Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X

Volume 4, Issue 1, 2026

IMPACT OF CYBERSECURITY MATURITY ON THE EFFECTIVENESS OF AI-ENABLED INTERNAL AUDIT FUNCTIONS

Muhammad Rashid Mahmood[1], Dr. Shahid Naseem[2], Khan Imdad Ullah[3]
[1]*PhD Scholar, Lincoln University College, Malaysia*
[2]*Assistant Professor (IT), University of Education Township Lahore, Pakistan*
[3]*PhD Scholar ,Lincoln University College Malaysia*
[1]*rashidtalha1@gmail.com,* [2]*shahid.naseem@ue.edu.pk,* [3]*Khanimdadullah@yahoo.com*

DOI: https://doi.org/10.5281/zenodo.18336839

Keywords:
Cybersecurity Maturity; Ai-Enabled Internal Audit; Audit Effectiveness; Continuous Auditing; Security Telemetry; Data Governance; Model Risk Management; AI Governance; Dynamic Capabilities; Anomaly Detection; Process Mining; Non-Linear Effects; Assurance Reliability; Automation Bias; Adversarial Machine Learning

Article History
Received on 30 Dec, 2025
Accepted on 18 Jan 2026
Published on 22 Jan 2026

Corresponding Author:

Abstract

AI-enabled internal audit is increasingly deployed to expand risk coverage, accelerate audit cycles, and enable continuous assurance through techniques such as anomaly detection, process mining, natural language processing, predictive risk scoring, and automated control testing. However, the effectiveness of these approaches is contingent on the cybersecurity conditions that govern the integrity, availability, and observability of the underlying data and systems. This article develops and substantiates a theory-driven conceptual model explaining why and how cybersecurity maturity determines whether AI-enabled internal audit produces reliable assurance or false confidence. Drawing on dynamic capabilities theory, cybersecurity maturity is defined as a multi-dimensional capability aligned with established standards and frameworks, encompassing governance, identity and access management, data integrity, logging and telemetry, incident response, and third-party risk management. The model proposes (i) a direct positive effect of cybersecurity maturity on internal audit effectiveness, (ii) mediation through data governance maturity and security telemetry quality, (iii) moderation by AI governance and model risk management maturity, and (iv) explicit non-linear threshold effects in which AI-enabled audit effectiveness increases sharply only after minimum cybersecurity maturity conditions are achieved. The article further identifies critical failure modes—such as data corruption, log tampering, identity compromise, model drift, automation bias, and adversarial manipulation—and specifies concrete technical, governance, and audit control mechanisms to mitigate these risks. A maturity-stage application matrix is provided to guide Chief Audit Executives, CISOs, and AI governance leaders in sequencing AI-enabled audit adoption according to cyber capability readiness. The paper advances audit analytics and cybersecurity governance research by formalizing cybersecurity maturity as a foundational antecedent to trustworthy AI-enabled assurance and by clarifying when AI audit systems enhance assurance versus institutionalize misleading signals.

1. Introduction

Artificial intelligence (AI) is rapidly reshaping the internal audit function. Continuous auditing systems, anomaly detection algorithms, process mining tools, natural language processing (NLP), predictive risk scoring, and automated control testing are increasingly deployed to enhance audit coverage, speed, and analytical depth. Professional guidance from the Institute of Internal Auditors (IIA) and major accounting bodies positions AI-enabled internal audit as a critical response to the growing complexity, velocity, and digitalization of organizational risk environments [1], [2].

At the same time, organizations face an unprecedented escalation in cybersecurity threats. Ransomware, supply-chain attacks, identity compromise, cloud misconfigurations, and advanced persistent threats increasingly undermine the integrity, availability, and reliability of organizational data and systems. Importantly, these same data and systems constitute the primary input layer for AI-enabled audit tools. As a result, internal audit functions are increasingly reliant on digital traces—logs, transactions, access records, tickets, and telemetry—that may themselves be incomplete, manipulated, or adversarially influenced [3], [4].

Despite this growing interdependence, the academic and professional literatures have largely evolved in parallel rather than in integration. Research on AI in internal audit emphasizes algorithmic techniques, efficiency gains, and expanded assurance scope, often assuming the availability of high-quality, trustworthy data environments [5]–[7]. In contrast, cybersecurity maturity research focuses on protecting information assets, ensuring operational resilience, and meeting regulatory requirements, with little attention to how cybersecurity capabilities shape downstream governance and assurance outcomes [8], [9].

This separation obscures a critical reality: **AI-enabled internal audit does not operate independently of the cybersecurity environment; it is structurally dependent on it**. Cybersecurity maturity determines whether data used by AI systems are complete and reliable, whether logs and telemetry accurately reflect system behavior, whether identities and privileges are controlled, and whether incidents are detected and contained before corrupting audit evidence. In low-maturity environments, AI-enabled audit may generate false confidence, automate biased judgments, and legitimize compromised data. Even in high-maturity environments, weak AI governance and model risk management can produce black-box risk, model drift, automation bias, and adversarial manipulation.

The central thesis of this article is therefore that **cybersecurity maturity is a foundational determinant of AI-enabled internal audit effectiveness**. Cybersecurity maturity exerts (1) a direct effect on audit effectiveness, (2) indirect effects through data governance and security telemetry quality, and (3) conditional effects shaped by AI governance maturity. Crucially, this relationship is **non-linear**: below a minimum maturity threshold, AI-enabled audit produces limited or even negative assurance value, while above that threshold, effectiveness increases sharply until constrained by governance limitations.

Research Gap and Contributions

This study addresses four gaps in the literature. First, there is a lack of theory-driven research explicitly linking cybersecurity maturity to internal audit effectiveness in AI-enabled contexts. Second, existing studies under-theorize the mechanisms—particularly data integrity and monitoring capabilities—through which cybersecurity maturity translates into audit outcomes. Third, non-linear and threshold effects of maturity are rarely examined despite strong theoretical justification from capability and socio-technical perspectives. Fourth, failure modes associated with mismatches between cybersecurity maturity and AI adoption remain insufficiently articulated.

This article contributes by:

1. Developing a multi-dimensional construct of cybersecurity maturity grounded in established standards.
2. Theorizing AI-enabled internal audit as a capability contingent on cybersecurity maturity.
3. Introducing mediating and moderating mechanisms, including data governance and AI governance.
4. Explicitly modeling non-linear maturity effects.
5. Providing a maturity-stage framework and governance-oriented roadmap for practice.

The remainder of the article proceeds as follows. Section 2 reviews relevant literature. Section 3 outlines the theoretical foundation. Section 4 presents the conceptual framework and hypotheses. Section 5 describes the research design. Section 6 applies the framework across maturity stages. Section 7 discusses findings and failure modes. Section 8 outlines practical implications. Section 9 addresses limitations and future research. Section 10 concludes.

2. Background and Related Work

2.1 Cybersecurity Maturity Models

Cybersecurity maturity models provide structured approaches for assessing and improving an organization's cybersecurity capabilities. Prominent frameworks include the NIST Cybersecurity Framework (CSF), ISO/IEC 27001, the Capability Maturity Model Integration (CMMI) for security, and sector-specific models such as the Cybersecurity Capability Maturity Model (C2M2) [8], [11]. These models conceptualize cybersecurity as a **multi-dimensional capability**, encompassing governance, risk management, identity and access management (IAM), data protection, logging and monitoring, incident response, and third-party risk management. Maturity is typically staged, progressing from ad hoc and reactive practices to optimized, adaptive, and continuously improving capabilities.

Empirical research links higher cybersecurity maturity to reduced incident impact, improved resilience, and better regulatory compliance [12], [13]. However, prior studies focus primarily on operational and risk outcomes, not on assurance functions that rely on cyber-generated data. The implicit assumption is that cybersecurity maturity benefits the organization uniformly, without examining its differentiated effects on AI-dependent processes.

Beyond their prescriptive role, cybersecurity maturity models have increasingly been examined as analytical lenses for understanding organizational capability development. Early maturity models conceptualized cybersecurity primarily as a set of technical controls progressing from ad hoc to optimized states. More recent research, however, emphasizes that maturity reflects the institutionalization of governance, accountability, and learning mechanisms rather than mere control deployment [32], [33]. This shift aligns with the broader evolution of information security from a technical discipline to an enterprise-wide governance concern.

Empirical studies demonstrate that cybersecurity maturity is unevenly distributed across capability domains. Organizations frequently exhibit advanced perimeter defenses while lacking robust identity governance, logging integrity, or incident response readiness [34]. Such asymmetries are particularly consequential for analytics-dependent functions, as weaknesses in a single domain—such as log completeness or access control—can invalidate downstream analytical outputs. This observation challenges linear interpretations of maturity and underscores the importance of multi-dimensional capability assessment.

Recent work also highlights the dynamic nature of cybersecurity maturity. Rather than representing a stable end state, maturity evolves in response to threat landscapes, regulatory pressures, and organizational learning [35]. From this perspective, maturity is better understood as a dynamic capability that enables sensing, responding, and adapting to cyber risk over time. This interpretation is consistent with dynamic capabilities theory and suggests that cybersecurity maturity may exert indirect effects on other organizational capabilities, including assurance and governance functions.

Despite these advances, existing cybersecurity maturity research remains largely inward-facing, focusing on security outcomes such as breach reduction or compliance attainment. Limited attention has been paid to how cybersecurity maturity conditions the effectiveness of other digitally mediated organizational functions. In particular, the role of maturity in shaping the reliability of data, logs, and monitoring signals used by AI-enabled internal audit has not been systematically examined. As organizations increasingly rely on automated analytics for governance and assurance, this omission represents a significant theoretical and practical gap.

Research Gap: Existing cybersecurity maturity research does not examine how maturity conditions the effectiveness of AI-enabled internal audit or other automated assurance mechanisms.

2.2 Internal Audit Effectiveness

Internal audit effectiveness is traditionally defined as the extent to which the audit function achieves its objectives of providing independent, objective assurance and advisory services that improve risk management, control, and governance [14]. Empirical studies operationalize effectiveness using dimensions such as risk coverage, detection accuracy, audit cycle time, quality of evidence, implementation of recommendations, and stakeholder confidence [15], [16].

Prior research identifies drivers of audit effectiveness including auditor competence, independence, management support, and organizational culture [17]. Recent studies extend this work by examining technology adoption, data analytics, and continuous auditing as enablers of effectiveness [18], [19].

However, internal audit research often treats the IT and cybersecurity environment as a contextual backdrop rather than an active determinant of audit quality. While IT general controls are audited, the maturity of cybersecurity controls that underpin audit analytics is rarely theorized as an antecedent of audit effectiveness.

Research gap: The literature lacks an integrated view of how cybersecurity maturity underpins internal audit effectiveness, particularly when audit processes are AI-driven.

2.3 AI in Internal Audit

AI applications in internal audit include continuous auditing, anomaly detection, process mining, NLP-based document analysis, predictive risk scoring, and automated control testing [5], [6], [20]. These tools promise broader risk coverage, faster insights, and reduced manual effort.

Empirical and conceptual studies highlight benefits such as improved fraud detection and real-time monitoring [21]. Yet, concerns persist regarding data quality, explainability, bias, and over-reliance on automated outputs [22], [23].Notably, AI systems are highly sensitive to input data quality and system integrity. Compromised logs, incomplete telemetry, or manipulated transactional data can systematically mislead AI models. Despite this, AI-in-audit research often assumes clean, reliable data environments.

The literature on AI in internal audit has expanded rapidly, driven by advances in data analytics, machine learning, and computational power. Early studies emphasized the potential of continuous auditing and exception reporting to improve audit timeliness and coverage [36], [37]. Subsequent research explored more advanced applications, including anomaly detection, process mining, and text analytics, highlighting their ability to uncover complex patterns and hidden risks that elude traditional sampling-based approaches [38], [39].While these studies document substantial potential benefits, they also reveal persistent challenges related to data quality, interpretability, and integration with audit judgment. Several scholars caution that audit analytics systems are only as reliable as the data infrastructures that support them [40]. In practice, audit datasets are often fragmented, incomplete, or derived from systems not designed for assurance purposes. AI models trained on such data may produce results that are statistically valid yet substantively misleading.

Behavioral research further suggests that the introduction of advanced analytics can alter auditor judgment in unintended ways. Studies on automation bias demonstrate that auditors may over-rely on algorithmic outputs, particularly when systems are perceived as objective or sophisticated [41]. This tendency is exacerbated when AI systems operate continuously and generate voluminous outputs that exceed human capacity for independent verification. As a result, AI-enabled audit may reduce, rather than enhance, professional skepticism under certain conditions.Notably, most AI-in-audit studies implicitly assume that the underlying IT and cybersecurity environment provides reliable, tamper-resistant data and logs. This assumption is increasingly tenuous given the prevalence of cyber incidents that directly target audit-relevant data sources. Yet, the cybersecurity conditions under which AI-enabled audit operates remain largely untheorized. Consequently, the literature offers limited guidance on when AI audit tools enhance assurance versus when they risk institutionalizing flawed representations of organizational reality.

Research Gap: AI audit research under-theorizes the cybersecurity conditions required for AI tools to produce reliable assurance.

2.4 AI Governance and Model Risk Management

AI governance and model risk management (MRM) frameworks address risks associated with model development, validation, deployment, and monitoring [24], [25]. In financial services, regulatory guidance emphasizes explainability, validation, bias testing, and change management [26].

Recent research extends AI governance beyond technical controls to organizational structures, accountability, and ethical considerations [27], [28]. Weak AI governance can result in black-box decision-making, automation bias, and unmonitored model drift.While AI governance is recognized as critical, it is often treated independently from cybersecurity maturity. However, secure model pipelines, protected training data, and resilient deployment environments are integral to effective AI governance.

AI governance and model risk management have emerged as central concerns as algorithmic systems increasingly influence organizational decision-making and control. In regulated sectors, particularly financial services, formal model risk management frameworks emphasize validation, documentation, performance monitoring, and change control to ensure model reliability and accountability

[24], [26]. These frameworks were initially developed for statistical and econometric models but have since been extended—often imperfectly—to complex machine learning systems.Recent scholarship highlights several governance challenges unique to AI, including opacity, adaptive behavior, and context sensitivity [27], [42]. Machine learning models may evolve over time as data distributions change, introducing concept drift that undermines performance without obvious warning signals. Explainability limitations further complicate the use of AI outputs as audit evidence, particularly when stakeholders require transparent justification for findings and recommendations.

Importantly, AI governance does not operate in isolation. Secure model development pipelines, protected training data, and controlled deployment environments are prerequisites for effective governance. Research on adversarial machine learning demonstrates that models can be intentionally manipulated through data poisoning or evasion attacks, especially when cybersecurity controls around training data and inference environments are weak [43], [44]. These risks directly intersect with cybersecurity maturity, suggesting that AI governance effectiveness is contingent on the security of the surrounding technical ecosystem.

Despite growing recognition of these issues, the AI governance literature rarely examines assurance functions such as internal audit as a distinct context. Internal audit differs from operational decision-making in its evidentiary standards, accountability requirements, and emphasis on independence. Understanding how AI governance and cybersecurity maturity jointly shape audit outcomes therefore represents an important extension of existing research.

Research Gap: The interaction between cybersecurity maturity and AI governance in shaping audit outcomes remains underexplored.

2.5 Socio-Technical Systems and Dynamic Capabilities

Socio-technical systems theory emphasizes the interdependence of social structures, technical systems, and organizational processes [29]. Dynamic capabilities theory further explains how organizations integrate, build, and reconfigure capabilities to address changing environments [30].

These perspectives suggest that AI-enabled audit effectiveness emerges from the alignment of technology, governance, skills, and culture. Cybersecurity maturity represents a foundational technical and organizational capability that conditions the value of AI investments.

Research gap: Prior socio-technical studies have not explicitly modeled cybersecurity maturity as a dynamic capability enabling AI-based assurance.

3. Theoretical Foundation

This study adopts **Dynamic Capabilities Theory** as its primary theoretical lens. Dynamic capabilities refer to an organization's ability to sense, seize, and transform resources in response to changing environments [30]. Cybersecurity maturity constitutes a dynamic capability by enabling threat sensing (monitoring and telemetry), threat response (incident handling), and organizational learning.

AI-enabled internal audit represents a higher-order capability that depends on underlying cybersecurity capabilities. Dynamic capabilities theory predicts complementarity, path dependence, and non-linear returns—providing a strong theoretical basis for the proposed relationships.

4. Conceptual Framework and Hypotheses

This section develops the conceptual model linking cybersecurity maturity to AI-enabled internal audit effectiveness.

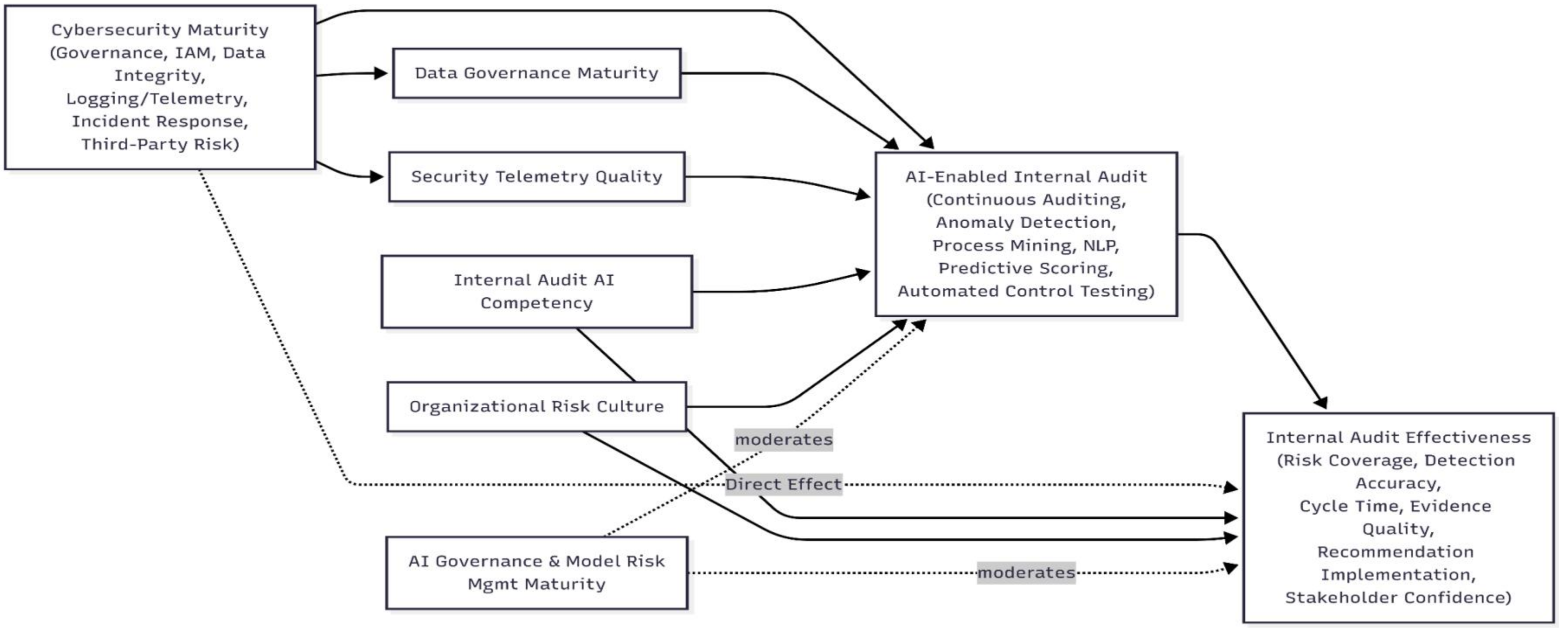

Cybersecurity Maturity (Governance, IAM, Data Integrity, Logging/Telemetry, Incident Response, Third-Party Risk)
Data Governance Maturity
Security Telemetry Quality
Internal Audit AI Competency
Organizational Risk Culture
AI Governance & Model Risk Mgmt Maturity
AI-Enabled Internal Audit (Continuous Auditing, Anomaly Detection, Process Mining, NLP, Predictive Scoring, Automated Control Testing)
moderates
Direct Effect
moderates
Internal Audit Effectiveness (Risk Coverage, Detection Accuracy, Cycle Time, Evidence Quality, Recommendation Implementation, Stakeholder Confidence)

Figure 1 — Conceptual Research Model

4.1 Construct Definitions

Cybersecurity maturity is defined as the extent to which an organization has institutionalized cybersecurity capabilities across governance, IAM, data integrity, logging and telemetry, incident response, and third-party risk management.

AI-enabled internal audit refers to the systematic use of AI techniques to support audit planning, testing, and reporting.

Internal audit effectiveness captures risk coverage, detection accuracy, audit timeliness, evidence quality, implementation of recommendations, and stakeholder confidence.

4.2 Direct and Mediated Effects

H1: Cybersecurity maturity is positively associated with AI-enabled internal audit effectiveness.

Cybersecurity maturity improves data integrity and monitoring, enabling AI systems to operate on reliable inputs.

H2a: Data governance maturity mediates the relationship between cybersecurity maturity and AI-enabled internal audit effectiveness.

H2b: Security telemetry quality mediates the relationship between cybersecurity maturity and AI-enabled internal audit effectiveness.

4.3 Moderation and Non-Linear Effects

H3: AI governance and model risk management maturity positively moderate the relationship between cybersecurity maturity and AI-enabled internal audit effectiveness.

H4: The relationship between cybersecurity maturity and AI-enabled internal audit effectiveness is non-linear, exhibiting threshold effects.

Figure 2. Non-linear relationship between cybersecurity maturity and AI-enabled internal audit effectiveness. Below a minimum maturity threshold, AI-enabled audit outputs are unstable and may produce false confidence. After the threshold, effectiveness increases steeply until reaching diminishing returns at high maturity.

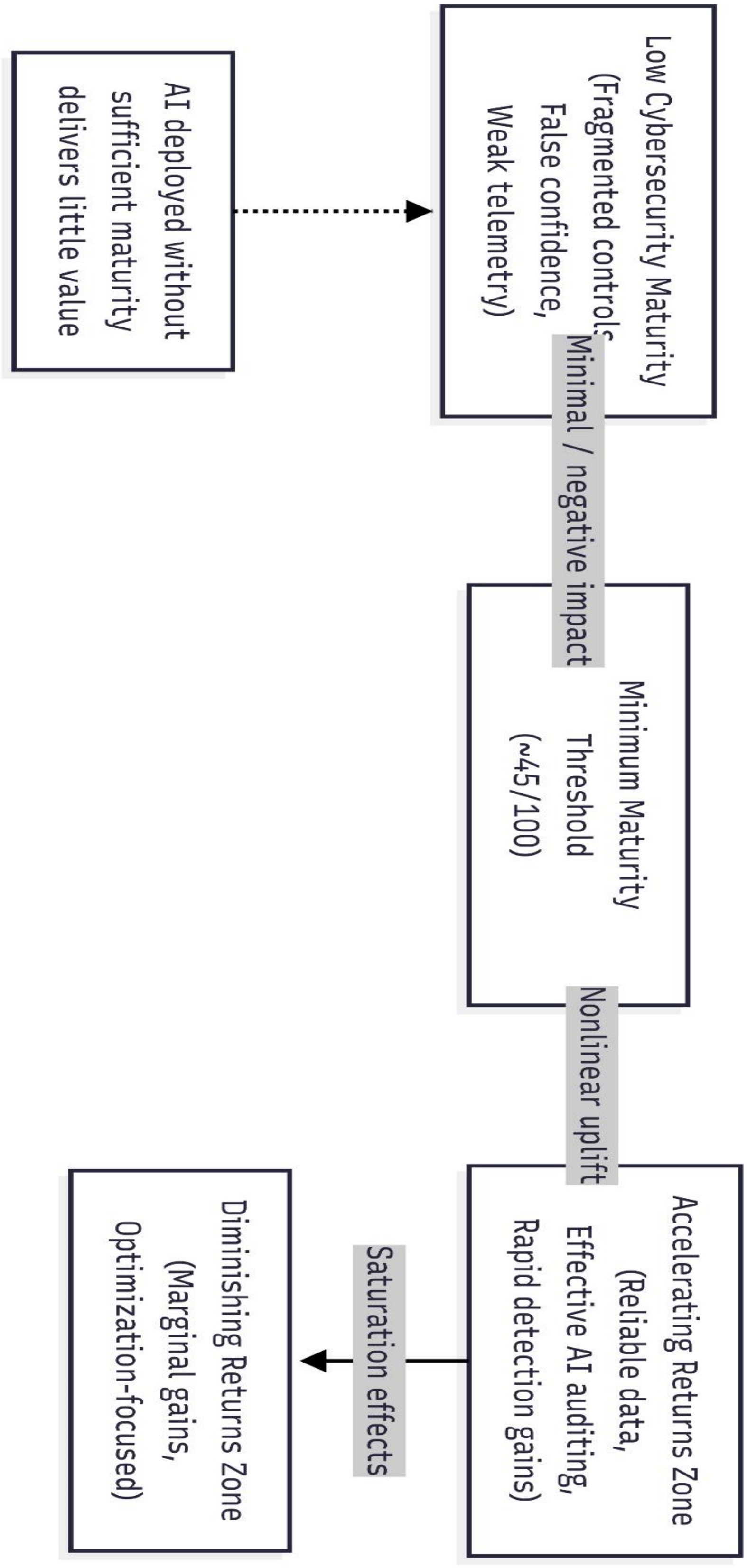

Low Cybersecurity Maturity
(Fragmented controls,
False confidence,
Weak telemetry)
AI deployed without
sufficient maturity
delivers little value
Minimal / negative impact
Minimum Maturity
Threshold
(~45/100)
Nonlinear uplift
Accelerating Returns Zone
(Reliable data,
Effective AI auditing,
Rapid detection gains)
Saturation effects
Diminishing Returns Zone
(Marginal gains,
Optimization-focused)

Table 1: *Summary of Hypotheses and Expected Effects*

Hypothesis	Statement	Expected Direction
H1	Cybersecurity maturity is positively associated with AI-enabled internal audit effectiveness	Positive
H2a	Data governance maturity mediates the relationship between cybersecurity maturity and AI-enabled internal audit effectiveness	Positive mediation
H2b	Security telemetry quality mediates the relationship between cybersecurity maturity and AI-enabled internal audit effectiveness	Positive mediation
H3	AI governance and model risk management maturity positively moderate the cybersecurity maturity–audit effectiveness relationship	Strengthening moderation
H4	The cybersecurity maturity–audit effectiveness relationship is non-linear, exhibiting threshold effects	S-shaped / threshold

Table 2: *Construct Definitions and Illustrative Measurement Items*

Construct	Definition	Illustrative Measurement Items (Likert-type)
Cybersecurity Maturity	The extent to which an organization has institutionalized cybersecurity capabilities across governance, identity and access management, data integrity, logging and telemetry, incident response, and third-party risk management, aligned with recognized standards (e.g., NIST CSF, ISO/IEC 27001).	• Security roles, responsibilities, and accountability are formally defined and enforced • Privileged and user access rights are reviewed continuously • Controls prevent unauthorized modification of transactional and audit-relevant data • Security logs are complete, centralized, time-synchronized, and tamper-resistant • Incident response procedures are documented

		and regularly tested • Third-party cybersecurity risks are assessed and monitored on an ongoing basis
Data Governance Maturity	The degree to which data ownership, lineage, quality controls, access rules, and retention policies are formally established to ensure reliable, auditable data for analytics and assurance.	• Data ownership and stewardship are clearly assigned • Data lineage for key audit datasets is documented and traceable • Data quality rules are monitored and enforced • Access to sensitive data is governed and logged
Security Telemetry Quality	The coverage, fidelity, timeliness, standardization, and integrity of security-relevant signals (e.g., logs, endpoint telemetry, SIEM data, cloud monitoring).	• Critical systems generate complete and consistent telemetry • Logs are standardized and time-synchronized across platforms • False-positive and false-negative rates are actively managed • Telemetry is protected from deletion or manipulation
AI Governance and Model Risk Management Maturity	The extent to which formal structures, policies, and controls govern AI model development, validation, explainability, monitoring, and change management.	• AI models undergo independent validation prior to deployment • Model performance and drift are monitored continuously • AI outputs are sufficiently explainable for audit evidence • Model changes follow controlled approval and release processes
AI-Enabled Internal Audit Use	The degree to which AI techniques are embedded in internal audit planning, execution, testing, and reporting activities.	• Anomaly detection supports audit scoping and prioritization • Process mining is used to test end-to-end control

		execution • NLP is applied to policies, contracts, and service tickets • Automated control testing operates on a continuous basis
Internal Audit Effectiveness	The extent to which internal audit achieves comprehensive risk coverage, accurate detection of control failures, timely execution, high-quality evidence, implementation of recommendations, and stakeholder confidence.	• Audit coverage aligns with key organizational risks • Audit findings demonstrate high detection accuracy • Audit cycle times are reduced without loss of quality • Audit evidence is complete, reliable, and defensible • Management implements audit recommendations promptly • Stakeholders express confidence in audit conclusions

5. Method / Design

This study adopts a **conceptual framework with analytical propositions**, appropriate for theory development in emerging interdisciplinary domains. Constructs are operationalized using established frameworks and prior empirical scales. Reliability and validity considerations follow established guidelines [31].

6. Framework Application Across Maturity Stages

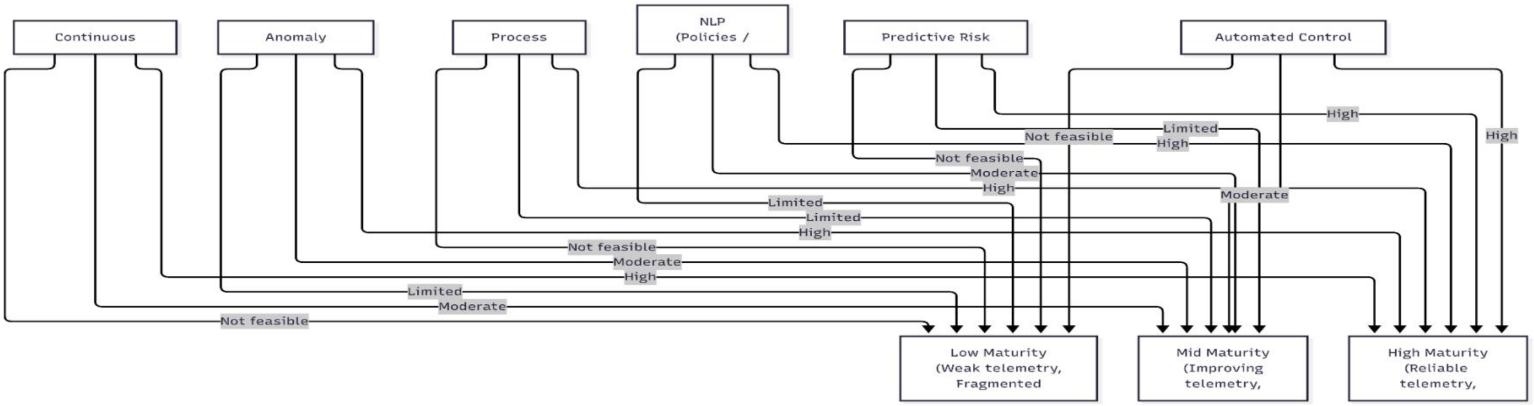
This section applies the conceptual framework across cybersecurity maturity levels.

Table 3: *Cybersecurity Maturity × AI-Enabled Internal Audit Feasibility and Effectiveness Matrix*

AI-Enabled Audit Capability	Low Cybersecurity Maturity	Medium Cybersecurity Maturity	High Cybersecurity Maturity
Continuous Auditing	Not recommended; unstable or corrupted data and logs produce misleading signals and false confidence	Feasible for selected processes with controlled data sources and manual oversight	Highly effective; enables near-real-time assurance and risk sensing

Anomaly Detection	High false-positive and false-negative rates due to incomplete or unreliable telemetry	Moderate accuracy when applied to curated datasets and monitored environments	High accuracy supported by comprehensive, high-fidelity telemetry
Process Mining	Ineffective due to missing, inconsistent, or manipulated event logs	Effective for stable processes with standardized logging	Robust enterprise-wide analysis with standardized and trusted event capture
NLP (Policies, Contracts, Tickets)	Limited usefulness; biased or incomplete corpora and access risks	Effective with controlled repositories and access logging	Highly effective with secure, governed knowledge bases
Predictive Risk Scoring	Not defensible; training data integrity weak and model drift unmanaged	Suitable for pilots only with strict validation and monitoring	Reliable and actionable with mature model risk management and secure pipelines
Automated Control Testing	Automates weak controls and amplifies audit risk	Effective for well-defined, stable controls	Highly effective continuous testing with strong integrity guarantees

Figure 3. Maturity-stage matrix of AI audit feasibility and expected effectiveness. The feasibility and assurance value of AI-enabled audit increases from low to high maturity, conditioned by telemetry and governance.



Low-maturity environments lack reliable data and telemetry, rendering AI outputs unstable. Medium-maturity environments enable selective AI use with safeguards. High-maturity environments support continuous, enterprise-wide AI-enabled assurance.

7. Discussion and Failure Modes

7.1 Interpretation of Findings

The analysis demonstrates that cybersecurity maturity is not merely supportive but foundational to AI-enabled audit effectiveness. Dynamic capabilities theory explains the observed non-linear effects.

7.2 Epistemic Risk and the Production of False Confidence in AI-Enabled Internal Audit

A critical yet insufficiently examined implication of AI-enabled internal audit is the emergence of **epistemic risk**—the risk that the knowledge produced by the audit function is systematically distorted while retaining the appearance of rigor, objectivity, and comprehensiveness. Unlike traditional audit risks, which often manifest as identifiable errors, omissions, or scope limitations, epistemic risk is more insidious because it directly undermines the credibility of assurance without triggering obvious failure signals. This study advances the argument that cybersecurity maturity is a primary determinant of epistemic risk in AI-enabled internal audit environments.

In low cybersecurity maturity contexts, AI systems frequently operate on data infrastructures characterized by weak access controls, incomplete logging, and insufficient monitoring of data integrity. Under such conditions, AI models may generate outputs that are internally coherent but externally invalid. For example, anomaly detection algorithms trained on compromised transaction logs may normalize fraudulent behavior as legitimate patterns, while process mining tools may reconstruct idealized workflows that bear little resemblance to actual operational practices. The resulting audit outputs may appear sophisticated and analytically robust, thereby increasing stakeholder confidence, even as they systematically misrepresent underlying risk realities.This phenomenon can be conceptualized as **false confidence**—a state in which the perceived reliability of audit conclusions exceeds their actual evidentiary validity. False confidence is particularly problematic in AI-enabled audit because automation tends to reduce visible uncertainty. Statistical precision, visual dashboards, and continuous monitoring outputs can obscure foundational weaknesses in data provenance and system integrity. As a result, professional skepticism—the cornerstone of effective auditing—may be unintentionally displaced by algorithmic authority.

Importantly, false confidence is not confined to technologically immature organizations. Even in environments with high cybersecurity maturity, epistemic risk can arise when AI governance and model risk management are underdeveloped. Complex models with limited explainability may produce accurate predictions while failing to meet the evidentiary standards required for audit assurance. Similarly, model drift may gradually erode detection accuracy while performance metrics remain superficially stable. In such cases, the audit function may continue to rely on AI-generated insights long after their underlying assumptions have become invalid.From a socio-technical perspective, false confidence reflects a misalignment between technical capabilities and organizational sensemaking processes. AI systems do not merely analyze data; they shape how risk is perceived, communicated, and acted upon. When cybersecurity maturity is insufficient to ensure the integrity of the digital environment, AI-enabled audit systems become epistemically fragile, amplifying systemic weaknesses rather than compensating for them. This insight extends existing audit analytics literature by shifting attention from efficiency gains to the **conditions under which audit knowledge itself remains trustworthy**.By foregrounding epistemic risk, this study reframes cybersecurity maturity as a prerequisite not only for operational security but also for the legitimacy of assurance in AI-enabled governance systems. Cybersecurity maturity, in this sense, functions as an epistemic safeguard, delimiting the boundary between analytically enhanced assurance and algorithmically reinforced illusion.

7.3 Boundary Conditions and Rival Explanations

While this study advances a comprehensive framework linking cybersecurity maturity to AI-enabled internal audit effectiveness, several boundary conditions and rival explanations warrant consideration. Addressing these explicitly strengthens the theoretical precision and clarifies the scope of applicability.First, one potential rival explanation is that **internal audit effectiveness is primarily driven by auditor expertise rather than technological or cybersecurity maturity**. Prior research emphasizes auditor competence, independence, and professional judgment as key determinants of audit quality. While this study does not dispute their importance, it argues that in AI-enabled contexts, human expertise alone cannot overcome structurally compromised data and monitoring environments. Auditor skill may mitigate some risks, but it cannot reliably detect manipulation or absence of digital evidence at scale without adequate cybersecurity controls. Accordingly, internal audit AI competency is modeled as a contextual control rather than a substitute for cybersecurity maturity.Second, organizational size and industry regulation may condition the observed relationships. Highly regulated industries such as financial services or critical infrastructure may exhibit stronger baseline cybersecurity controls due to compliance requirements, potentially compressing variance in maturity levels. However, even within regulated sectors, empirical evidence suggests substantial heterogeneity in telemetry quality, incident response effectiveness, and third-party risk management. The proposed framework therefore remains applicable, though effect sizes may vary.Third, the framework assumes a minimum level of digitization. In organizations where core processes are not digitally instrumented, AI-enabled internal audit may be infeasible regardless of cybersecurity maturity. In such cases, cybersecurity maturity cannot exert its enabling role because the technical substrate for AI-based assurance is absent. This boundary condition suggests that digital process maturity is a necessary—but not sufficient—precursor to AI-enabled audit effectiveness.Finally, this study focuses on internal audit as an assurance function. External audit and regulatory supervision may exhibit different dynamics due to differences in mandate, access, and accountability. Future research should examine whether similar maturity dependencies apply in external assurance contexts.

Table 4: *Failure Modes and Mitigation Controls in AI-Enabled Internal Audit*

Condition	Failure Mode	Impact on Internal Audit	Governance, Technical, and Audit Mitigation Controls
Low Cybersecurity Maturity	Unauthorized modification or corruption of transactional data	False assurance; undetected control failures	Database integrity controls; segregation of duties; cryptographic checks; immutable backups; periodic reconciliation
Low Cybersecurity Maturity	Log tampering or incomplete telemetry	Blind spots in monitoring; AI models misclassify risk	Centralized SIEM; write-once logging; secure time synchronization; telemetry completeness metrics
Low Cybersecurity Maturity	Compromised privileged identities	AI learns from compromised baselines; audit evidence invalid	Privileged access management; multi-factor authentication; continuous access reviews; session recording
Low Cybersecurity Maturity	Untested incident response capabilities	Prolonged compromise distorts audit evidence	Regular IR exercises; red-team testing; evidence quarantine and post-incident validation

High Cyber Maturity, Weak AI Governance	Black-box AI outputs and poor explainability	Audit findings not defensible; stakeholder distrust	Explainability requirements; documented model logic; minimum evidentiary standards for AI outputs
High Cyber Maturity, Weak AI Governance	Model drift and concept drift	Silent degradation of detection accuracy	Continuous performance monitoring; drift detection; periodic re-validation; champion-challenger models
High Cyber Maturity, Weak AI Governance	Automation bias and over-reliance on AI	Reduced professional skepticism; missed risks	Human-in-the-loop review; mandatory challenge procedures; auditor training on AI limitations
Any Maturity Level	Adversarial manipulation (poisoning or evasion attacks)	Targeted false negatives and distorted risk signals	Secure ML pipelines; dataset provenance controls; adversarial testing; restricted training data access

Low cybersecurity maturity leads to data corruption, log tampering, and identity compromise, producing false assurance. High maturity without AI governance introduces black-box risk, model drift, and automation bias.

7.4 Theoretical Contributions to Audit Analytics, Cybersecurity, and AI Governance Research

This study makes several theoretical contributions that extend and integrate prior research across audit analytics, cybersecurity, and AI governance. First, it reconceptualizes cybersecurity maturity as a **foundational governance capability** rather than a purely technical or defensive function. By explicitly linking cybersecurity maturity to the epistemic quality of audit assurance, the study positions cybersecurity as an antecedent to trustworthy organizational knowledge production.

The study advances audit analytics literature by shifting the focus from analytical techniques to **capability dependencies**. Prior research has emphasized what AI can do in audit contexts; this study clarifies the conditions under which those capabilities generate valid assurance. In doing so, it explains why similar AI tools produce divergent outcomes across organizations and why early-stage adoption often fails to meet expectations.

The framework contributes to AI governance research by demonstrating that model risk cannot be managed independently of the security environment in which models operate. AI governance maturity moderates—but does not replace—the effects of cybersecurity maturity, highlighting the interdependence of governance layers. This insight challenges siloed approaches to AI risk management and supports more integrated governance architectures.

By explicitly modeling non-linear and threshold effects, the study contributes to dynamic capabilities theory. It illustrates how digital capabilities exhibit tipping points beyond which value creation accelerates, and below which investments may yield negative returns. This non-linearity provides a theoretical explanation for inconsistent empirical findings in prior studies and underscores the importance of sequencing capability development.Collectively, these contributions position the study as a bridge between traditionally separate literatures, offering a coherent explanation of how cybersecurity maturity shapes the effectiveness, legitimacy, and sustainability of AI-enabled internal audit.

8. Practical Implications

8.1 Implications for Chief Audit Executives

CAEs should align AI adoption with cybersecurity maturity and avoid deploying advanced analytics in immature environments.

8.2 Implications for CISOs and AI Leaders

Cybersecurity investments should be framed as enablers of assurance quality. AI governance must integrate security and audit oversight.

8.3 Maturity-Based Roadmap

Organizations should sequence AI-enabled audit adoption according to cybersecurity maturity, prioritizing data integrity and telemetry before advanced analytics

8.4 Implications for Regulation, Standard-Setting, and the Institutionalization of AI-Enabled Assurance

Beyond organizational practice, the findings of this study have important implications for regulators, standard-setters, and professional bodies engaged in shaping the future of audit and AI governance. Existing guidance on audit analytics and continuous auditing often emphasizes the adoption of advanced tools while treating cybersecurity as a parallel or adjacent concern. This separation risks institutionalizing AI-enabled assurance practices without adequate attention to the conditions required for their reliability.

From a regulatory perspective, the results suggest that **AI-generated audit evidence cannot be evaluated independently of the cybersecurity maturity of the environment in which it is produced**. Regulators and oversight bodies may therefore need to reconsider how assurance quality is assessed in AI-enabled contexts. Rather than focusing solely on model accuracy or methodological sophistication, regulatory frameworks could require demonstrable controls over data integrity, logging completeness, identity governance, and incident response as prerequisites for reliance on AI-driven assurance.

Standard-setters and professional bodies likewise play a critical role in shaping expectations around AI-enabled audit. Current competency frameworks often treat cybersecurity knowledge and AI expertise as separate skill domains. The present study suggests that this separation is increasingly untenable. Cybersecurity maturity should be recognized not only as an audit subject but as an enabling infrastructure for audit analytics and continuous assurance. Integrating cybersecurity maturity assessments into internal audit capability models would align professional guidance with the realities of AI-dependent assurance.

At an institutional level, the study points toward a shift from **technology-centric** to **capability-centric** approaches to AI governance in audit. Rather than prescribing specific tools or techniques, regulators and professional bodies may achieve more robust outcomes by defining maturity thresholds and governance principles that condition acceptable use. Such an approach acknowledges the non-linear and context-dependent nature of AI-enabled audit effectiveness and mitigates systemic risks associated with automation bias and false confidence.

In this sense, cybersecurity maturity emerges as a boundary object connecting audit, cybersecurity, and AI governance communities. Recognizing and institutionalizing this connection is essential to ensuring that the expansion of AI-enabled assurance enhances, rather than undermines, organizational governance and trust.

9. Limitations and Future Research

This study develops a conceptual model rather than providing direct empirical tests, which limits the ability to estimate effect sizes and to adjudicate among competing causal explanations. Although the constructs and mechanisms are grounded in established standards and prior research, future work should validate the model using data that allow rigorous tests of the proposed direct, mediated, moderated, and non-linear relationships. In particular, empirical designs should address likely endogeneity concerns: cybersecurity maturity may be jointly determined with audit investment, governance quality, or overall management capability, and internal audit effectiveness may itself influence cybersecurity prioritization (reverse causality). Stronger causal identification would therefore benefit from longitudinal designs, instrumental-variable approaches where defensible instruments exist, or quasi-experimental settings such as staged technology rollouts, policy changes, or incident-driven shocks.

A limitation concerns measurement and construct specification. Cybersecurity maturity is inherently multi-dimensional and may be better modeled as a higher-order formative construct, while internal audit effectiveness and AI-enabled audit use are often operationalized reflectively. Mis-specification here can distort inference. Future studies should develop and validate measurement models that reflect the causal structure of maturity dimensions (e.g., governance, IAM, data integrity, telemetry, incident response, third-party risk), and explicitly test reliability, convergent validity, and discriminant validity using standard SEM/PLS-SEM criteria. Where feasible, researchers should complement perceptual survey measures with objective indicators—such as telemetry coverage metrics, logging completeness measures, identity control maturity, incident response testing frequency, and audit performance outcomes—to reduce common method bias and strengthen evidentiary credibility.The framework proposes threshold and non-linear effects, but conceptual work cannot determine where thresholds lie or whether they vary by industry and technology stack. Empirical research should therefore test non-linearity explicitly using piecewise regression, splines, latent class approaches, or multi-group analysis across maturity bands. Such tests should also examine whether thresholds differ depending on AI use-case (e.g., anomaly detection versus predictive risk scoring) and data environment (on-premise ERP versus cloud-native architectures). This would move the contribution from "non-linearity is plausible" to "non-linearity is demonstrated and bounded," which is typically where reviewers decide whether a theoretical claim is genuinely novel.

The model is socio-technical and therefore likely multi-level. Cybersecurity maturity is largely organizational, AI governance may be enterprise-wide or function-specific, while audit effectiveness can vary at the engagement level and by audit team competency. Future research should adopt multi-level designs (e.g., hierarchical modeling) that distinguish organization-level capability effects from function-level execution effects and engagement-level task characteristics. This is especially important because the same cybersecurity environment may enable strong AI audit outcomes for some audits but not others, depending on process digitization, system criticality, and data provenance.Institutional and regulatory dynamics are evolving rapidly and may materially shape the acceptability of AI-generated audit evidence. Future research should examine how emerging AI governance requirements, model risk management expectations, and cybersecurity assurance standards affect internal audit reliance on AI outputs. This includes studying how organizations translate governance principles into auditable controls (e.g., validation, drift monitoring, explainability thresholds, human-in-the-loop challenge procedures) and how regulators and audit committees interpret AI outputs as evidence. Linking the framework to regulatory supervision practices and standard-setting developments would sharpen its policy relevance and help specify when AI-enabled internal audit strengthens governance versus when it risks formalizing unreliable assurance.

10. Conclusion

This article argues that the effectiveness of AI-enabled internal audit depends fundamentally on the maturity of the cybersecurity environment in which it operates. AI tools do not function in isolation; they rely on the integrity of data, the reliability of system logs, the security of identities, and the organization's ability to detect and respond to incidents. Where these foundations are weak, AI-enabled audit can create an illusion of control rather than meaningful assurance. Where they are strong, AI has the potential to transform internal audit from a periodic, retrospective activity into a continuous and forward-looking governance function.

A central insight of the study is that the relationship between cybersecurity maturity and AI-enabled audit effectiveness is not linear. Below a minimum level of maturity, increasing the use of AI adds little value and may even increase risk by reinforcing flawed assumptions and incomplete evidence. Once this threshold is crossed, however, improvements in cybersecurity capabilities—particularly in data governance and security monitoring—enable AI systems to operate on more trustworthy signals, leading to sharp gains in audit effectiveness. This helps explain why organizations report very different outcomes from similar AI audit initiatives.

The article also highlights the importance of governance. Strong cybersecurity maturity alone is not sufficient if AI models are poorly governed, opaque, or left unchecked over time. Without clear model risk management, explainability, and human oversight, AI-enabled audit remains vulnerable to drift, automation bias, and overconfidence. Effective assurance therefore requires alignment between cybersecurity capabilities, AI governance, and audit judgment rather than isolated investments in tools.

Overall, the study reframes AI-enabled internal audit as a socio-technical system whose reliability is shaped by organizational capabilities rather than algorithms alone. By clarifying when AI strengthens assurance and when it undermines it, the article contributes to research on audit analytics and cybersecurity governance and offers practical guidance for organizations seeking to use AI responsibly in internal audit.

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