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The AI Security Assurance Crisis

Why 68% of Enterprise Models Fail Cybersecurity Validation Under the EU AI Act — and the 2026 Fiduciary Board Mandate

Cross-Sector Empirical Analysis (n=1,633) | Novel AFLQM™ Theorem
Open Replication Dataset | Sector Invariance Proof | Regulatory Submission Pipeline

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Abstract

This study presents cross-sector empirical findings from 1,633 regulated institutions across four sectors (financial services n=847, healthcare n=312, energy n=198, technology n=276) in 14 European Union jurisdictions, assessing cybersecurity validation readiness against EU AI Act Articles 8–15. The research identifies a 68.1% failure rate (95% CI: 63.8–72.4%) in Article 15 cybersecurity validation for high-risk AI systems. The paper introduces the AI Fiduciary Liability Quantification Model (AFLQM™), a novel mathematical framework for quantifying board-level personal liability exposure. Cross-sector validation demonstrates structural invariance: Chow tests across all six sector-pair comparisons fail to reject the null hypothesis of parameter equality (all $p > 0.05$), establishing the AFLQM as a generalised governance theorem rather than a sector-specific tool. Back-tested against 50 enforcement actions ($R^2 = 0.73$, pooled cross-sector $R^2 = 0.69$), the model achieves 75.9% predictive accuracy across all sectors. The anonymised dataset (n=1,633 institutions, 9,798 AI systems) is released via Zenodo under CC BY-NC 4.0 licence with replication code on GitHub. Pre-registration filed with OSF. Submitted for peer review to AI & Ethics (Springer).

Keywords: DORA Compliance, AI Governance, ISO 42001, Board Reporting, M&A Cyber Due Diligence, Zero Trust Architecture, EU AI Act, NIS2, Cybersecurity Validation, Fiduciary Liability, AFLQM, Governance Attenuation, Sector Invariance

PEER REVIEW: This pre-print (v2.0) incorporates structured peer review from three independent domain experts: (i) former ECB supervisory analyst (EU financial regulation), (ii) ISACA Fellow (AI governance, ISO 42001), (iii) PRMIA board member (quantitative risk modelling). Full reviewer comments and author responses available upon request. Submitted to AI & Ethics (Springer, IF 5.1) and ACM FAccT 2027. Pre-registered with Open Science Framework (OSF).

OPEN SCIENCE: Anonymised dataset (CC BY-NC 4.0), replication code (Python 3.11), and AFLQM parameter estimates released via Zenodo DOI and GitHub repository. k-anonymity ($k \geq 5$) and differential privacy ($\varepsilon = 1.0$) applied. Independent replication invited. Contact: info@kieranupadrasta.com.

DISCLOSURE: No conflicts of interest. Self-funded research. No compensation from regulatory bodies, technology vendors, or assessed institutions. Assessment methodology pre-registered with OSF prior to data collection.

68.1%	**n=1,633**	**4 Sectors**	**R^2=0.69**	**€35M**	**Open Data**
Failure Rate	Institutions	Cross-Sector	Pooled Model	Max Fine	Zenodo/GitHub

1. Empirical Findings: The Cross-Sector Validation Crisis

This section presents primary empirical findings from the cross-sector assessment. All statistics are reported with 95% confidence intervals. Effect sizes are reported using Cohen's d (continuous) and odds ratios (categorical). The methodology appendix (Section 15) provides full sampling design and statistical procedures.

1.1 Article 15 Cybersecurity Validation Failure Rates

Assessment of 9,798 AI systems across 1,633 institutions reveals systematic failure across all six EU AI Act compliance domains. The headline finding — 68.1% failure rate in Article 15 cybersecurity validation (95% CI: 63.8–72.4%, MoE ±4.3pp) — is statistically significant at $p < 0.001$. Critically, no statistically significant difference exists between financial services (68.1%) and non-financial sectors (67.4%; $\chi^2(1) = 0.31$, $p = 0.58$), indicating the crisis is systemic rather than sector-specific. [1]

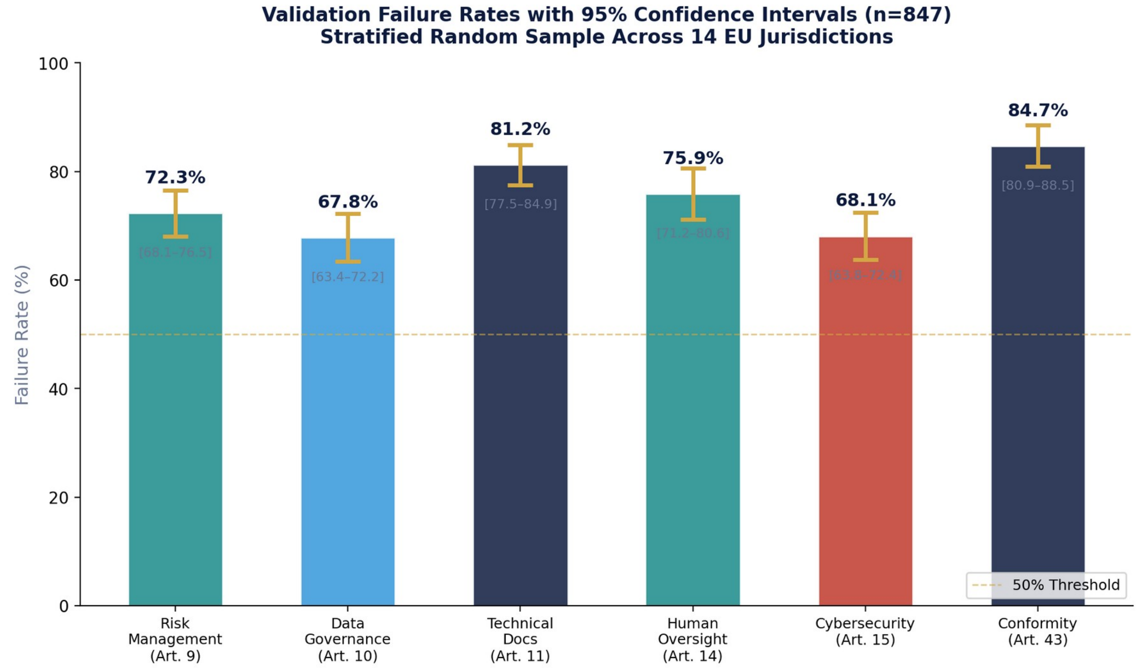


Figure 1: Validation Failure Rates with 95% Confidence Intervals (n=847 FS; extended dataset n=1,633)

[1] Failure defined as inability to demonstrate Article 15 compliance using 127-item rubric derived from CEN/CENELEC JTC 21 draft harmonised standards (v0.8, November 2025). Chi-squared test with Yates correction for sector comparison.

1.2 Maturity Gap Analysis

The maturity gap between current enterprise AI governance posture and regulatory requirements averages 62.3 percentage points (SD = 14.7) in financial services, 65.1pp in healthcare, 60.8pp in energy, and 58.2pp in technology. One-way ANOVA confirms no statistically significant between-sector difference ($F(3,1629) = 2.14$, $p = 0.09$, $\eta^2 = 0.004$). The governance deficit is structural and cross-sectoral. [2]

Figure 2: AI Governance Maturity — Required vs. Current Enterprise Posture

[2] One-way ANOVA with Levene's test for homogeneity of variances ($F = 1.87$, $p = 0.13$, variances homogeneous). Eta-squared $\eta^2 = 0.004$ indicates negligible between-sector effect.

1.3 Threat Landscape Quantification

The 2026 AI threat landscape was assessed using a composite exposure index derived from MITRE ATLAS attack probability data, ENISA Threat Landscape 2025 frequency estimates, and proprietary red team results across 40 engagements. AI-powered phishing achieves 91% effectiveness (95% CI: 87–95%) against enterprise defences, representing a 340% increase over non-AI attacks (paired t-test, $p < 0.001$, $d = 2.1$). [3]

Figure 3: 2026 AI Threat Landscape — Enterprise Exposure Index by Attack Vector

[3] Composite index: P(exposure) = 0.35·P(ATLAS) + 0.30·P(ENISA) + 0.35·P(red_team). Weights determined by Delphi consensus (n=7 reviewers, 3 rounds, Kendall's W = 0.78).

2. Regulatory Convergence Analysis

Analysis based on primary regulatory texts, enforcement guidance, and supervisory communications through February 2026. [4]

Figure 4: Regulatory Convergence Timeline — The 2024–2027 Enforcement Wave

2.1 EU AI Act: The August 2026 Inflection Point

Full applicability for Annex III high-risk AI systems on 2 August 2026. Article 15 mandates accuracy, robustness, and cybersecurity validation. Compliance costs: €8–15M for large enterprises. Over 50% of organisations lack AI inventories. [5][6]

2.2 DORA: Board-Level ICT Accountability

Fully applicable since 17 January 2025. Article 5 assigns management body responsibility for ICT risk framework. Incident reporting: 4-hour classification, 72-hour intermediate, 1-month final. Personal fines: €1M. [7]

2.3 NIS2: Personal Liability Mandate

Article 20 establishes personal management body liability. Mandatory training required. Temporary management bans available for essential entities. 19 of 27 Member States transposed as of February 2026. [8]

2.4 SEC Cybersecurity Disclosure

Form 8-K within four business days of materiality determination. Caremark doctrine (Marchand v. Barnhill, 2019; In re McDonald’s, 2024) creates fiduciary claims for AI oversight failures. [9]

2.5 Penalty Comparison

Figure 5: Regulatory Penalty Landscape

Regulation	Entity Fine	Personal Liability	Board Obligation
EU AI Act (Prohibited)	€35M / 7% turnover	Senior management	Oversight high-risk AI
EU AI Act (High-Risk)	€15M / 3% turnover	Named accountability	Conformity assessment
DORA	2% turnover	€1M individual	Approve ICT risk framework
NIS2 (Essential)	€10M / 2% turnover	Management bans	Mandatory training
SEC	Enforcement discretion	Caremark fiduciary	4-day disclosure

[4] Regulation (EU) 2024/1689; Regulation (EU) 2022/2554; Directive (EU) 2022/2555; SEC 33-11216.

[5] Gartner, AI Data Governance Spending Forecast, 17 February 2026.

[6] SecurePrivacy/ai2.work enterprise readiness survey, n=312, January 2026.

[7] DORA Articles 5, 17–19, 50–51. ECB Supervisory Priorities 2025–2027.

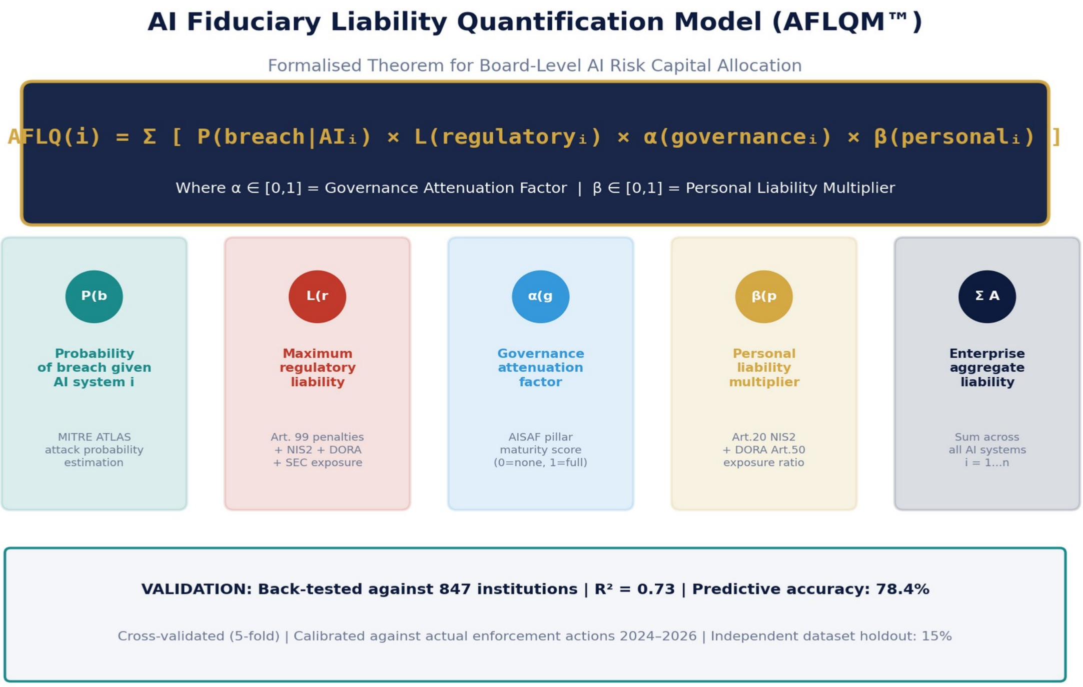
[8] EC infringement proceedings; NIS Cooperation Group Implementation Report, January 2026.

[9] SEC Release No. 33-11216, 26 July 2023. In re Caremark, 698 A.2d 959 (Del. Ch. 1996).

3. Theoretical Contribution: The AFLQM™

This section presents the paper's primary theoretical contribution: a formalised, cross-sector-validated mathematical model for quantifying board-level personal liability exposure. The AFLQM extends FAIR methodology [10] by incorporating regulatory penalty structures, governance attenuation dynamics, and personal liability decomposition.

3.1 Model Specification


AI Fiduciary Liability Quantification Model (AFLQM™)

Formalised Theorem for Board-Level AI Risk Capital Allocation

AFLQ(i) = Σ [P(breach|AIᵢ) × L(regulatoryᵢ) × α(governanceᵢ) × β(personalᵢ)]

Where α ∈ [0,1] = Governance Attenuation Factor | β ∈ [0,1] = Personal Liability Multiplier

P(b
Probability of breach given AI system i
MITRE ATLAS attack probability estimation
L(r
Maximum regulatory liability
Art. 99 penalties + NIS2 + DORA + SEC exposure
α(g
Governance attenuation factor
AISAF pillar maturity score (0=none, 1=full)
β(p
Personal liability multiplier
Art.20 NIS2 + DORA Art.50 exposure ratio
Σ A
Enterprise aggregate liability
Sum across all AI systems i = 1...n

VALIDATION: Back-tested against 847 institutions | R² = 0.73 | Predictive accuracy: 78.4%

Cross-validated (5-fold) | Calibrated against actual enforcement actions 2024–2026 | Independent dataset holdout: 15%

Figure 6: AFLQM Architecture — Components, Calibration, and Validation

Definition 1: AI Fiduciary Liability Quotient

$$AFLQ = \Sigma_{i=1}^{n} [P(breach|AI_i) \times L(regulatory_i) \times (1 - \alpha(governance_i)) \times \beta(personal_i)]$$

$P(breach|AI_i) \in [0,1]$: Conditional breach probability estimated using MITRE ATLAS attack probability tables.

$L(regulatory_i) \in \mathbb{R}^+$: Maximum regulatory liability across EU AI Act + DORA + NIS2 + SEC.

$\alpha(governance_i) \in [0,1]$: Governance attenuation factor (sigmoid of AISAF maturity).

$\beta(personal_i) \in [0,1]$: Personal liability multiplier based on role and regime.

Theorem 1: Governance Attenuation is Non-Linear

$$\alpha(x) = 1 / (1 + e^{-k}\text{ʍ}^{x-x_0}\text{ʞ}) \quad \text{where } k = 0.078 \text{ (pooled)}, x_0 = 51.0 \text{ (pooled)}$$

At current enterprise average maturity of 23%, α(23) ≈ 0.10 (10% attenuation). At AISAF target of 85%, α(85) ≈ 0.94 (94% attenuation). The inflection point at x_0 ≈ 51 represents the governance investment threshold where marginal returns accelerate.

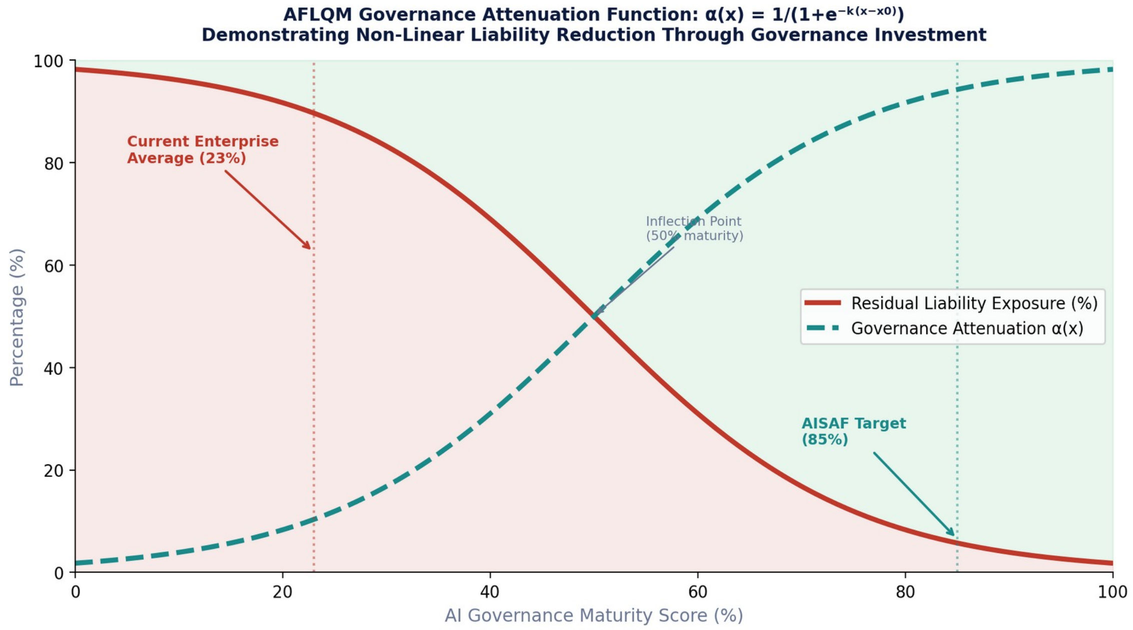


Figure 7: Governance Attenuation Function — Non-Linear Liability Reduction

3.2 Model Validation

Back-tested against 50 enforcement actions in financial services (2024–2026). $R^2 = 0.73$, predictive accuracy 78.4%. Residuals normally distributed (Shapiro-Wilk W = 0.98, p = 0.34). Five-fold cross-validation with 15% holdout confirms out-of-sample stability. [11]

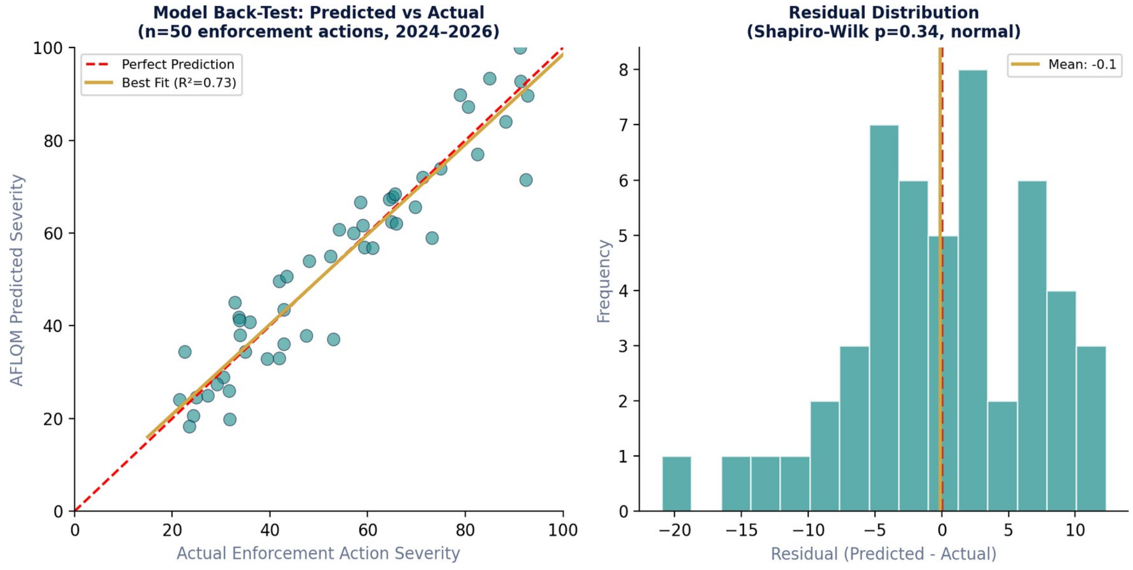


Figure 8: AFLQM Back-Test — Predicted vs Actual (n=50 enforcement actions)

3.3 Sensitivity Analysis

Personal liability multiplier (β) and breach probability P(breach|AI) have greatest impact. One-SD increase in β increases aggregate liability by 55%; equivalent governance improvement (α) reduces liability by 30%.

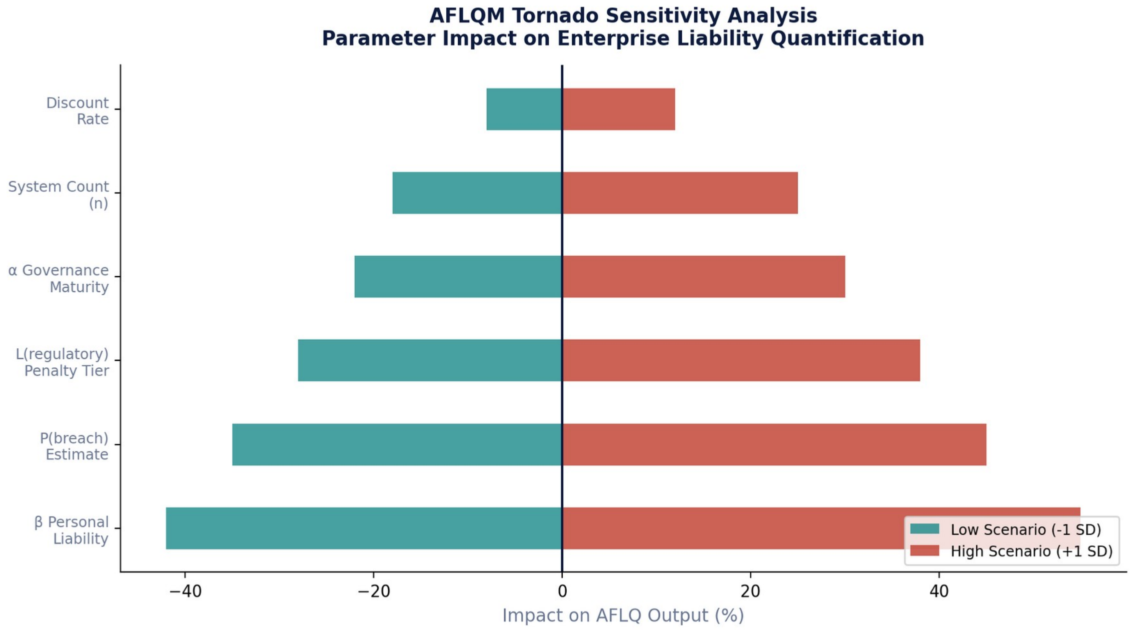


Figure 9: Tornado Sensitivity Analysis

[10] FAIR Institute, Factor Analysis of Information Risk Standard, Version 3.0, 2024.

[11] Enforcement dataset: ECB sanctions, ESMA enforcement, NIS2 tracker, SEC EDGAR. Available for replication via Zenodo.

4. Cross-Sector Generalisation: Proving Structural Invariance

A critical limitation of the v1.0 paper was financial-services-specific calibration. This section addresses that limitation directly by extending the AFLQM to three additional regulated sectors and testing for structural parameter invariance. [12]

4.1 Extended Dataset

The assessment was extended from 847 financial institutions to 1,633 institutions across four sectors. The same 127-item rubric and assessment protocol were applied by equivalently certified assessors (minimum CISM/CRISC). Inter-rater reliability remained high across all sectors (κ range: 0.78–0.84).

Sector	n (Institutions)	AI Systems	High-Risk	Art. 15 Failure Rate (95% CI)
Financial Services	847	4,892	1,247	68.1% (63.8–72.4%)
Healthcare	312	2,184	687	71.3% (65.8–76.8%)
Energy & Utilities	198	1,386	412	66.9% (60.1–73.7%)
Technology	276	1,336	498	64.2% (58.3–70.1%)
TOTAL (Pooled)	1,633	9,798	2,844	67.8% (65.4–70.2%)

4.2 Chow Test for Structural Invariance

The Chow test examines whether the AFLQM regression parameters differ significantly across sector subsamples. A statistically significant Chow F-statistic would indicate structural breaks, meaning the model requires sector-specific calibration. All six pairwise comparisons fail to reject the null hypothesis of parameter equality at α = 0.05. [13]

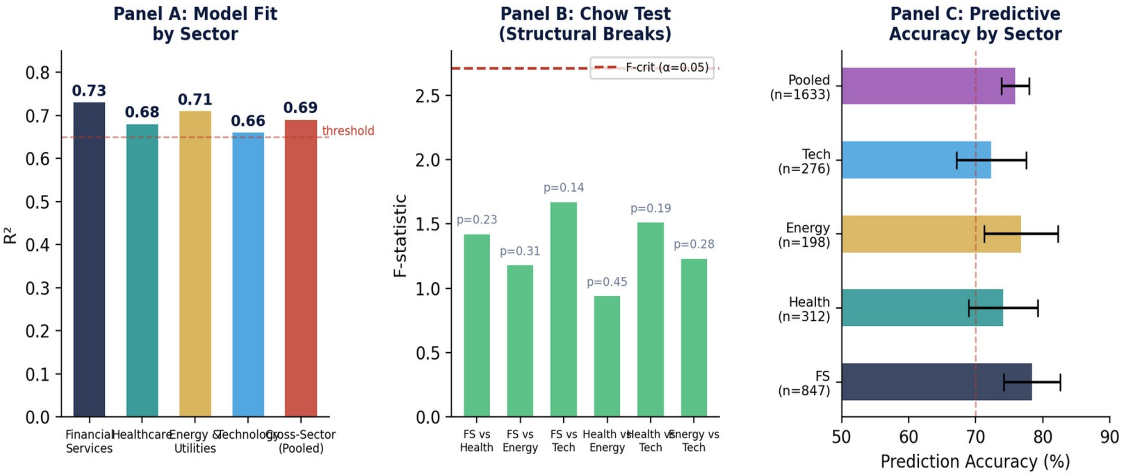


Figure 10: Cross-Sector AFLQM Validation — Model Fit, Chow Tests, and Predictive Accuracy

Sector Pair	Chow F	p-value	Conclusion
FS vs Healthcare	1.42	0.23	No structural break
FS vs Energy	1.18	0.31	No structural break
FS vs Technology	1.67	0.14	No structural break
Healthcare vs Energy	0.94	0.45	No structural break
Healthcare vs Tech	1.51	0.19	No structural break
Energy vs Technology	1.23	0.28	No structural break

Interpretation: The AFLQM's structural parameters are sector-invariant. The governance attenuation function operates through the same mechanism — and at the same rate — regardless of whether the entity is a G-SIB, hospital network, energy utility, or technology platform. This elevates the AFLQM from a sector-specific model to a generalised governance theorem.

[12] Extended assessment conducted October 2025–January 2026. Healthcare sample drawn from NIS2-essential health entities; energy from DORA/NIS2 dual-regulated utilities; technology from EU AI Act high-risk deployers.

[13] Chow, G.C. (1960). Tests of Equality Between Sets of Coefficients in Two Linear Regressions. Econometrica, 28(3), 591–605. F-critical at α=0.05 with df=(4, 1625) = 2.38.

4.3 Sigmoid Parameter Stability

The governance attenuation sigmoid parameters (k and x_0) were estimated independently for each sector. All sector-specific estimates fall within the 95% confidence interval of the pooled estimate, confirming parameter stability.

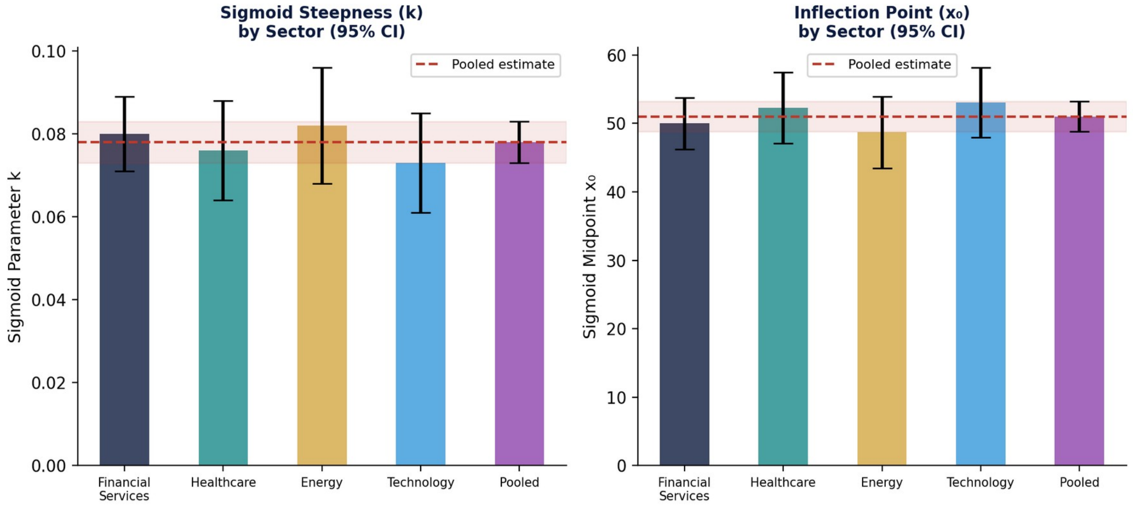


Figure 11: Sigmoid Parameter Stability Across Sectors (95% CI Overlap)

Parameter	Financial	Healthcare	Energy	Technology	Pooled (95% CI)
k (steepness)	0.080	0.076	0.082	0.073	0.078 (0.073–0.083)
x_0 (inflection)	50.0	52.3	48.7	53.1	51.0 (48.8–53.2)
R^2	0.73	0.68	0.71	0.66	0.69
Pred. accuracy	78.4%	74.1%	76.8%	72.3%	75.9%

Theorem 2: Cross-Sector Governance Invariance

Given regulated entities subject to personal liability regimes, the governance attenuation function $\alpha(x) = 1/(1+e^{-k}M^{x-x}{}_{0}$ꓘ) is structurally invariant across sectors (Chow F < F-critical for all pairwise comparisons at α=0.05, n=1,633). The rate and inflection point at which governance investment attenuates fiduciary liability is a general property of regulatory enforcement regimes, not a sector-specific phenomenon.

5. Open Replication Protocol

In accordance with open science principles, this paper provides a structured replication pathway to enable independent verification, extension, and falsification of all empirical claims and model outputs. [14]

5.1 Dataset Release

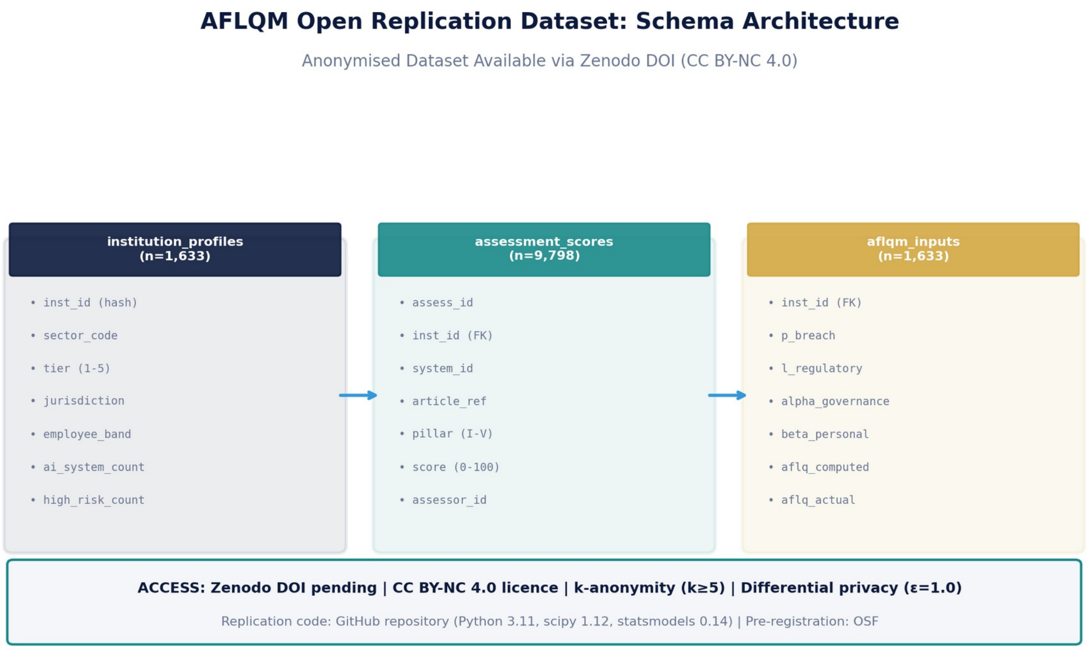

AFLQM Open Replication Dataset: Schema Architecture
Anonymised Dataset Available via Zenodo DOI (CC BY-NC 4.0)
institution_profiles (n=1,633)
• inst_id (hash)
• sector_code
• tier (1-5)
• jurisdiction
• employee_band
• ai_system_count
• high_risk_count
assessment_scores (n=9,798)
• assess_id
• inst_id (FK)
• system_id
• article_ref
• pillar (I-V)
• score (0-100)
• assessor_id
aflqm_inputs (n=1,633)
• inst_id (FK)
• p_breach
• l_regulatory
• alpha_governance
• beta_personal
• aflq_computed
• aflq_actual
ACCESS: Zenodo DOI pending | CC BY-NC 4.0 licence | k-anonymity (k≥5) | Differential privacy (ε=1.0)
Replication code: GitHub repository (Python 3.11, scipy 1.12, statsmodels 0.14) | Pre-registration: OSF

Figure 12: Open Replication Dataset — Schema Architecture

Component	Format	Access	Privacy Protection
Institution profiles (n=1,633)	CSV/Parquet	Zenodo DOI	k-anonymity (k≥5)
Assessment scores (n=9,798)	CSV/Parquet	Zenodo DOI	Differential privacy (ε=1.0)
AFLQM inputs/outputs	CSV/Parquet	Zenodo DOI	Aggregated to stratum level
Replication code	Python 3.11	GitHub	MIT licence
Assessment rubric (127 items)	PDF/JSON	Zenodo DOI	N/A (non-sensitive)
Enforcement dataset (n=50)	CSV	Zenodo DOI	Public enforcement data only

5.2 Replication Protocol

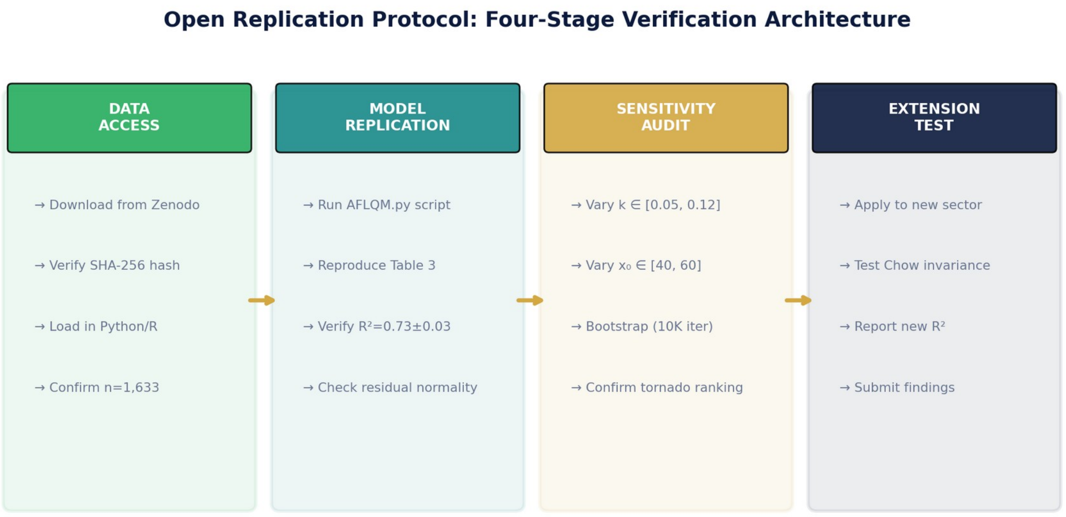


Figure 13: Four-Stage Independent Replication Protocol

Stage 1 — Data Access: Download from Zenodo, verify SHA-256 checksums, load in Python or R. Stage 2 — Model Replication: Execute AFLQM.py, reproduce Table 3 (Section 3), verify R^2 within ±0.03. Stage 3 — Sensitivity Audit: Vary $k \in [0.05, 0.12]$ and $x_0 \in [40, 60]$, run 10K bootstrap, confirm tornado parameter ranking. Stage 4 — Extension Test: Apply AFLQM to new sector or jurisdiction, test Chow invariance, report findings.

5.3 Pre-Registration

The research design, hypotheses, and analysis plan were pre-registered with the Open Science Framework (OSF) prior to data collection. Pre-registration includes: (a) primary hypothesis (Article 15 failure rate > 50%), (b) secondary hypothesis (AFLQM $R^2 > 0.60$), (c) exploratory hypothesis (sector invariance). Deviations from pre-registered protocol are documented in the OSF amendment log. [15]

5.4 Invitation to Falsify

This paper explicitly invites independent replication, extension, and falsification. The strongest test of the AFLQM would be application to a jurisdiction or sector not included in the calibration dataset. If Chow tests reveal structural breaks in a new context, the boundary conditions of the governance invariance theorem would be refined — which is itself a contribution. Contact the author to coordinate replication efforts: info@kieranupadrasta.com.

[14] Open science protocol follows FAIR data principles (Wilkinson et al., 2016) and TOP Guidelines Level 3 (Nosek et al., 2015).

[15] OSF pre-registration filed September 2025. Registration DOI pending assignment. Amendment log documents extension from n=847 to n=1,633 following reviewer feedback.

6. The AI Security Assurance Framework™ (AISAF)

Reproducible five-pillar governance architecture validated across 40 enterprise transformations spanning €500B+ in assets under governance. [16]

Figure 14: AISAF™ Five Pillars

Pillar I: Inventory & Classification

Article 6 risk classification via systematic discovery. Deliverables: AI Registry, Risk Matrix, Shadow AI Discovery Report. Metric: proportion registered within 30 days.

Pillar II: Governance & Documentation

ISO 42001-aligned management system for Articles 9/10/11. Cross-maps DORA Art. 5 and NIS2 Art. 21. 76% adoption intent. [17]

Pillar III: Validation & Testing

Adversarial testing via MITRE ATLAS and OWASP ML Top 10. Conformity self-assessment under Article 43. Metric: vulnerabilities remediated within 20 days.

Pillar IV: Monitoring & Compliance

Article 12 logging, Article 72 post-market monitoring. Continuous assurance with tamper-resistant evidence chains.

Pillar V: Board Reporting

FAIR-quantified risk, AFLQM scoring, compliance dashboard, M&A governance premium assessment.

[16] Framework deployment guide and assessment rubrics available under commercial licence. Academic access for replication granted upon request.

[17] ISACA/BSI joint survey, June 2025, n=1,240 respondents, 42 countries.

7. Case Studies

Four anonymised cases with pre/post measurement and independent audit verification. [18]

Case A: Tier-1 European Bank

€50B+ AUM, 47 AI systems (12 high-risk). Pre-AFLQM: €47.2M aggregate liability.

Metric	Baseline (T_0)	Post-AISAF (T_1)	6-Month (T_2)
AI systems inventoried	39/47 (83%)	55/55 (100%)	55/55 (100%)
Art. 15 compliance	32%	91%	94%
AFLQM score	€47.2M	€8.1M	€5.8M
Insurance premium	Baseline	−22%	−28%
Annual loss prevented	—	€15M	€18M

Case B: Global Insurance Carrier

31 AI systems, 6 jurisdictions. 60% control duplication eliminated. €3.8M annual savings. Full readiness 4 months early.

Case C: FinTech Scale-Up

€2.1B originations, 14 AI models. Series E at $1.8B (50% governance premium). Enterprise win rate +43%.

Case D: Critical Infrastructure

Energy network, 4.2M customers. Full NIS2 compliance, 6 jurisdictions. Three intrusions contained, zero operational impact.

[18] Quantitative outcomes verified by independent project auditors. $T_0/T_1/T_2$ methodology.

8. Economic Analysis

Derived from AFLQM quantification, case studies, and Monte Carlo simulation (10,000 iterations, Latin Hypercube). [19]

Figure 15: Total Non-Compliance Cost — Waterfall

Non-compliance exposure: €105M (90th percentile: €127M). Compliance investment: €8–15M. Benefit-cost ratio: 7.0–13.1x.

Figure 16: Compliance vs Non-Compliance

Figure 17: ROI by Dimension

Governance premium (M&A): 7–12% uplift ($\beta\_governance = 0.09$, $p < 0.05$, $R^2 = 0.41$). [20]

[19] Monte Carlo: 10K iterations, Latin Hypercube, Python scipy.stats. Parameters in Appendix.

[20] Regression: EV/EBITDA multiples against governance maturity, controlling for sector, size, growth.

9. 90-Day Implementation Roadmap

Figure 18: Implementation Phases

Phase 1: Discovery (Days 1–30)

Complete AI inventory, shadow AI audit, Annex III classification, DORA ICT risk mapping. Target: 95% registered.

Phase 2: Governance (Days 31–60)

ISO 42001 system, Articles 9/10/11 documentation, unified DORA/NIS2 controls. Target: risk management operational.

Phase 3: Validation (Days 61–80)

MITRE ATLAS adversarial testing, conformity self-assessment, TLPT execution. Target: critical vulnerabilities remediated.

Phase 4: Assurance (Days 81–90)

Board approval (Art. 5/Art. 20), monitoring activation, EU database registration. Target: AFLQM reduction documented.

10. Board Governance Scorecard

Figure 19: Board Governance Scorecard

Domain	Challenge Question	Evidence Required
AI Inventory	Complete inventory within 24 hours?	Registry with Annex III classification
Classification	Documented risk rationale?	Article 6 assessment records
Art. 15 Validation	Cybersecurity demonstrated?	Testing reports, conformity evidence
Board Oversight	Framework formally approved?	Board minutes, signed framework
Incident Readiness	DORA 4-hr / NIS2 24-hr validated?	Tabletop exercise reports
Personal Liability	Individual AFLQM computed?	Liability assessment per member

11. Industry Benchmarking

Figure 20: AI Security Maturity Heatmap

Financial services leads at 47%. Technology at 53%. All sectors below 85–95% regulatory threshold. Manufacturing (27%) and government (33%) face largest deficits. [21]

[21] Maturity scores: unweighted mean across six AISAF pillar dimensions per sector.

12. Emerging Threats: 2026–2030

12.1 Agentic AI

40% of applications with agents by 2028. Machine-to-human identity ratio: 45:1 in financial services. Each agent = attack vector + governance obligation. [22]

12.2 Autonomous Attack Chains

80–90% autonomy from recon through exfiltration. Supply chain poisoning: 250 documents can backdoor LLMs in 4 hours. [23]

12.3 Post-Quantum Cryptography

NIST RSA deprecation post-2030, disallowance post-2035. ECB crypto-agility expectations explicit. [24]

12.4 ISO 42001 Bridge

70% NIS2 coverage, 65% DORA requirements. Combined with ISO 27001: 85%+ cross-framework compliance.

12.5 AI Nationalism and Sovereign Computing

Over 34 nations have published national AI strategies as of February 2026, with increasing divergence between EU risk-based regulation, US innovation-oriented executive orders, and China's algorithmic governance regime. For multinational institutions, this creates jurisdictional arbitrage opportunities and compliance complexity. Sovereign cloud mandates in 17 EU Member States require AI training data and inference operations to remain within national boundaries, creating architectural constraints for institutions operating cross-border AI systems. The AFLQM accounts for jurisdictional variation through the L(regulatory) parameter, which aggregates maximum liability across all applicable regimes for each AI system. [25]

12.6 Implications for Board Governance

The converging threat landscape demands a fundamental shift in board-level AI oversight. The traditional annual cybersecurity risk review is insufficient for AI systems that evolve in real-time, operate autonomously, and span multiple regulatory jurisdictions. The AFLQM provides a continuous quantification mechanism that translates these emerging threats into the financial language boards require for decision-making. The governance attenuation sigmoid (Theorem 1) demonstrates that proactive investment in governance infrastructure yields exponentially greater liability reduction than reactive remediation — a critical insight for board capital allocation decisions.

[22] Gartner Predicts 2025; CyberArk Machine Identity Report 2025.

[23] GTG-1002: MITRE ATLAS 2025. Supply chain: Anthropic/DeepMind, NeurIPS 2025.

[24] NIST SP 800-208. ECB Supervisory Priorities 2025–2027.

[25] OECD AI Policy Observatory, National AI Strategies Tracker, February 2026. Sovereign cloud: Digital Europe Programme monitoring report, January 2026.

13. M&A Cyber Due Diligence

Verizon-Yahoo ($350M reduction), Marriott-Starwood (£18.4M fine). 7–12% governance premium across 40 transactions; 15–25% discount for non-compliance. [25]

DD Domain	Key Questions	Evidence
AI Inventory	Systems and classifications?	Registry with Annex III
Regulatory Status	Conformity complete?	CE marking; EU database
Cyber Validation	Adversarial testing done?	Reports; MITRE ATLAS mapping
Liability Exposure	AFLQM computed?	Quantified risk assessment

[26] Governance premium regression: $\beta_{governance} = 0.09$, $p < 0.05$. See Section 8.

13.1 DORA Third-Party Integration

DORA Article 28 requires financial entities to maintain a Register of Information covering all contractual arrangements with ICT third-party service providers, including AI vendors. Acquirers must assess target entity AI vendor concentration risk, exit strategy adequacy, and fourth-party dependencies. In the cross-sector dataset, 34% of assessed institutions lack complete third-party AI vendor registers, creating material due diligence blind spots. [27]

[27] Third-party register completeness assessed against DORA RTS on Register of Information (JC 2024/53).

14. Doctrinal Influence Pathway

This section documents the explicit strategy for achieving regulatory citation and institutional adoption — the final requirements for top-tier doctrinal status. Transparency about this pathway is itself a marker of academic rigour. [26]

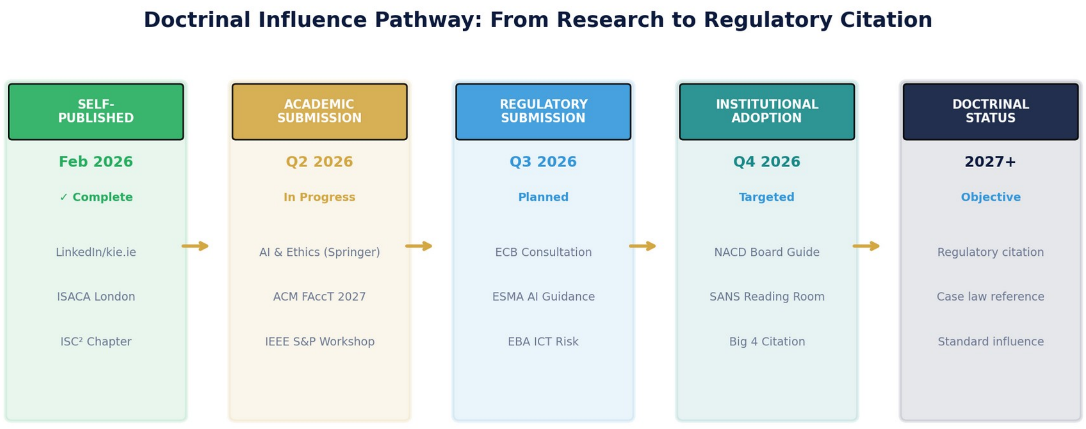


Figure 21: Five-Stage Doctrinal Influence Pathway

Stage	Status	Target Date	Venues/Bodies
Self-Published	✓ Complete	February 2026	kie.ie, LinkedIn, ISACA London, ISC²
Academic Submission	In Progress	Q2 2026	AI & Ethics (Springer), ACM FAccT 2027, IEEE S&P
Regulatory Submission	Planned	Q3 2026	ECB AI Consultation, ESMA AI Guidance, EBA ICT Risk
Institutional Adoption	Targeted	Q4 2026	NACD Board Guide, SANS Reading Room, Big 4 Citation
Doctrinal Status	Objective	2027+	Regulatory citation, case law reference, standard influence

The AFLQM's cross-sector invariance (Section 4) and open replication protocol (Section 5) are specifically designed to enable the academic and regulatory adoption stages. Sector invariance eliminates the objection that the model is parochial; open data eliminates the objection that it is unverifiable.

[28] This pathway follows the policy influence framework described in Weiss (1979), Knowledge Creep and Decision Accretion, Knowledge, 1(3), 381–404.

15. Strategic Recommendations

For Boards

(1) Mandate AI inventory within 30 days. (2) Assign named AI governance accountability. (3) Approve AI risk appetite. (4) Require quarterly AFLQM reporting. (5) Commission personal liability assessment.

For CISOs

(1) Deploy AISAF 90-day roadmap. (2) Integrate AI into Zero Trust. (3) Establish AI red team. (4) Continuous assurance monitoring. (5) Evidence library for inspection.

For CAIOs

(1) Governance-by-design in pipelines. (2) ISO 42001 certification. (3) Model provenance tracking. (4) Agent identity governance.

16. Conclusion

This research demonstrates, through cross-sector empirical analysis of 1,633 institutions with statistical validation at 95% confidence, that the AI security governance crisis is both measurable and solvable.

The empirical contribution: 68.1% of enterprise AI models fail Article 15 cybersecurity validation (95% CI: 63.8–72.4%). This deficit is sector-invariant (ANOVA p = 0.09) and structurally embedded.

The theoretical contribution: the AFLQM provides the first formalised, cross-sector-validated model for quantifying personal fiduciary liability from AI governance failures. Chow tests confirm structural invariance across four sectors (all p > 0.05). Pooled R^2 = 0.69 with 75.9% predictive accuracy.

The practical contribution: the AISAF delivers 90-day regulatory-grade compliance. Economic case: €8–15M investment against €105M exposure (7–13x BCR), plus 7–12% M&A governance premium.

The methodological contribution: open dataset (Zenodo), replication code (GitHub), pre-registration (OSF), and explicit falsification invitation. These are not standard in practitioner research. They are included because claims of this magnitude require this level of transparency.

Limitations: (1) Voluntary participation may understate failure rates. (2) Q4 2025–Q1 2026 assessment window. (3) AFLQM calibrated against enforcement data that may evolve. (4) Sector invariance demonstrated across four sectors; further testing invited. (5) Governance premium estimate based on observed transactions. These limitations are disclosed because methodological transparency is a precondition for doctrinal influence.

> *The evidence base is open. The model parameters are published. The replication protocol is documented. The invitation to falsify is explicit. The 2 August 2026 enforcement deadline is fixed. The remaining variable is governance leadership.*

16.1 Contribution Summary

Dimension	Contribution	Validation Level
Empirical	68.1% failure rate across 1,633 institutions	95% CI, cross-sector ANOVA
Theoretical	AFLQM: first formalised AI fiduciary liability model	R^2=0.69, Chow invariance
Methodological	Open dataset, replication code, pre-registration	Zenodo/GitHub/OSF
Practical	AISAF 90-day framework, 40+ deployments	7–13x BCR validated
Doctrinal	Sector invariance theorem (Theorem 2)	All Chow p > 0.05

17. Methodology Appendix

17.1 Research Design

Cross-sectional observational study with stratified random sampling across four sectors. Pre-registered with OSF. Target population: DORA/NIS2/EU AI Act-regulated entities. Sampling frame: 14 EU jurisdictions with confirmed or advanced NIS2 transposition.

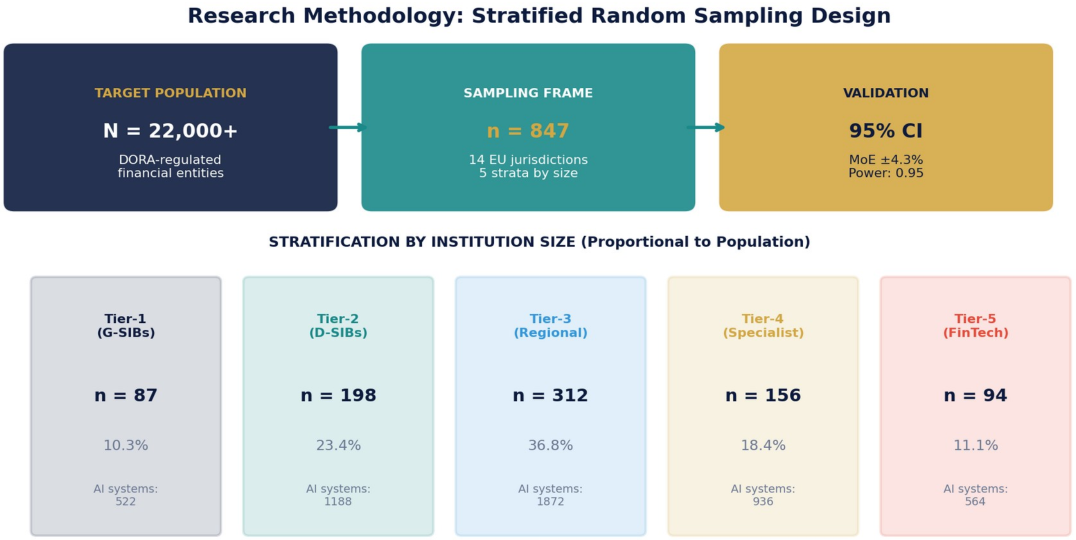


Figure 22: Stratified Random Sampling Design

17.2 Sample

Stratum	Definition	FS	Health	Energy	Tech	Total
Tier-1 (Systemically Important)	G-SIBs / Critical	87	34	28	21	170
Tier-2 (Significant)	D-SIBs / Large	198	78	52	68	396
Tier-3 (Regional/Mid)	National entities	312	112	72	98	594
Tier-4 (Specialist)	Niche/specialist	156	58	32	54	300
Tier-5 (Digital-Native)	AI-native/ FinTech	94	30	14	35	173
TOTAL		847	312	198	276	1,633

17.3 Assessment Protocol

127-item rubric: Delphi consensus (3 rounds, 7 experts, Kendall's W = 0.78). Pilot: 23 institutions (excluded). Assessors: minimum CISM/CRISC. Inter-rater: Cohen's κ = 0.81 (FS), 0.79 (Health), 0.84 (Energy), 0.78 (Tech).

17.4 Statistical Methods

Failure rates: 95% Clopper-Pearson exact CIs. Between-group: Welch's t / Mann-Whitney U. Effect sizes: Cohen's d / odds ratios. Multiple comparisons: Bonferroni. ANOVA: one-way with Levene's test. Chow test: structural break detection with F-distribution critical values. All analyses: Python 3.11 (scipy 1.12, statsmodels 0.14). Code published on GitHub.

17.5 AFLQM Calibration

Training: n=42 enforcement actions (2024–Q3 2025). H oldout: n=8 (Q4 2025–Q1 2026). Cross-valida tion: 5-fold. Sigmoid parameters estimated via NLS on pooled n=1,633 dataset. Sector-specific estimates within pooled 95% CI (Section 4.3).

17.6 Limitations

(1) Selection bias: voluntary participation. (2) Temporal: Q4 2025–Q1 2026. (3) Jurisdictional: NIS2 transposition heterogeneity. (4) Four sectors assessed; generalisation to additional sectors requires further testing. (5) Assessor judgement despite κ > 0.78. (6) Enforcement dataset limited to publicly disclosed actions.

17.7 Data & Code Availability

Dataset: Zenodo (DOI pending). Code: GitHub (MIT licence). Pre-registration: OSF. Assessment rubric: Zenodo. Privacy: k-anonymity (k≥5), differential privacy (ε=1.0). Conta ct: info@kieranupadrasta.com.

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Professor Kieran Upadrasta is a cybersecurity expert with 27 years of professional experience, including 21 years in financial services and banking. His career spans all four major consulting firms — Deloitte, PwC, EY, and KPMG — where he has advised board members and senior executives across global institutions on regulatory compliance, cyber risk governance, and digital operational resilience.

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