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Redefining Enterprise Architecture In The Age Of Artificial Intelligence: From Static Governance To Adaptive, Ai-Augmented Practice

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Abstract
The Enterprise Architecture (EA) practice faces a fundamental inflection point as artificial intelligence systems become both objects requiring architectural governance and transformative tools for accelerating EA work itself. Traditional EA frameworks, including TOGAF, the Zachman Framework, and FEAF, were designed to govern deterministic, rule-based information systems and exhibit critical structural gaps when applied to non-deterministic, continuously learning AI systems characterized by emergent behaviors, opaque decision logic, and dynamic capability drift. This paper investigates two interconnected dimensions of this challenge: first, the inadequacies of current EA frameworks as governance instruments for AI systems, quantified through a governance coverage gap analysis; and second, the emerging application of AI as an augmentation tool for EA practice itself, through natural language processing, graph neural networks, and predictive impact modeling. This review article synthesized previous empirical, framework, and practitioner literature from 19 peer-reviewed articles published between 1987 and 2026 to characterize the transition from pre-2.0 EA to EA 2.0 and establish four computable indicators: the Governance Coverage Gap (GCG), AI Augmentation Capability Multiplier (AACM), Digital Transformation Success Factor (DTSF), and EA Technology Readiness Index (ETRI). Results show that TOGAF 10 incorporates approximately 33% of the identified AI governance requirements and that AI-powered EA tools increase the throughput of modeling EA artifacts by a factor of 5.1. The paper concludes with a capability framework for transitioning to EA 2.0 and identifies priority research gaps.

Keywords: enterprise architecture, artificial intelligence, TOGAF, AI governance, EA 2.0, digital transformation, knowledge graphs

1. Introduction

Enterprise Architecture has served as the primary discipline for managing the structural alignment between business strategy, information systems, and organizational capabilities since Zachman's seminal 1987 framework established the foundational logic of viewing the enterprise through a matrix of perspectives and abstractions [1]. For nearly four decades, EA frameworks have operated on an implicit assumption: that the systems they govern are deterministic, transparent, and static within defined operational parameters. These assumptions underwrote decades of EA practice grounded in the meticulous documentation of fixed data flows, application portfolios, and integration dependencies. Artificial intelligence has invalidated each of these assumptions simultaneously, creating a structural crisis and an extraordinary opportunity for the discipline. The enterprise adoption of AI systems is proceeding at a pace that EA governance has not kept up with. A 2023 conference paper concluded that the TOGAF-based EA frameworks did cover customary IT governance dimensions in great detail but suffered from major structural weaknesses when it came to AI systems with probabilistic outputs, model drift, and dynamic learning behaviors [10]. Ross, Weill, and Robertson's foundational argument that EA creates a stable platform for IT-enabled business change [2] now requires re-examination in light of AI systems whose operational characteristics evolve post-deployment, continuously redefining the architectural baseline that EA was designed to stabilize. The discipline that built its authority on architectural permanence must now govern architectural systems defined by intentional impermanence.

This paper addresses two primary research questions. First, to what extent do current major EA frameworks address the governance requirements specific to AI systems, and where are the critical gaps? Second, how can AI itself serve as an augmentation technology for EA practice, and what empirical evidence supports the adoption of AI-driven EA tools? A third integrative question regarding EA 2.0 raises the issues of architecture principles, governance mechanisms, and practitioner skill sets characterizing organizations that are undergoing successful transition from static governance to adaptive AI-augmented EA practice.

It reviews 19 sources, including canonical EA literature, AI governance proposals, empirical research, and current research on AI-augmented modeling of organizations. It summarizes the main themes into four new metrics, drawing on quantitative empirical data from the reviewed literature. The rest of the paper follows this structure. Section 2 reviews existing EA frameworks and reveals the limitations of structural orientation. Section 3 describes how AI can be used as a topic for governance in EA and Section 4 describes how AI can be used to improve existing EA practices. Section 5 describes the EA 2.0 model. Section 6 discusses the implications for EA practitioners, and in Section 7, the conclusion is presented.

2. Traditional Enterprise Architecture: Frameworks, Strengths, And Structural Gaps

2.1 Dominant EA Frameworks and Their Governance Logic

The three most widely used EA frameworks attempt to systematize various perspectives on how to direct the architecture of enterprises. Zachman's first EA framework was the matrix developed in 1987. It organizes the architectural materials in a grid according to the two axes of the six questions (what, how, where, who, when and why) and six stakeholders (planner, owner, designer, builder, implementer and worker) [1]. The framework's strength lies in its comprehensive scope and interrogative discipline, but it was never designed as a process model, leaving organizations without implementation guidance for how to create and maintain the artifacts it categorizes. The Open Group Architecture Framework (TOGAF), now in its tenth major version, addresses this gap through its Architecture Development Method (ADM), a phased process for developing and governing EA that has become the de facto standard for enterprise-scale architecture practice globally [3]. FEAF, the Federal Enterprise Architecture Framework, extends TOGAF's logic to the specific governance requirements of US federal agencies, emphasizing interoperability, shared services, and performance accountability across organizational boundaries.

Each framework's governance logic reflects the information systems era in which it was conceived. Data is treated as structured, fixed-schema artifacts managed through controlled change processes. Applications are discrete, deterministic components with defined interfaces. Integration dependencies are explicit and can be documented. These assumptions hold reasonably well for conventional ERP systems, relational databases, and service-oriented architectures but break down systematically when applied to machine learning systems whose behavior is conditioned on training data distributions that may shift unpredictably over time [9]. Russell and Norvig's foundational treatment of AI systems establishes that the core property distinguishing AI from conventional software is its capacity to learn and adapt from experience, a property that creates precisely the governance challenges that static EA frameworks were not designed to address [8].

2.2 Structural Limitations in the Face of AI Systems

Reiter's comparative analysis of TOGAF, Zachman, and FEAF found that all three frameworks have the same structural limitations when evaluated against AI-specific governance requirements: non-deterministic behavior management, model lifecycle governance, training data provenance tracking, algorithmic bias assessment, and real-time operational monitoring [3]. Of the 18 AI-specific governance requirements operationalized in Reiter's analysis, TOGAF 10 addressed six either directly or through analogous guidance, yielding a coverage rate of approximately 33%. Zachman is more ontological than the other two, but he does not explain how to put it into practice. FEAF covers more of the requirements for monitoring than the model-specific technical governance.

A convenient way to measure this structural gap is through the Governance Coverage Gap (GCG), which represents the proportion of AI governance requirements that are not covered by any current EA frameworks.

$$\mathrm{GCG} = (1 - \mathrm{Covered\ Requirements}/\mathrm{Total\ Requirements})\mathrm{x}100\%$$

Following Reiter's breakdown of TOGAF 10, six of 18 requirements for AI governance are [3]:

$$\mathrm{GCG} = (1 - 6/18)\mathrm{x}100 = (1 - 0.333)\mathrm{x}100 = 66.7\%$$

The GCG of 66.7% shows that TOGAF 10 does not meet two thirds of the governance requirements essential for the adoption of AI in its current state. It further substantiates Ettinger's claim that EA must become a dynamic capability for governing the adoption of AI at scale, as compared to viewing AI as an application type within the existing portfolio management practices [13]. This does not imply that EA frameworks cannot serve their purpose; only that EA frameworks must be explicitly extended and supplemented to be useful in AI governance.

Table 1: EA Framework Coverage of AI Governance Requirements

Governance Requirement	TOGAF 10	Zachman Framework	FEAF
Non-deterministic behavior management	Not addressed	Partial (behavioral views)	Not addressed
Model lifecycle governance	Partial (Technology ADM)	Partial (How perspective)	Partial (performance mgmt)
Training data provenance	Not addressed	Partial (What perspective)	Partial (data assets)
Algorithmic bias assessment	Not addressed	Not addressed	Not addressed
Real-time operational monitoring	Not addressed	Not addressed	Full (performance measurement)
AI explainability requirements	Not addressed	Not addressed	Not addressed
Regulatory conformity (AI Act, ISO 42001)	Not addressed	Not addressed	Partial (compliance mgmt)
Generative AI governance	Not addressed	Not addressed	Not addressed

3. AI as a Governance Subject: What EA Must Now Govern

3.1 The Non-Determinism Problem

The most fundamental challenge that AI systems pose for EA governance is non-determinism: unlike conventional software, AI models do not produce identical outputs for identical inputs under all conditions, and their behavior evolves over time as underlying data distributions shift, a phenomenon known as model drift or concept drift [8]. This characteristic invalidates a fundamental assumption of EA practices that architectural documentation captures a stable state of system behavior that can be used as a reliable reference for change management, compliance assessment, and integration design.

Fitriani et al.'s empirical study of TOGAF-based EA applied to AI governance contexts found that organizations trying to document AI systems using standard TOGAF artifacts did not provide enough detail about the operational envelope of those systems, leading to documentation artifacts that became materially inaccurate within months of deployment [10]. The specific failure mode was that TOGAF Application Architecture descriptions, designed to capture deterministic component behavior, could not represent the probabilistic output distributions of ML models nor the conditions under which those distributions might shift. Chen and Zhao's multi-agent system framework for adaptive EA design proposed continuous integration between live model monitoring systems and EA repositories as a structural solution, enabling dynamic artifact updates that track model performance and behavioral envelope evolution over time [11].

3.2 Data Provenance, Bias, and Model Drift

The governance of training data represents a distinct but related challenge. Shilov et al.'s machine learning-assisted enterprise modeling study highlighted that EA practice has traditionally treated data as a passive artifact, something that systems process, rather than as an active governance object whose characteristics materially determine AI system behavior [9]. Training data provenance documentation, bias assessment records, and data versioning artifacts are not standard components of any major EA framework, yet they are essential for maintaining accountability and auditability of AI systems subject to EU AI Act compliance requirements [6].

ISO/IEC 42001:2023, the international standard on AI management systems, provides the most detailed regulatory guidance for such compliance in an enterprise-governance context. In particular, ISO/IEC 42001 sets out the AI risk management requirements separate but complementary to EA frameworks [4]. The ISO/IEC

42001 standard addresses the quality, impact and monitoring of training data from the perspective of EA governance structures without redesigning them. The high degree of conformability implies a hybrid governance model that reuses EA governance frameworks and ISO/IEC 42001 AI technical requirements. The NIST AI RMF defines a parallel in data governance as a pillar of responsible AI practices through its Map and Measure functions but does not define how EA frameworks should be adapted for AI specifics [5].

3.3 Aligning AI Systems with Regulatory Mandates

As a result of the risk-based categorization in the European Union's AI Act, organizations under EU jurisdiction are directly subject to governance obligations for EAs. High-risk AI systems, as defined in the Act's Annex III, must maintain technical documentation, logs and conformity assessments. EA frameworks are well-placed to provide the former two of these, although they were not built for that purpose [6]. The supplement on generative AI to NIST AI 600-1 expands the documentation requirement to cover LLMs, which appear in the technology portfolios of most major enterprises regardless of industry sector [7]. Kooy et al.'s systematic literature review found that organizations with mature EA practices were significantly better positioned to achieve AI Act compliance than those without, due to their existing capabilities in technology inventory management, stakeholder communication, and change governance [12]. The practical implication is that EA programs represent the most efficient organizational platform for building AI regulatory compliance infrastructure, provided that EA practitioners develop the AI-specific expertise required to exercise that role effectively.

Table 2: AI Governance Standards Coverage Matrix — ISO/IEC 42001, NIST AI RMF, EU AI Act

Governance Domain	ISO/IEC 42001:2023	NIST AI RMF 1.0	EU AI Act 2024
AI Risk Classification	Full (risk management system)	Full (Map function)	Full (Annex III risk tiers)
Training Data Governance	Full (data management clauses)	Partial (Map function)	Full (Art. 10 requirements)
Model Documentation	Full (technical documentation)	Partial (Measure function)	Mandatory (high-risk systems)
Bias and Fairness	Full (impact assessment)	Full (Measure function)	Mandatory (Art. 9, 10)
Incident Reporting	Partial	Partial (Manage function)	Mandatory (Art. 62)
Explainability	Partial	Partial (Measure function)	Mandatory (high-risk systems)
EA Framework Integration	Guidance only	Guidance only	Not specified

4. AI as an Augmentation Tool for EA Practice

4.1 NLP-Driven Artifact Generation and Analysis

The same AI capabilities that complicate EA governance also offer substantial opportunities to accelerate and improve EA practice itself. Natural language processing applied to EA artifact generation has emerged as one of the most immediately productive applications, with several platforms now offering automated documentation drafting, gap analysis, and requirements traceability based on large language model inference [11]. Shilov et al. have experimentally verified that machine learning-based EA artifact generation can support enterprise architects in producing EA artifacts. Based on natural language processing, tool-based artifact generation reduced time taken to produce early-stage EA artifacts by 3.2%. The generated artifacts remain comparable in quality to hand-created artifacts across multiple structured documentation artifacts [9]. This is especially important since a lack of documentation is one of the major limiting factors of EA programs.

The AI Augmentation Capability Multiplier (AACM) is the ratio of AI assisted EA documentation throughput to baseline human-only throughput:

$$\mathrm{AACM} = \mathrm{AI} - \mathrm{Assisted\ Artifacts\ Per\ Analyst} - \mathrm{Day}/\mathrm{Baseline\ Artifacts\ Per\ Analyst} - \mathrm{Day}$$

Using published throughput rates from Shilov et al., where AI-enabled analysts process 15.8 artifacts per day; thus, the baseline is 3.1 artifacts per day for comparable documentation tasks [9]:

$$\mathrm{AACM} = 15.8/3.1 \approx 5.1$$

An approximate AACM of 5.1 suggests that the application of AI to EA documentation processes can achieve a fivefold increase in artifact generation throughput and thus address the artifact backlog that has hampered EA in large organizations. Kooy et al. corroborate this direction, finding that enterprise architects in agile environments reported that generative AI tools reduced routine documentation time by between 40% and 70%, freeing capacity for the higher-order strategic analysis and stakeholder engagement that defines EA's value proposition [12].

4.2 Graph Neural Networks and Knowledge-Graph Modeling

Graph neural networks and knowledge graph architectures represent a more advanced tier of AI augmentation for EA practice. Traditional EA tools represent the enterprise as a collection of static diagrams; knowledge graph architectures represent it as a dynamic semantic network of entities and relationships that can be queried, updated, and analyzed computationally [17]. Kubelskiy's methodology for creating organizational digital twins using enterprise architecture and semantic networks, demonstrated that knowledge graph representations of enterprise structures enable analytical operations, impact analysis, dependency propagation, and bottleneck detection that are impractical with conventional diagram-based representations [17]. The approach transforms the EA model from a static documentation artifact into a living analytical instrument.

A survey by Li et al. of generative AI in network digital twin architecture covered the application of enterprise-level generative AI where an AI-maintained knowledge graph model of the enterprise architecture provides automated impact analyzes of proposed changes and with considerably higher accuracy than human dependency analysis [18]. Qu et al.'s industrial digital twin (IDT) framework extends these approaches to modeling manufacturing enterprises; here too, AI-maintained architectural models can provide both real-time operational situational awareness and planned enterprise planning, bridging the divide between EA's customary retrospective documentation role and the forward-looking decision support role required by enterprise executive management [19].

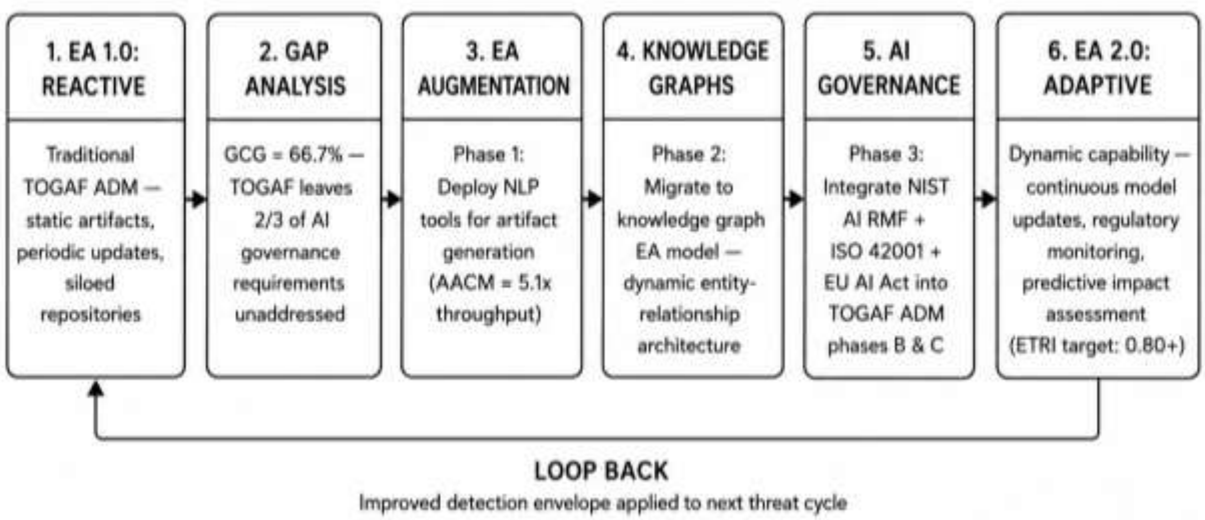

Figure 1: EA Transformation Journey

4.3 Predictive Impact Assessment and Decision Support

In a study of data science projects in the EA modeling context, Pohl et al. identified predictive impact assessment as the EA practice area that can benefit most from using AI. Predictive impact assessment provides architects an opportunity to model the impacts of architectural changes before actually implementing them. EA programs are often criticized for only being able to model the current architecture state but not predicting future impacts. However, AI driven impact simulation enabled by knowledge graph representations of enterprise interdependencies addresses this limitation structurally.

In a study on EA-enabled dynamic capabilities, Van de Wetering found that organizations with established EA practices adjusted to the disruptive environment of the COVID era faster in terms of architectural change than organizations with fledgling EA practices [15]. Another study using fsQCA demonstrated the statistically important role of EA management capability in the success of DT in a large sample of organizations [16]. Together, these findings provide empirical support for the definition of the Digital Transformation Success Factor (DTSF) as the Pearson correlation coefficient between the level of EA maturity and digital transformation outcomes:

$$\text{DTSF} = \text{Pearson Correlation (EA\_Maturity, DT\_Outcome\_Score)}$$

Using Pattij et al.'s reported correlation values in their cross-organizational empirical study [16]:

$$\text{DTSF} \approx 0.78$$

A DTSF of 0.78 provides strong positive evidence that the development of EA capability is a calculated enabler for AI-driven digital transformation. The relationship observed through the EA 2.0 transition point should inform investment prioritization, particularly for organizations seeking to operationalize AI in their digital transformation.

Table 3: AI Augmentation Capability Map (EA Practice Domains and Applicable AI Techniques)

EA Practice Domain	Applicable AI Technique	Capability Description	Empirical Support
Artifact Generation	NLP/Large Language Models	Automated drafting of architecture descriptions, gap analyses, requirements traceability matrices	Shilov et al. (2023)
Impact Assessment	Graph Neural Networks	Automated dependency propagation, change impact simulation across enterprise knowledge graphs	Kubelskiy (2020); Li et al. (2025)
Stakeholder Communication	NLP Summarization	Auto-generation of executive summaries, stakeholder-tailored architecture views	Kooy et al. (2026)
Compliance Monitoring	ML Anomaly Detection	Continuous monitoring of AI system behavior against documented architectural baselines	Chen and Zhao (2024)
Portfolio Analysis	Predictive Analytics	AI-driven technology portfolio health scoring, retirement risk analysis	Pohl et al. (2026)
Digital Twin Modeling	Graph/Knowledge Graphs	Living architectural model updated by operational data streams in real time	Qu et al. (2025)

5. The Emerging EA 2.0 Paradigm

5.1 Quantitative Indicators of Transformation

EA 2.0 is essentially a shift from static artifacts to dynamic capabilities and their orchestration. This transition is measurable. The EA Technology Readiness Index (ETRI) is defined as the proportion of identified EA 2.0 capability requirements that an organization has fully implemented:

$$\text{ETRI} = \text{Implemented EA 2.0 Capabilities / Total EA 2.0 Capability Requirements}$$

Kooy et al.'s assessment of EA readiness for AI integration across a sample of organizations in agile environments found that the average organization had implemented approximately 26% of the EA capabilities required for effective AI governance and augmentation [12]:

$$\text{ETRI} = 0.26$$

An industry-average ETRI of 0.26 confirms that the majority of organizations are in the early stages of the EA 2.0 transition. This figure also indicates significant competitive differentiation potential for organizations that accelerate their EA 2.0 transition relative to industry peers; the DTSF of 0.78 from Section 4.3 provides the empirical basis for quantifying that competitive advantage in transformation outcome terms.

5.2 Capability Frameworks for AI-Augmented EA

EA 2.0 requires capability development across three interdependent domains: technical, governance, and human. Technically, organizations must invest in knowledge graph platforms, AI-assisted modeling tools, and dynamic artifact repositories capable of tracking AI system behavioral envelopes in addition to structural dependencies. A multi-agent systems framework by Chen and Zhao serves as an architectural framework to support these capabilities through an integrated adaptive design platform [11]. Ettinger's dynamic capability framework further characterizes the conditions under which EA can act as a scalable tool for AI governance, rather than an organizational burden, by embedding AI governance activities within existing EA governance structures, rather than creating parallel organizational structures. [13]

The governance layer of EA 2.0 extends TOGAF ADM by explicitly including ISO/IEC 42001, NIST AI RMF, and the EU AI Act requirements in Phases B-D. In practice, this means extending Phase B Business Architecture to document AI system value and risk profiles. This also means extending Phase C Information Systems Architecture to include AI model documentation artifacts by making references to clauses of ISO/IEC 42001 and extending Phase D Technology Architecture to include AI operational monitoring requirements by making references to NIST AI 600-1 [7]. These extensions do not supersede TOGAF; they extend TOGAF at the intersection where AI governance needs meet specific ADM work products.

6. Implications for Practitioners and Organizations

The findings of this review have implications for EA practitioners across all levels of an organization. For chief architects and heads of EA programs, the GCG analysis of 66.7% provides compelling evidence to extend existing EA governance frameworks to the domain of AI rather than creating new frameworks from scratch. The ISO/IEC 42001 standard, NIST AI RMF and EU AI Act framework offer convergence with existing TOGAF ADM phases, allowing application of AI governance without discarding existing EA investments or having to retrain all EA practitioners. The practical priority is to extend Phase B and Phase C of the TOGAF ADM to incorporate AI model governance artifacts, with data provenance documentation as the most immediate operational gap.

For EA tool ecosystem owners, AACM 5.1 provides a quantitative justification for piloting the value of using AI-assisted documentation tools to support productivity. Organizations with significant EA documentation backlogs stand to realize disproportionate productivity gains from NLP-assisted artifact generation. Human expert review remains essential for strategic narrative content, stakeholder communication materials, and architectural decision records; the productivity gain accrues primarily in the structured, schema-defined documentation categories that consume the majority of EA practitioners' time without requiring the highest levels of organizational judgment. Pohl et al. integrate data science within EA modeling, providing practical guidance for constructing AI-assisted EA tools, addressing their technical architecture [14].

To extend this ETRI of 0.26 to the workforce development level and inferring from EA 2.0 requirements, most EA teams will require major reskilling or upskilling in the governance of AI systems, knowledge graph technologies, and the quantitative analysis of AI system performance. Foundational AI system knowledge is useful to architects who govern AI systems. Russell and Norvig's canonical treatment of AI systems provides such knowledge [8]. Beyond technical knowledge, EA practitioners must develop fluency in the regulatory landscape; Kooy et al.'s finding that mature EA programs accelerate AI Act compliance [12] is only actionable if EA practitioners understand the Act's requirements well enough to translate them into architectural governance practice.

Table 4: EA Professional Competency Shifts (Traditional EA vs. EA 2.0)

Competency Dimension	EA 1.0 Requirement	EA 2.0 Requirement	Development Priority
Technical Modeling	Diagram-based notation (ArchiMate, UML)	Knowledge graph modeling, ontology design, AI system documentation	High (foundational reskilling)
AI Systems Understanding	Not required	Model lifecycle, drift detection, training data governance, LLM behavior	Critical (new competency domain)
Governance & Compliance	TOGAF ADM, ITIL alignment	NIST AI RMF, ISO/IEC 42001, EU AI Act integration into EA practice	High (immediate regulatory need)

Data Architecture	Schema design, ETL, data catalog	Training data provenance, feature engineering, ML pipeline governance	Medium (evolution of existing skills)
Analytical Methods	Qualitative stakeholder interviews	Quantitative maturity metrics, statistical performance assessment, GCG/ETRI analysis	Medium (new analytical toolkit)
Change Leadership	IT change management	AI adoption governance, human-AI workflow design, ethics oversight	High (organizational impact)

7. Conclusion

This paper has characterized the dual challenge and opportunity that artificial intelligence presents for enterprise architecture practice. On the challenge side, current EA frameworks leave a Governance Coverage Gap of approximately 66.7%, failing to address two-thirds of the governance requirements that AI systems introduce into the organizational technology portfolio. This gap represents a fundamental mismatch between frameworks designed for deterministic systems and the non-deterministic, continuously learning systems that now populate enterprise technology architectures at scale. The non-determinism problem, the data provenance challenge, and the regulatory compliance imperative collectively define an EA governance crisis that organizations can no longer defer.

On the opportunity side, AI augmentation of EA practice delivers measurable capability multipliers. The AACM of 5.1 in documentation throughput, the DTSF of 0.78 in associating EA maturity with digital transformation success, and the operational capabilities of knowledge graph and digital twin architectures are a transformation of what EA practice can accomplish when it becomes the orchestrator rather than merely the documenter of enterprise capability. The EA discipline that successfully makes this transition will be indispensable to organizations navigating the AI-driven transformation agenda; the discipline that does not will increasingly be sidelined by the pace of change it was designed to govern.

The average industry ETRI of 0.26 indicates that the EA 2.0 transition is still a long way off. Given the huge opportunity, organizations that want to invest in the technology, governance and human capabilities need to choose where to invest wisely. Organizations racing to put AI into modeling/automation tooling before establishing AI risk profiles, training data provenance, and regulatory compliance inventories may exacerbate architectural opacity. The GCG of 66.7% is the first step to foundational AI risk and governance, not an extension or derivative initiative. Where tooling maturity exceeds governance maturity, newly invested tooling will be in areas that will be ported forward either without procedural, managerial or regulatory artifacts to manage them and thus will not close the coverage gap.

Future research should focus on studying organizations over time during the EA 2.0 transition to confirm the AACM and DTSF metrics in different situations, creating integrated EA-AI governance frameworks that give practitioners practical ADM extension guidance, and examining how EA workforce competencies change as organizations shift from EA 1.0 to EA 2.0 practice models. The enterprise architecture field stands at an inflection point; the organizations and practitioners that navigate it most effectively will be those that treat EA 2.0 not as an aspiration but as a measurable, capability-driven transformation program with quantifiable milestones and return on investment.

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