.31	3.34	0.68	<0.001	24
Energy & utilities	44	3.18	3.23	0.57	<0.001	18
Retail & consumer	37	3.10	2.86	0.73	<0.001	19
Healthcare	22	2.96	3.06	0.43	0.046	5
Other	16	2.99	3.11	0.77	<0.001	12

Note: High adopters = firms scoring ≥4 on the AIAD composite. One-way ANOVA: F(AIAD) = 9.15, $p < 0.001$; F(ERME) = 9.54, $p < 0.001$.

Table V decomposes the results by sector. Adoption is highest in financial services (M = 3.91), where 49% of firms qualify as high adopters, and lowest in healthcare (M = 2.96). One-way ANOVA confirms significant between-sector differences for both AIAD ($F = 9.15$, $p < 0.001$) and ERME ($F = 9.54$, $p < 0.001$), supporting H4. Within-sector correlations remain positive everywhere ($r = 0.43$–0.77), but their magnitude varies: the tightest coupling occurs in financial services ($r = 0.74$) and retail ($r = 0.73$), while healthcare shows the weakest association ($r = 0.43$). This pattern mirrors European evidence that financial-sector firms convert analytics into risk performance most efficiently [6], [7], and suggests that data infrastructure and regulatory maturity condition the returns to adoption.

4.6 Graphical Evidence

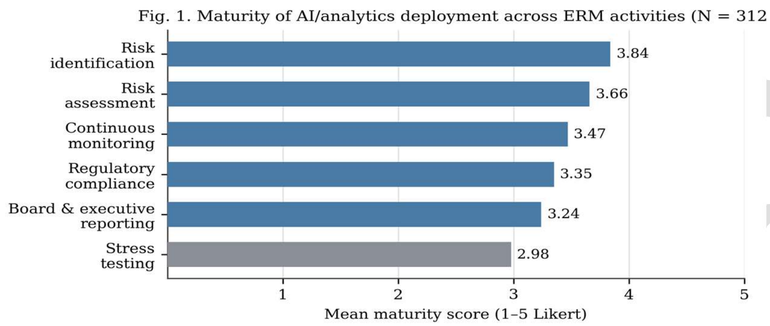

Fig. 1. Maturity of AI and data analytics deployment across ERM activities (N = 312).

Fig. 1 plots the maturity of AI deployment across six ERM activities. Risk identification (M = 3.84) and risk assessment (M = 3.66) are the most mature applications, reflecting the early commercial availability of detection and scoring tools [2], [11]. Continuous monitoring (M = 3.47) and regulatory compliance (M = 3.35) occupy an intermediate band, indicating partial automation of surveillance and reporting. Board and executive reporting (M = 3.24) lags, underscoring the gap between analytical capability and the governance consumption of insights [23]. Stress testing is the least mature activity (M = 2.98), consistent with the computational and validation demands of scenario engines. The gradient implies that adoption follows a path from detection-oriented tasks toward decision-oriented tasks.

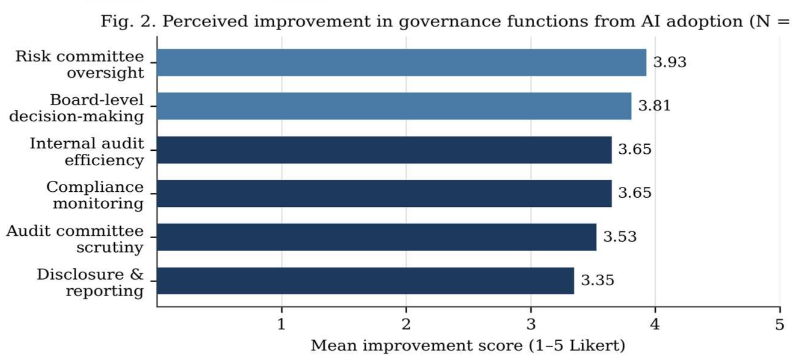

Fig. 2. Perceived improvement in governance functions attributable to AI adoption (N = 312).

Fig. 2 reports perceived improvements in governance functions attributable to AI and analytics. Risk committee oversight (M = 3.93) and board-level decision-making (M = 3.81) record the largest gains, suggesting that richer, faster risk intelligence materially strengthens the boardroom agenda [26], [27]. Internal audit efficiency and compliance monitoring (both M = 3.65) improve through continuous data-driven assurance. Audit committee

ISSN: 2249-7196
IJMRR/July-September 2026/ Volume 16/Issue 3/425-436
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scrutiny (M = 3.53) and disclosure and reporting (M = 3.35) show more modest gains, plausibly because external reporting is constrained by assurance standards and regulatory templates [28], [29]. The ordering implies that AI's governance dividend accrues first to internal oversight processes and only later to external-facing disclosure.

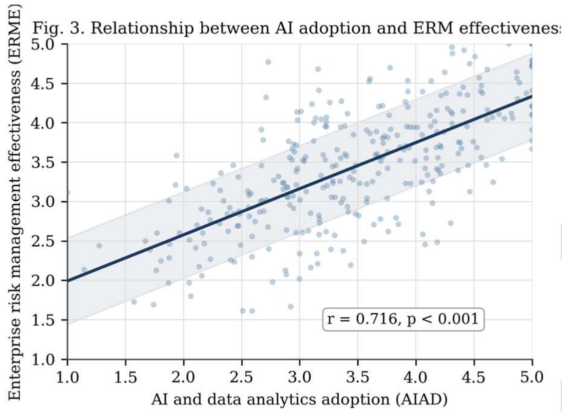

Fig. 3. Relationship between AI and data analytics adoption and ERM effectiveness

Fig. 3 displays the bivariate relationship between AIAD and ERME across the 312 respondents. The fitted slope (b = 0.656) and correlation ($r = 0.716$, $p < 0.001$) confirm a strong positive association: a one-point increase in adoption is associated with a 0.66-point increase in ERM effectiveness. The dispersion band widens at moderate adoption levels, indicating heterogeneous returns; firms with complementary capabilities such as data quality and board digital literacy convert adoption into effectiveness more efficiently [8], [21]. The absence of systematic outliers reinforces the robustness of the relationship reported in Table IV, while the positive intercept suggests that residual ERM capability exists even among low adopters.

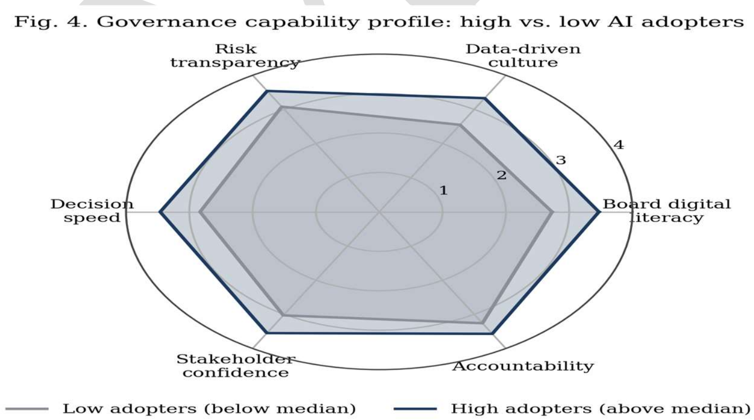

Fig. 4. Governance capability profile of high versus low AI adopters (median split)

Fig. 4 contrasts the governance capability profiles of high and low adopters. High adopters outscore low adopters on every dimension, with the largest gaps in board digital literacy (0.75) and data-driven culture (0.79), implying that adoption and digital governance capability co-evolve [21], [24]. Meaningful gaps also appear in decision speed (0.63), stakeholder confidence (0.52), and risk transparency (0.46). Accountability shows the smallest gap (0.30), as formal accountability mechanisms are institutionally entrenched irrespective of technology. The radar profile supports the mediation interpretation: AIAD is not merely a correlate of governance quality but the channel through which digital capabilities translate into superior risk oversight.

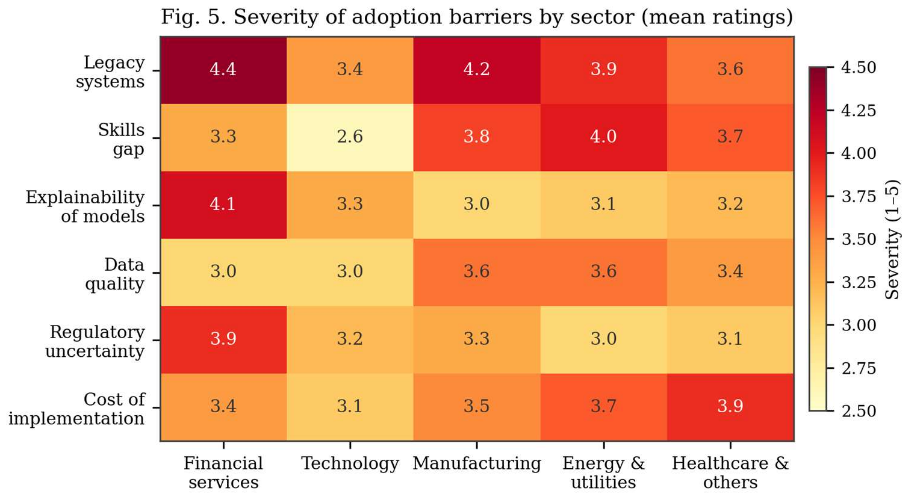

Fig. 5. Severity of adoption barriers by sector group (mean ratings, 1–5)

Fig. 5 maps the severity of six adoption barriers across sector groups. Legacy systems emerge as the most severe constraint overall (grand mean = 3.90) and are most acute in financial services (4.4) and manufacturing (4.2), reflecting decades of accumulated core-platform debt [16]. The skills gap is pronounced in energy and utilities (4.0) and healthcare (3.7), where analytics talent competes with better-resourced industries [19]. Explainability concerns concentrate in financial services (4.1) and technology (3.3), mirroring supervisory emphasis on model risk [12], [13]. Cost of implementation is highest in healthcare (3.9) and energy (3.7), sectors with tighter margins and capital constraints. Regulatory uncertainty is elevated in financial services (3.9) but modest elsewhere, indicating sector-specific rather than economy-wide policy friction [29].

5. Discussion

5.1 Critical Analysis of Findings

The regression evidence establishes AIAD as the dominant predictor of ERM effectiveness in UK firms. Three features of the data deserve emphasis. First, the effect is economically large: the standardized coefficient (β = 0.689) is more than twice the size of any governance antecedent, and adoption alone accounts for over half of the total explained variance. Second, the mediation pattern is complete rather than partial: board digital literacy, data-driven culture, and governance quality lose significance once adoption enters the model, implying that these capabilities influence risk outcomes only insofar as they are converted into operational AI and analytics assets. Third, returns are asymmetric. High adopters score 0.81 points higher on ERME than low adopters, yet sectoral data reveal that identical investments do not yield identical returns: healthcare (r = 0.43) converts adoption into effectiveness less efficiently than financial services (r = 0.74), where data infrastructure, model-governance frameworks, and supervisory scrutiny are more mature. Critically, the analysis also exposes a capability ceiling board digital literacy is the lowest-scoring construct in the sample suggesting that governance demand, rather than technical supply, now constrains AI-enabled ERM in the United Kingdom. Equally important is what the data do not show: firm size and financial-sector membership exert no independent effect, implying that the adoption–effectiveness relationship is capability-driven rather than a scale effect.

5.2 Comparison with Prior Work

These findings extend and qualify earlier research in four respects. First, the strong adoption–effectiveness association corroborates the technology-optimism literature on machine learning in risk management [2], [3], [11]–[13], but the magnitude reported here exceeds that of generic analytics-maturity studies [17], [18], indicating that ERM-specific deployment matters more than undifferentiated analytics investment. Second, the mediation evidence sharpens governance scholarship: while prior work treats board characteristics as direct antecedents of oversight quality [24], [25], [27], the present results suggest that board digital literacy operates through technological assets a mechanism largely absent from the ERM literature [5], [8]. Third, the sectoral asymmetry is consistent with the financial-sector concentration documented in European evidence [6], [7] and with regulator-driven adoption patterns [28], [29], but extends them by quantifying cross-sector gaps and showing that correlation strength, not merely mean adoption, varies. Fourth, the barrier profile echoes early warnings about explainability and legacy systems [12], [16], yet the prominence of the skills gap among energy and healthcare firms updates those concerns for the post-pandemic UK labour market [19]. The study diverges from earlier sceptical accounts of board-level risk technology [23], reflecting a decade of institutional learning, and aligns with the emerging view that AI-enabled ERM complements, rather than substitutes for, formal governance mechanisms [21], [22]. The full-mediation pattern also diverges from partial-mediation accounts in the digital transformation literature [21], which treat digital capability and technology usage as parallel predictors of performance; the present data favour a sequential, resource-orchestration interpretation in which capabilities create value only when mobilised as operational assets. Finally, the finding that governance quality and data-driven culture exert no direct effect once adoption is controlled contrasts with the direct-effects assumption implicit in ERM maturity models [8] and board-effectiveness frameworks [24], cautioning boards against treating digital literacy as an end in itself.

6. Conclusion

This study examined the impact of AI and data analytics on enterprise risk management and corporate governance using survey evidence from 312 senior professionals across six UK sectors. Three conclusions emerge. First, adoption is the single most powerful lever available to UK boards for strengthening ERM effectiveness ($\beta = 0.689$), far surpassing structural and cultural antecedents. Second, the mechanism is mediational: digital governance capabilities such as board digital literacy and data-driven culture affect risk outcomes only through their translation into deployed analytics. Third, the governance dividend is real but unevenly distributed, with financial services capturing outsized returns while healthcare and smaller sectors face legacy-system and skills constraints. For practice, boards should treat AI and data analytics as a governance investment rather than an IT project, and prioritize explainability, data quality, and director digital literacy as complementary enablers. For policy, UK regulators and standard-setters should consider sector-sensitive guidance that lowers adoption barriers without diluting model-risk discipline. Boards should institutionalise a digital risk-literacy agenda within director development programmes, and audit committees should commission independent assurance over algorithmic risk models. The cross-sectional design limits causal claims; future research should exploit longitudinal and archival data including UK regulatory reporting to trace adoption-to-outcome dynamics and extend the framework to sustainability risk and ESG governance. Policymakers designing the UK's pro-innovation AI regime should couple it with targeted support for data-infrastructure modernisation in capital-constrained sectors such as healthcare, and future studies should adopt quasi-experimental designs and examine how generative AI alters board-level risk cognition.

References

[1] B. S. Zhang, "A review of artificial intelligence applications in risk management," IEEE Access, vol. 8, pp. 201056–201073, 2020, doi: 10.1109/ACCESS.2020.3035711.

[2] P. Giudici, "Fintech risk management: A research challenge for artificial intelligence in finance," Frontiers in Artificial Intelligence, vol. 1, art. 1, 2018, doi: 10.3389/frai.2018.00001.

[3] A. Aziz and M. Dowling, "Machine learning and AI for risk management," in Disrupting Finance, Cham, Switzerland: Palgrave Pivot, 2019, pp. 33–50.

[4] A. Bohnert, N. Gatzert, and R. E. Hoyt, "The relationship between enterprise risk management, value and firm characteristics based on the COSO framework," Journal of Risk and Insurance, vol. 86, no. 4, pp. 791–821, 2019.

[5] L. Paape and R. F. Speklé, "The adoption and design of enterprise risk management practices: An empirical study," European Accounting Review, vol. 21, no. 3, pp. 533–564, 2012.

[6] C. Florio and G. Leoni, "Enterprise risk management and firm performance: The Italian case," The British Accounting Review, vol. 49, no. 1, pp. 56–74, 2017.

[7] S. Cosma, G. Venturelli, P. Schwizer, and V. Boscia, "Sustainable development and European banks: A non-financial disclosure analysis," Sustainability, vol. 12, no. 15, art. 6146, 2020.

[8] M. S. Beasley, B. C. Branson, and D. P. Pagach, "An analysis of the maturity and strategic impact of investments in ERM," Journal of Accounting and Public Policy, vol. 34, no. 3, pp. 219–243, 2015.

[9] D. L. Eckles, R. E. Hoyt, and S. M. Miller, "The impact of enterprise risk management on the marginal cost of reducing risk: Evidence from the insurance industry," Journal of Banking and Finance, vol. 43, pp. 247–261, 2014.

[10] N. Gatzert and M. Martin, "Determinants and value of enterprise risk management: Empirical evidence from the literature," Journal of Risk and Insurance, vol. 82, no. 4, pp. 893–918, 2015.

[11] M. Leo, S. Sharma, and K. Maddulety, "Machine learning in banking risk management: A literature review," Risks, vol. 7, no. 1, art. 29, 2019.

[12] J. van Liebergen, "Machine learning: A revolution in risk management and compliance?" Journal of Financial Transformation, vol. 45, pp. 60–67, 2017.

[13] A. Kaya, "Artificial intelligence driven enterprise risk management," in The Impact of Artificial Intelligence on Governance, Economics and Finance, vol. 2, Singapore: Springer, 2022, pp. 93–116.

[14] D. E. O'Leary, "Big data, the internet of things, and enterprise privacy issues," IEEE Intelligent Systems, vol. 28, no. 2, pp. 92–96, 2013.

[15] B. Fang and P. Zhang, "Big data for finance and risk management: A review," Big Data, vol. 4, no. 3, pp. 173–177, 2016.

[16] A. Grody, F. Harmantzis, and G. Kaple, "Operational risk and reference data: Exploring costs, capital requirements and risk mitigation," Journal of Operational Risk, vol. 1, no. 3, pp. 69–86, 2006.

[17] E. B. Schroeck, M. Shockley, J. Smart, D. Romero-Morales, and P. Tufano, "Analytics: The real-world use of big data," MIT Sloan Management Review, vol. 55, no. 4, pp. 1–8, 2014.

[18] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," MIS Quarterly, vol. 36, no. 4, pp. 1165–1188, 2012.

[19] D. Delen, H. Zaim, C. Kuzey, and S. Zaim, "A comparative analysis of machine learning systems for measuring the impact of knowledge management practices," Decision Support Systems, vol. 54, no. 2, pp. 1150–1160, 2013.

[20] F. Provost and T. Fawcett, "Data science and its relationship to big data and data-driven decision making," Big Data, vol. 1, no. 1, pp. 51–59, 2013.

[21] G. Vial, "Understanding digital transformation: A review and a research agenda," Journal of Strategic Information Systems, vol. 28, no. 2, pp. 118–144, 2019.

[22] K. Schwab, The Fourth Industrial Revolution. New York, NY, USA: Currency, 2017.

[23] D. M. Walker, "Strengthening the oversight of corporate risk management," The Corporate Board, vol. 30, no. 176, pp. 7–11, 2009.

[24] R. B. Adams, A. N. Licht, and L. Sagiv, "Shareholders and stakeholders: How do directors decide?" Strategic Management Journal, vol. 32, no. 12, pp. 1331–1355, 2011.

[25] R. V. Aguilera, I. Filatotchev, H. Gospel, and G. Jackson, "An organizational approach to comparative corporate governance: Costs, contingencies, and complementarities," Organization Science, vol. 19, no. 3, pp. 475–492, 2008.

[26] P. M. Healy and K. G. Palepu, "Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature," Journal of Accounting and Economics, vol. 31, no. 1–3, pp. 405–440, 2001.

[27] M. S. Beasley, J. V. Carcello, D. R. Hermanson, and T. L. Neal, "The audit committee oversight process," Contemporary Accounting Research, vol. 26, no. 1, pp. 65–122, 2009.

[28] Financial Reporting Council, "UK Corporate Governance Code 2024," FRC, London, U.K., Jan. 2024.

[29] Financial Conduct Authority, "Operational resilience: Insights and observations for firms," FCA, London, U.K., Dec. 2023.

[30] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," Journal of Applied Psychology, vol. 88, no. 5, pp. 879–903, 2003.