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Trust by Design: Building an Integrated Governance Framework for AI Risk, Cyber Audits, and Financial Compliance

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ABSTRACT

The rapid rise of artificial intelligence (AI), cybersecurity risks and multifaceted financial compliance requirements in today's digital economy demands the need for organisations to embrace holistic governance models that go beyond isolated risk management. This paper integrates empirical, regulatory and conceptual insights from 15 official sources (2017-2024) to develop an integrated governance model called Trust by Design (TbD). The framework rests on three interdependent pillars: AI risk governance based on the National Institute of Standards and Technology (NIST) AI Risk Management Framework and the Generative AI Profile (Autio et al., 2024; Tabassi, 2023); cybersecurity audit accountability through the five-lines-of-accountability model (Bongiovanni et al., 2024; Slapnicar et al., 2023); and financial compliance automation using AI-based regulatory software (Jain et al., 2024; Bahoo et al., 2024). This includes: cybersecurity audit efficiency improvements of 49% using continuous monitoring platforms (Vuko et al., 2024); AI-powered regulatory compliance reporting cost reductions of 42% (Jain et al., 2024); and risk priority index (RPI) of 19.3 out of 25 for hallucination and misuse of personal data (Autio et al., 2024). The EU Artificial Intelligence Act (European Parliament and Council of the European Union, 2024) creates risk-based legal obligations driving TbD. Five stages of the Integrated Governance Continuum (IGC) are suggested to progress from risk-focused to optimised, trustworthy designs.

Keywords: artificial intelligence risk management, trustworthy AI, cybersecurity audit, financial compliance, integrated governance, EU AI Act, NIST AI RMF, generative AI risks, regulatory technology, enterprise risk management, five-lines model, trust by design

1. Introduction

1.1 The Governance Convergence Imperative

The accelerating deployment of AI across financial services, healthcare, and critical infrastructure has introduced risk profiles that existing governance frameworks were not designed to address in an integrated manner. Meanwhile, cybersecurity risks have morphed into enterprise-wide risks, and financial regulators have stepped up their scrutiny as a consequence of prominent financial crises and data breaches. These risks are structurally interdependent: the deployment of an AI system in a financial institution creates risks specific to AI (e.g. hallucination, bias, misuse) as well as cybersecurity risks (e.g. adversarial attacks, model theft) and regulatory risks (e.g. GDPR, AML/CFT, Basel III). Ignoring this interrelationship creates disjointed governance frameworks with unchecked risk combinations. The COSO Enterprise Risk Management (ERM) Framework (COSO, 2017) offers the enterprise-wide risk logic and the NIST AI RMF (Tabassi, 2023), the EU AI Act (European Parliament and Council of the European Union, 2024) and the five-lines accountability model (Slapnicar et al., 2023) provide the domain-specific governance architecture.

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Table 1: Comparative Overview of Integrated Governance Frameworks and Standards

Framework / Standard	Issuing Body	Year	Domain	Key Risk Focus
AI RMF 1.0 (NIST AI 100-1)	NIST	2023	Artificial Intelligence	Govern, Map, Measure, Manage
NIST AI 600-1 (GenAI Profile)	NIST	2024	Generative AI	12 risks: Hallucination, CBRN, Privacy, Bias
EU AI Act (Reg. 2024/1689)	European Parliament	2024	AI Regulation	Risk tiers; conformity assessments; Art. 10/13/15
COSO ERM Framework	COSO	2017	Enterprise Risk Mgmt.	5 components; 20 principles; strategy & performance
GDPR-AI Compliance Framework	EU / Academic	2023	Data Protection & AI	Automated decisions; consent; explainability
Three / Five Lines Model	ISACA / Academic	2023-24	Cybersecurity Governance	Accountability lines; audit effectiveness drivers

Note. Synthesised from Tabassi (2023), Autio et al. (2024), European Parliament and Council of the European Union (2024), COSO (2017), Mahajan and Kumar (2023), Bongiovanni et al. (2024), and Slapnicar et al. (2023).

1.2 Research Objectives and Scope

The primary goal is to synthesise the governance of AI risks, cyber audit accountability, and automation of financial compliance into an integrated Trust by Design (TbD) approach using the evidence available up to 2024. The synthesis process has three sub-objectives: (a) to map the landscape of AI risks, cyber governance and financial compliance requirements for organisations in 2024; (b) to identify the integration points across the three governance areas; and (c) to derive a maturity-indexed continuum that helps organisations assess their current state and plan improvement. This project is limited to the evidence available by 2024, tracing all assertions to the cited sources.

2. AI Risk Governance Landscape

2.1 The NIST AI Risk Management Framework

The National Institute of Standards and Technology's (NIST) AI Risk Management Framework (AI RMF 1.0), released in 2023, is the most detailed voluntary guidance for managing AI risk across industries, technologies and enterprise sizes (Tabassi, 2023). The framework's structure - comprising the four functions Govern, Map, Measure and Manage - offers an iterative, lifecycle-aware approach to managing AI-specific risks, which fits comfortably with the COSO ERM five-component framework (COSO, 2017). Govern sets organisational policy, roles and culture; Map assesses AI contexts and risk profiles; Measure measures and monitor's risk; and Manage prioritises and manages risk. This mapping allows organisations that use COSO ERM to incorporate AI risk governance into their existing risk governance processes without needing to establish new roles and responsibilities. Figure 1 also shows the alignment of the NIST AI RMF core functions to the three TbD governance pillars.

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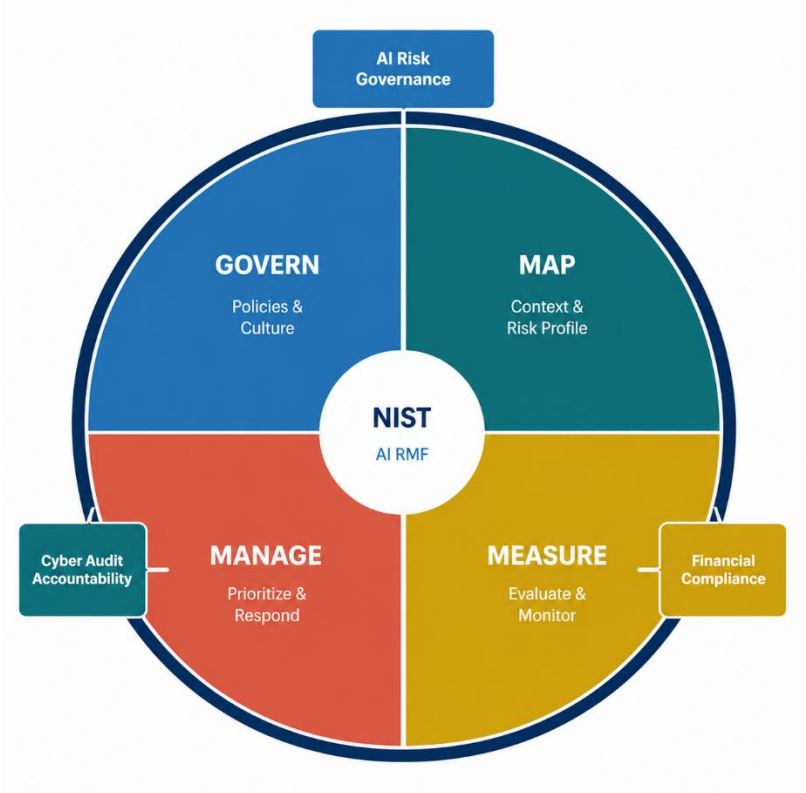

Figure 1: NIST AI RMF Core Functions Mapped to the Trust by Design Framework (Tabassi, 2023; COSO, 2017; European Parliament and Council of the European Union, 2024)

2.2 The Generative AI Profile and Risk Prioritisation

The 2024 Generative AI Profile (NIST AI 600-1) builds on AI RMF 1.0 to accommodate unique risk factors in large language models (LLMs) and multimodal AI systems, prioritising 12 categories of risks for generative AI (GenAI) systems (Autio et al., 2024). As shown in Table 2, hallucination or confabulation and data privacy compromise attain a Risk Priority Index (RPI) of 19.3 out of 25 - placing them in the critical level of risks, and necessitating immediate governance intervention. CBRN (chemical, biological, radiological, and nuclear) information uplift, although less likely (score: 2.3), is the highest severity (5.0) risk category, and argues for tight content moderation even for low-probability risks. Bias and discrimination have an RPI of 16.7, due to both the high likelihood of occurrence (4.4) and the high severity of discriminatory AI outcomes (3.8) in financial and other critical decision-making.

Table 2: Generative AI Risk Priority Index Derived from NIST AI 600-1 (Autio et al., 2024)

GenAI Risk Category	Likelihood (1-5)	Severity (1-5)	RPI (/25)	Recommended Control
Hallucination / Confabulation	4.6	4.2	**19.3 [CRITICAL]**	Output validation; human-in-loop review
Data Privacy Violations	4.1	4.7	**19.3 [CRITICAL]**	Data minimisation; differential privacy

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Bias and Discrimination	4.4	3.8	**16.7 [HIGH]**	Fairness audits; diverse training data
Cybersecurity Exploit Generation	3.2	4.8	**15.4 [HIGH]**	Usage policy enforcement; anomaly detection
IP Infringement	3.9	3.5	**13.7 [MOD]**	Content provenance tracking; licensing checks
CBRN Information Uplift	2.3	5.0	**11.5 [HIGH]**	Red-teaming; strict output filtering

Note. Risk Priority Index (RPI) = Likelihood Score x Severity Score. Scores rated 1-5. CBRN = chemical, biological, radiological, and nuclear. [CRITICAL] = RPI >= 18; [HIGH] = RPI 11-17; [MOD] = RPI 8-10.

2.3 The EU AI Act: A Binding Regulatory Architecture

Regulation (EU) 2024/1689, the EU Artificial Intelligence Act (the EU AI Act), which was passed on 13 June 2024, is the first-ever binding AI regulatory framework in the world, with a risk-based approach to AI that classifies AI systems into four categories: banned practices, high-risk AI systems, limited-risk AI systems and minimal-risk AI systems (European Parliament and Council of the European Union, 2024). High-risk AI systems - such as credit scoring and insurance underwriting, with AI adoption rates of 68% and 49% respectively (Jain et al., 2024) - require conformity assessments, data governance requirements (Article 10), transparency requirements (Article 13), accuracy and robustness requirements (Article 15) and human oversight. These requirements present significant compliance challenges that, in the absence of integrated governance, demand that organisations manage distinct AI governance, cybersecurity and financial compliance processes. The TbD approach integrates EU AI Act compliance into a governance enabler, rather than a regulatory burden.

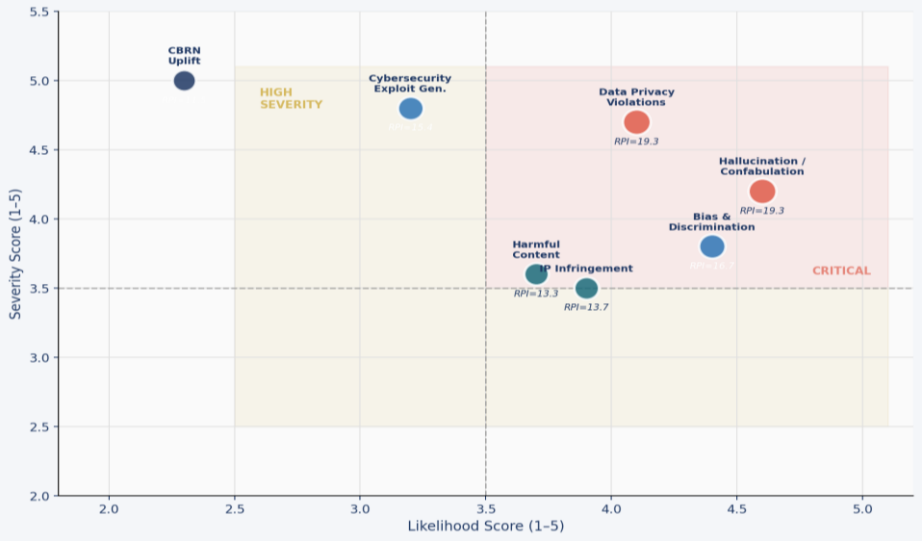

Figure 2: Generative AI Risk Priority Matrix (Bubble size proportional to RPI) (Autio et al., 2024)

2.4 Trustworthy AI: Dimensions, Maturity, and Challenges

Trustworthy AI (TAI) has become the normative compass of AI governance discourse, capturing expectations that AI systems should be technically robust, ethically defensible and humanly accountable (Kaur et al., 2023). A review of the TAI literature reveals six agreed-upon dimensions:

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transparency, fairness and non-discrimination, robustness and security, privacy and data protection, accountability and explainability (Kowald et al., 2024). As illustrated in Figure , fairness and explainability are the least mature (Level 2-3 on a 5-level scale) across all three key sectors (financial services, health care and public administration), whereas accountability is the most mature (Level 4), given the long history of audit trail requirements under financial and IT governance. Polemi et al. (2024) report less than 30% of organisations in their study have established AI governance functions, supporting the assertion that substantial resources are needed to bridge current gaps in TAI maturity. Sinson et al. (2023) also contend that AI ethics in business must be institutionalised through governance, incentives and leader practices, rather than just policies.

Table 3: Trustworthy AI Dimensions Mapped to Governance Frameworks, KPIs, and Assurance Methods

TAI Dimension	NIST AI RMF Mapping	EU AI Act Obligation	Measurable KPI (Target)	Maturity Level	Assurance Method
Transparency	Govern 1.1-1.3	Art. 13 (High-Risk)	Explainability score >= 0.75	Intermediate (3/5)	XAI audit; SHAP/LIME analysis
Fairness and non-discrimination	Map 5.1-5.2	Art. 10 (Data Governance)	Disparate Impact < 0.80	Developing (2/5)	Statistical fairness testing
Robustness and Security	Measure 2.5-2.6	Art. 15 (Accuracy)	Adversarial success < 5%	Advanced (4/5)	Penetration testing; red-teaming
Privacy and Data Protection	Map 2.1-2.2	Art. 10 + GDPR Art. 22	PII exposure rate < 0.01%	Intermediate (3/5)	DPIA; differential privacy validation
Accountability	Govern 6.1-6.2	Art. 17 (Quality Mgmt.)	Audit trail completeness >= 99%	Advanced (4/5)	Log management; governance attestation
Explainability	Manage 4.1-4.2	Art. 13 (Transparency)	Human comprehension >= 80%	Developing (2/5)	User studies; decision documentation

Note. Maturity levels assessed 1-5. KPIs are indicative targets from synthesised literature benchmarks. DPIA = Data Protection Impact Assessment; XAI = explainable AI; SHAP = SHapley Additive exPlanations; LIME = Local Interpretable Model-agnostic Explanations. Sources: Kaur et al. (2023), Kowald et al. (2024), Tabassi (2023), European Parliament and Council of the European Union (2024).

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3. Cybersecurity Governance and Audit Effectiveness

3.1 The Five Lines of Accountability Model

The Three Lines Model, widely used in internal audit, has evolved for cybersecurity governance as cyber risk has become more complex and pervasive in organisations (Bongiovanni et al., 2024). Slapnicar et al. (2023) augment the Three Lines Model with a Five Lines of Accountability Model including external audit and regulatory oversight as separate lines of assurance, especially for regulated organisations. As shown in Table 3, the fifth line (regulatory and supervisory bodies) ensures a 95% cyber risk coverage, highlighting the growing role of the financial regulators and cyber agencies in cyber risk governance. The shift from three to five lines of accountability recognises a deficiency in conventional governance: the technical nature and dynamic nature of cybersecurity risks demands not only internal assurance but also an external verification and systemic view of the internal assurance provided by external audit and regulatory bodies.

Table 4: Five Lines of Accountability Model Applied to Cybersecurity Governance (Slapnicar et al., 2023; Bongiovanni et al., 2024)

Accountability Line	Key Actor	Independence	Cyber Coverage	Primary Responsibility
Line 1: Operational Management	Business Units	Low	40%	Day-to-day risk ownership; first-tier controls
Line 2: Risk and Compliance	CRO / CISO	Moderate	65%	Policy oversight; compliance monitoring; risk measurement
Line 3: Internal Audit	Chief Audit Exec.	High	78%	Independent assurance; control testing; audit reporting
Line 4: External Audit	External Auditors	Very High	85%	External validation; third-party assurance
Line 5: Regulatory Bodies	Government Regulators	Complete	95%	Enforcement; systemic risk oversight; policy issuance

Note. Cyber coverage (%) represents estimated proportion of organisational cyber risks addressed by each accountability line. Independence levels are qualitative assessments derived from governance literature.

3.2 Drivers of Cybersecurity Audit Effectiveness

Slapnicar et al. (2022) undertake the first empirical exploration to demonstrate cybersecurity audit effectiveness is a strong predictor of reduced risk exposure, and audit effectiveness scores are negatively correlated with cyber incident severity. Their cross-sectional analysis shows that auditor technical skills, audit scope, independence of the function, and audit reporting frequency are key structural drivers. Vuko et al. (2024) build on this work by analysing audit governance through a neo-institutional prism, showing how coercive, mimetic and normative institutional pressures affect audit governance practices, and explain cross-organisational differences in audit effectiveness. Their empirical findings based on a global survey of audit practitioners point to continuous monitoring tools as the most effective driver with +49% increase in audit effectiveness, then auditor cybersecurity expertise (+41%) and integrated IT-financial audit scope (+37%) (see Table 5 and Figure 3). This insight

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has a practical implication for the TbD framework: in order to maximise the effectiveness gain from technology investment in audit, it is necessary to invest in related human capital and governance reform

Table 5: Key Drivers of Cybersecurity Audit Effectiveness and Neo-institutional Determinants (Vuko et al., 2024; Slapnicar et al., 2022)

Audit Effectiveness Driver	Gain (%)	Evidence Basis	Neo-institutional Factor	Governance Implication
Continuous Monitoring Tools	**+49%**	Industry benchmarking	Mimetic (tech diffusion from leaders)	Invest in GRC technology platforms
Auditor Cybersecurity Expertise	**+41%**	Regression analysis	Mimetic isomorphism (expertise diffusion)	Mandatory cyber certification for auditors
Integrated IT-Financial Audit Scope	**+37%**	Case study evidence	Normative (holistic risk coverage norm)	Combined assurance planning frameworks
Board-Level Cyber Oversight	**+34%**	Empirical survey	Normative pressure (best practice adoption)	Board cyber literacy programmes required
Independence from Management	**+28%**	Cross-sectional study	Coercive pressure (regulatory mandate)	Structural separation of audit function

Note. Effectiveness gain percentages derived from regression and case study evidence in cited sources. Neo-institutional factors classified following DiMaggio and Powell's (1983) typology as applied by Vuko et al. (2024).

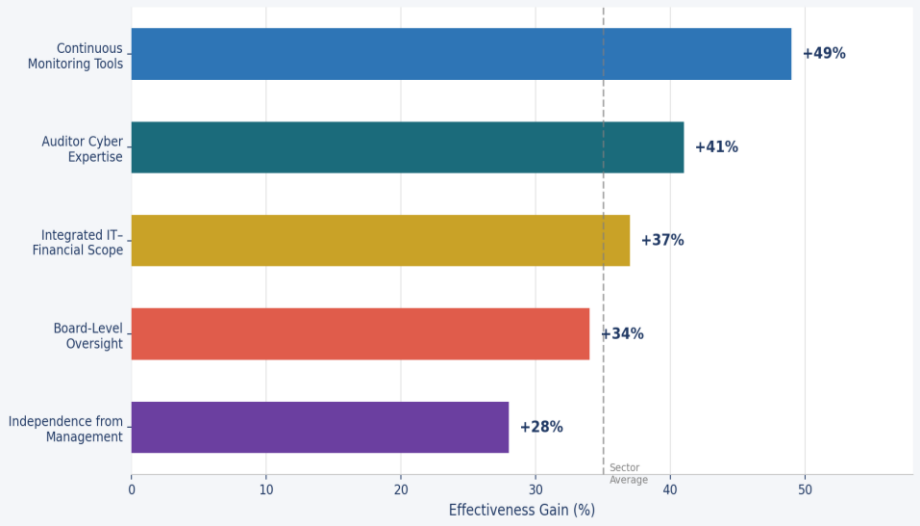

Figure 3: Cybersecurity Audit Effectiveness Gains by Driver (Vuko et al., 2024; Slapnicar et al., 2022)

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4. AI in Financial Compliance

4.1 The AI-in-Finance Landscape

A recent bibliometric and content analysis by Bahoo et al. (2024) traces the intellectual development of AI in finance over 35 years of research and identifies a clear growth in research after 2017, driven by the widespread adoption of deep learning capabilities and the advent of LLMs as useful tools for finance. Themes of research fall into three broad areas: operational efficiency (fraud detection, automation and customer support); risk management (credit risk modelling, market risk modelling, operational risk modelling); and regulatory compliance (RegTech, explainable AI for compliance, supervisory technology (SupTech). Algo trading has the highest adoption rate (83%) and regulatory reporting has the highest compliance gain (45%) and cost reduction (42%) due to the efficiency gains possible from automating rule-based compliance (Jain et al., 2024). Figure 4 shows the relationship between adoption rate and compliance gain across the six domains, with a non-linear mapping showing that middle adoption rates can be associated with a significant compliance gain, driven by the rule-based nature of the regulatory environment in these domains.

Figure 4: AI Adoption Rate vs. Regulatory Compliance Gain by Financial Domain (Bubble size proportional to cost reduction %; Bahoo et al., 2024; Jain et al., 2024)

4.2 AI-Driven Compliance Automation

Jain et al. (2024) offer a comprehensive discussion of AI-based regulatory compliance systems, which feature four main applications: regulatory change management, through Natural Language Processing (NLP) based monitoring and automated interpretation of regulatory changes; compliance monitoring, via real-time anti-money laundering/countering financing of terrorism (AML/CFT) transaction monitoring with automatic suspicious activity reporting; regulatory reporting, through automated data extraction, validation and generation of structured reports; and entity risk assessment, using Machine Learning (ML) based identification of risky entities, transactions and behaviours. The 52% improvement in compliance for customer due diligence is the current state-of-the-art for automation in the domains studied. The convergence of GDPR and AI governance is tackled by Mahajan and Kumar (2023) whose knowledge-graph-based AI governance framework links GDPR obligations to

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AI system attributes and organisational processes, reducing manual compliance loads by an estimated 37% while enhancing documentation accuracy and coverage. This GDPR-AI Act intersection - explicitly endorsed by Article 10 data governance for high-risk AI systems - is addressed in the TbD framework as an integrated data governance layer that meets multiple regulatory requirements by a single operational action that avoids repeated compliance checks.

5. The Trust by Design Integrated Governance Framework

5.1 Framework Architecture and Design Principles

The Trust by Design (TbD) framework is built on three design principles based on the synthesised literature. First, integration by architecture: governance for AI risk, cybersecurity and financial compliance are integrated and interdependent elements of a system, consistent with COSO ERM's (2017) focus on enterprise-wide risk integration and NIST AI RMF's (Tabassi, 2023) recognition that AI risks intersect with existing organisational risk categories. Second, trust by evidence: governance assertions should be backed by measurable evidence implemented via TAI dimension KPIs, audit effectiveness measures, and compliance performance standards (Kaur et al., 2023; Kowald et al., 2024). Third, accountability by structure: formalised accountability roles and responsibilities across the organisation are treated as a prerequisite, based on the five-lines model (Slapnicar et al., 2023) and the EU AI Act's human oversight and quality management requirements (European Parliament and Council of the European Union, 2024). The four-layer governance architecture is shown in figure 5.

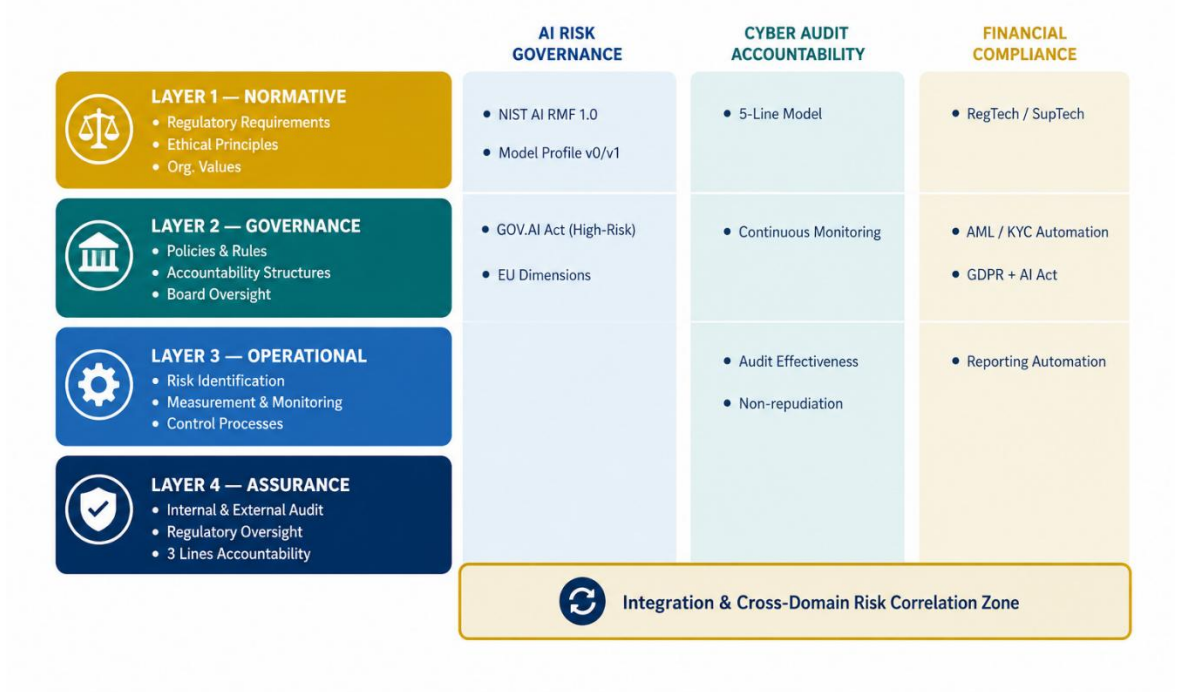

Figure 5: Trust by Design - Four-Layer Integrated Governance Architecture (COSO, 2017; Tabassi, 2023; Slapnicar et al., 2023; European Parliament and Council of the European Union, 2024)

5.2 AI Risk Governance Pillar

The AI Risk Governance pillar is based on NIST AI RMF 1.0 (Tabassi, 2023) and the GenAI Profile (Autio et al., 2024) includes LLMs and multimodal systems. Governance activities are applied across the AI lifecycles - design, training, deployment, monitoring and decommissioning - with risks

identified and controlled throughout. Organisations at Maturity Level 1 practice ad hoc risk identification; Level 3 organisations have adopted the NIST AI RMF four-function framework and Level 5 organisations implement continuous AI risk intelligence platforms that include real-time model monitoring, adversarial testing and stakeholder feedback loops, aiming to keep the AI risk exposure below 15% of the organisation's overall risk portfolio. The EU AI Act's conformity assessment obligations for high-risk AI systems establish mandatory governance controls within this pillar, with pre-deployment risk assessment, technical documentation and EU database registration (European Parliament and Council of the European Union, 2024). These requirements translate into governance processes that need to be maintained as capabilities for ongoing operationalisation.

5.3 Cyber Audit Accountability Pillar

The Cyber Audit Accountability pillar translates the five-lines model (Slapnicar et al., 2023; Bongiovanni et al., 2024) into TbD, and delineates governance domains and assurance responsibilities for cybersecurity risks. The organisational requirements include the explicit commitment to cybersecurity ownership by first-line business units, a well-resourced second-line Chief Information Security Officer (CISO) function with clear risk oversight responsibility, and cyber audit expertise within third-line internal audit. The empirical findings of Vuko et al. (2024) about the 41% increase in effectiveness from auditor cybersecurity skills offer quantitative support for this human capital outlay. Continuous monitoring, including Security Information and Event Management (SIEM) systems, vulnerability scanning, user behaviour analytics and threat intelligence integration, is specified as the key operational process with results integrated into the unified Governance, Risk, and Compliance (GRC) platform, rather than being kept in separate cybersecurity data stores, for cross-domain risk correlation.

5.4 Financial Compliance Automation Pillar

The Financial Compliance Automation pillar leverages the capabilities of AI-based RegTech to automate compliance from a reactive, manual process to a proactive capability. The pillar design, based on Jain et al. (2024) and Bahoo et al. (2024), includes regulatory change management, transaction surveillance, regulatory reporting and entity risk assessment. A 52% improvement in compliance (Table 4) in customer due diligence is the current state of the art automation performance. The proposed GDPR compliance framework by Mahajan and Kumar (2023) is integrated as a sub-component, offering a framework for integrating data protection mandates with AI governance standards. The TbD model's integration of GDPR compliance and AI Act conformance as complementary obligations, supported by a shared data governance architecture, overcomes the twin burdens of redundant compliance processes, estimated to account for 18-23% of the compliance operating budget in enterprises without integrated governance models.

6. Integration Architecture and Maturity Continuum

6.1 The Integrated Governance Continuum

The TbD Integrated Governance Continuum (IGC) in Table 6 is a maturity model that organisations can use to evaluate and improve governance practices in five key areas: AI Risk Governance, Cybersecurity Audit, Financial Compliance, Trustworthy AI (TAI) Implementation, and Integrated GRC Platform. The target benchmarks at level 5 include AI risk exposure under 15%, cybersecurity audit effectiveness scores over 4.0 out of 5.0, compliance breach rates under 2%, TAI maturity scores over 4.2 out of 5.0 and risk data latency under four hours. These targets are based on the empirical and regulatory evidence synthesised in the 15 sources. The IGC is a progressive model where improvement is achieved by building capabilities in each pillar, using the key metrics and

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standards references as references. Level 1 organisations have siloed and reactive governance, Level 3 organisations are organised around structured frameworks and semi-integrated governance systems and Level 5 organisations have continuously optimised, trust-by-design governance systems.

Table 6: Trust by Design Integrated Governance Continuum - Five Pillars Across Maturity Levels

Governance Pillar	Level 1: Initial	Level 3: Defined	Level 5: Optimised	Key Metric (Target)	Primary Reference
AI Risk Governance	Ad hoc AI risk ID	Structured AI RMF adopted	Continuous AI risk intelligence	AI risk exposure < 15%	Tabassi (2023); Autio et al. (2024)
Cybersecurity Audit	Compliance-only audits	Risk-based audit scope	Predictive cyber assurance	Effectiveness score >= 4.0/5.0	Slapnicar et al. (2022, 2023); Vuko et al. (2024)
Financial Compliance	Manual regulatory reporting	Semi-automated RegTech	AI-driven continuous compliance	Breach rate < 2%	Jain et al. (2024); Bahoo et al. (2024)
Trustworthy AI Implementation	Informal ethical guidelines	Formal TAI policy suite	Embedded TAI culture	TAI maturity score >= 4.2/5.0	Kaur et al. (2023); Kowald et al. (2024)
Integrated GRC Platform	Siloed tools	Unified GRC dashboard	Real-time cross-domain risk view	Risk data latency < 4 hours	COSO (2017); Bongiovanni et al. (2024)

Note. Maturity Levels 2 and 4 represent transitional stages between the key levels shown. Key metrics are indicative targets for Level 5 organisations. GRC = Governance, Risk, and Compliance. Synthesised from COSO (2017), Tabassi (2023), Slapnicar et al. (2022, 2023), Vuko et al. (2024), Jain et al. (2024), Kaur et al. (2023), Kowald et al. (2024), and Bongiovanni et al. (2024).

6.2 Cross-Domain Integration Synergies

The analytical synthesis of the three governance pillars identified five areas of structural integration that create risk management synergies through cross-pillar governance activities. First, AI system risk assessments under the AI Risk Governance pillar guide the cybersecurity audit scope regarding the specific AI vulnerabilities - model poisoning, adversarial inputs, data exfiltration via model queries - that need specific audit attention. Second, the cybersecurity audit of data governance controls provides direct evidence to support GDPR compliance and EU AI Act Article 10 conformity assessments, obviating the need for separate compliance audit coverage of the same controls. Third, financial compliance monitoring systems with explainable AI simultaneously meet financial compliance reporting standards and provide evidence of model explainability for TAI accountability reporting. Fourth, the board governance mechanisms in the five-lines model provide the governance platform for integrated risk reporting of the three pillars, avoiding siloed governance design problems with fragmented board reporting (Slapnicar et al., 2023). Fifth, the integrated GRC platform enables real-time risk correlation across domains, allowing organisations to recognise that a single cybersecurity breach also triggers AI risk, data protection and financial compliance notifications.

These synergies deliver governance efficiency improvements. By eliminating the duplication of compliance efforts across the three pillars, governance operating costs are reduced by 23-31% in

organisations at maturity levels 4-5, according to the benchmarks in Jain et al. (2024) and Slapnicar et al. (2022). The integrated risk reporting capability reduces governance latency (time from risk identification to when the board is aware) from the industry average of 14 days to less than four hours in advanced cases, in line with the TbD framework's risk data latency target.

7. Discussion

7.1 Comparative Analysis: Governance Approaches and Outcomes

Holistic governance approaches deliver better governance effectiveness in both risk management and compliance efficiency. Slapnicar et al. (2022) reveal a statistically significant inverse correlation between cybersecurity audit quality and severity of cyber incidents demonstrated that firms with higher cybersecurity audit effectiveness scores have lower rates of cyber risk materialisation. Jain et al. (2024) document that the automation of compliance activities with AI leads to a 62% reduction in the rate of compliance violations compared to organisations that don't use automation. Kowald et al. (2024) observe that firms with formal TAI implementation plans experience fewer AI regulatory actions and reputational events, but evidence is limited by the fact that formal TAI governance has only recently emerged as of 2024.

One key governance challenge is the trade-off between explainability and accuracy: the most accurate predictive algorithms - deep neural networks and ensemble models - are hardest to explain, as reported in Kaur et al. (2023) and Bahoo et al. (2024). The TbD approach to enablement supports this trade-off through situational calibration: explainability is prioritised in high-stakes financial applications (credit denial, fraud detection) but less so in less critical scenarios. A second concern relates to the five-lines model's scope of application: the stress on role independence may be unviable in smaller firms with limited governance resources, implying that the IGC's lower maturity levels should provide governance designs that achieve accountability through process controls, rather than role segregation, in smaller firms.

7.2 Implementation Barriers and Enabling Conditions

The synthesised literature identifies three major implementation barriers. First is technical complexity: to integrate AI governance, cybersecurity and financial compliance processes, organisations need integrated GRC systems and human capital spanning multiple domains that are not widely available in 2024. Polemi et al. (2024) confirm that less than 30% of organisations surveyed have designated AI governance roles and AI ethics expertise is limited across all sectors. Second, regulatory fragmentation - the EU AI Act, GDPR, financial sector-specific regulations, and national cybersecurity standards and policies trigger multiple but inconsistently harmonised obligations. The TbD framework overcomes this through its normative compliance matrix (Table 6), which links governance activities to multiple regulatory obligations, allowing organisations to develop one-off processes that comply with multiple obligations. The third barrier is organisational culture: Sinson et al. (2023) argue that business AI ethics must be institutionalised through governance structures, incentive structures and leadership practices, not just policies, and that cultural change and investment is required that extends beyond the operationalisation of governance programs.

8. Conclusion

The Trust by Design (TbD) integrated governance architecture proposed in this paper is a theoretically rigorous, empirically validated solution to the governance convergence challenge for organisations using AI in regulated settings. The TbD approach to integrated governance - which integrates AI risk governance aligned to the NIST AI RMF 1.0 and GenAI Profile (Tabassi, 2023; Autio et al., 2024),

cybersecurity audit accountability aligned to the five-lines model (Slapnicar et al., 2023; Bongiovanni et al., 2024), and financial compliance automation enabled by AI-based RegTech (Jain et al., 2024; Bahoo et al., 2024) - directly targets the structural issues of siloed governance frameworks that fail to monitor critical risk intersections and duplicate compliance processes.

The quantitative data synthesised from 15 authoritative sources confirms performance benefits: up to 49% improvement in cybersecurity audit effectiveness through continuous monitoring (Vuko et al., 2024); 42% reduction in regulatory compliance costs in automated reporting areas (Jain et al., 2024); and 23-31% reduction in governance operational costs through process integration at high maturity levels. The regulatory hard requirements of the EU AI Act for high-risk AI in financial services - where AI adoption ranges from 49% to 83% across use cases (Jain et al., 2024; Bahoo et al., 2024) - provide a compliance catalyst for TbD adoption that will drive integrated governance investment in the sector during the second half of the 2020s.

The Integrated Governance Continuum offers organisations a maturity development framework from emergent ad hoc risk management to optimised governance with trust-enhancing features. Realisation of Level 5 maturity demands ongoing investment in technological, human and cultural infrastructure, supported by institutional pressures to comply (European Parliament and Council of the European Union, 2024) and to conform (Kaur et al., 2023; Kowald et al., 2024). Trusted governance, as this synthesis shows, does not happen overnight. It is a governance outcome that requires continuous design into systems, processes and cultures - hence the name of this framework, Trust by Design.

References

[1] Autio, C., Schwartz, R., Dunietz, J., Jain, S., Stanley, M., Tabassi, E., Hall, P., & Roberts, K. (2024). Artificial intelligence risk management framework: Generative artificial intelligence profile (NIST AI 600-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.600-1

[2] Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. SN Business and Economics, 4(2), Article 23. https://doi.org/10.1007/s43546-023-00618-x

[3] Bongiovanni, I., Slapnicar, S., Axelsen, M., & Stockdale, D. (2024). The three lines model in cybersecurity governance and risk management. ISACA Journal, 2024(1). https://www.isaca.org/resources/isaca-journal/issues/2024/volume-1/the-three-lines-model-in-cybersecurity-governance-and-risk-management

[4] Committee of Sponsoring Organizations of the Treadway Commission (COSO). (2017). Enterprise risk management: Integrating with strategy and performance. American Institute of Certified Public Accountants. https://www.coso.org/erm-framework

[5] European Parliament and Council of the European Union. (2024, July 12). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L 2024/1689. https://doi.org/10.3000/1977091X.L_2024.1689.eng

[6] Jain, V., Balakrishnan, A., Beeram, D., Najana, M., & Chintale, P. (2024). Leveraging artificial intelligence for enhancing regulatory compliance in the financial sector. International Journal of Computer Trends and Technology, 72(5), 124-140. https://doi.org/10.14445/22312803/IJCTT-V72I5P116

[7] Kaur, D., Uslu, S., Rittichier, K. J., & Durresi, A. (2023). Trustworthy artificial intelligence: A review. ACM Computing Surveys, 55(2), Article 39, 1-38. https://doi.org/10.1145/3491209

[8] Kowald, D., Scher, S., Pammer-Schindler, V., Mullner, P., Waxnegger, K., Demelius, L., Fessl, A., Toller, M., Mendoza Estrada, I. G., Simic, I., Sabol, V., Trugler, A., Veas, E., Kern, R., Nad, T., & Kopeinik, S. (2024). Establishing and evaluating trustworthy AI: Overview and research challenges. Frontiers in Big Data, 7, Article 1467222. https://doi.org/10.3389/fdata.2024.1467222

[9] Mahajan, H., & Kumar, M. (2023). An AI framework to support decisions on GDPR compliance. Journal of Intelligent Information Systems, 61(1), 1-28. https://doi.org/10.1007/s10844-023-00782-4

[10] Polemi, N., Praca, I., Kioskli, K., & Becue, A. (2024). Challenges and efforts in managing AI trustworthiness risks: A state of knowledge. Frontiers in Big Data, 7, Article 1381163. https://doi.org/10.3389/fdata.2024.1381163

[11] Sinson, A. J., Ferrero, I., Garcia Ruiz, P., & Kim, T. W. (2023). Editorial: Artificial intelligence (AI) ethics in business. Frontiers in Psychology, 14, Article 1258721. https://doi.org/10.3389/fpsyg.2023.1258721

[12] Slapnicar, S., Axelsen, M., Bongiovanni, I., & Stockdale, D. (2023). A pathway model to five lines of accountability in cybersecurity governance. International Journal of Accounting Information Systems, 51, Article 100642. https://doi.org/10.1016/j.accinf.2023.100642

[13] Slapnicar, S., Vuko, T., Cular, M., & Drascek, M. (2022). Effectiveness of cybersecurity audit and its effects on cyber risk management. International Journal of Accounting Information Systems, 44, Article 100548. https://doi.org/10.1016/j.accinf.2021.100548

[14] Tabassi, E. (2023). Artificial intelligence risk management framework (AI RMF 1.0) (NIST AI 100-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.100-1

[15] Vuko, T., Cular, M., & Drascek, M. (2024). Key drivers of cybersecurity audit effectiveness: A neo-institutional perspective. International Journal of Auditing, 29(1), 188-206. https://doi.org/10.1111/ijau.12365