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Research Article

Examining Shortcomings of Existing AI Maturity Models for Enterprises and Proposing an Enhanced Multi-Dimensional AI Maturity Framework

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ABSTRACT

Artificial Intelligence adoption in enterprises has accelerated dramatically over the past decade, yet organizations struggle to assess their AI readiness systematically. While numerous AI maturity models have been proposed, they often fail to provide comprehensive guidance that addresses the full spectrum of organizational transformation required. This paper examines critical shortcomings of existing maturity models for enterprise AI implementation, proposes an enhanced AI Maturity Model (AI-MM) that incorporates multiple dimensions beyond technical capabilities and compares this framework with established standards such as CMMI and TOGAF. Through systematic analysis of 30+ peer-reviewed sources and industry frameworks, we identify key gaps in current approaches and present a structured multi-dimensional model that encompasses strategic, technological organizational and governance perspectives. Our findings demonstrate that successful AI adoption requires integrated assessment across these dimensions, fundamentally different from traditional capability maturity models.

Keywords: Artificial Intelligence, Maturity Models, Digital Transformation, Enterprise Architecture, CMMI, TOGAF, AI Governance

1. Introduction

The digital transformation landscape is increasingly dominated by artificial intelligence technologies, which have become critical drivers of competitive advantage for enterprises[1]. However, the path from initial AI exploration to enterprise-wide adoption remains fraught with challenges. While maturity models have been recognized as effective tools for organizational assessment and development in other domains[2], their application to enterprise AI presents unique complexities that existing frameworks often inadequately address.

The fundamental challenge stems from the fact that AI maturity encompasses far more than technological implementation. It requires simultaneous evolution across strategy formulation, talent development, data infrastructure, governance frameworks, ethical considerations and organizational culture[3]. This multifaceted nature of AI adoption represents a departure from traditional software process maturity assessments, demanding new conceptual frameworks and measurement approaches.

The urgency of this research is underscored by empirical evidence indicating that despite AI's transformative potential, only

a minority of enterprises have achieved substantive AI maturity levels[4]. Organizations frequently face misalignment between their AI aspirations and the actual capabilities required to realize those visions. Technology providers and service integrators report persistent gaps between the skills possessed by enterprises and the capabilities demanded by advanced AI solutions, suggesting that current maturity assessment frameworks fail to capture critical readiness dimensions[5].

2. Existing AI Maturity Models: A Critical Review

2.1. Current models and their approaches

The literature reveals diverse approaches to AI maturity assessment, each with distinctive characteristics and limitations[2]. Several models have emerged from both academic research and industry practice, reflecting different conceptualizations of what constitutes "maturity" in AI contexts.

The AI-Driven Platform Enterprise Maturity Model (AIMM) proposed by Yablonsky represents one significant contribution, which constructs a formal organizational value chain taxonomy that identifies five maturity levels for platform companies[5]. This model recognizes the importance of explicit dimensions within the AI value chain and emphasizes human-machine interactions within legal and ethical contexts. However, its primary limitation lies in its focus on platform enterprises rather than broader organizational types, limiting its applicability to traditional corporate structures.

Building on CMMI principles, governance-focused models have been developed to address AI control and direction within enterprises[3]. The Measurable AI Governance Model (MAIGM) structures AI governance across four layers: Data, Technology, Ethical C Social and Legal. This governance-centric approach provides valuable frameworks for managing AI risks and establishing organizational controls, yet it does not comprehensively address the broader business and capability development dimensions necessary for full organizational AI maturity. Recent extensions of this approach to higher education contexts demonstrate the expanding applicability of CMMI-based AI governance models[6].

Innovative approaches incorporating Industry 4.0 readiness have also emerged, extending the 4IR maturity assessment model to explicitly include AI dimensions[7]. The CCMS2.0e model integrates AI assessment with manufacturing readiness, acknowledging the specific technical requirements of smart production environments. Similarly, models designed for trustworthy AI development recognize that trustworthiness must be embedded throughout the AI system development lifecycle rather than retrofitted at later stages[8].

2.2. Identified shortcomings

Despite their contributions, existing AI maturity models exhibit several fundamental limitations:

- **Insufficient multidimensionality:** Most current models focus predominantly on technical or governance dimensions while inadequately addressing strategic alignment organizational change management, talent development and business model innovation[2]. The Technology-Organization-Environment (TOE) framework, while useful, often receives incomplete treatment in AI maturity contexts. Strategic alignment between AI initiatives and business objectives remains insufficiently addressed in many models, creating situations where technically mature AI implementations fail to generate business value[4].
- **Lack of attention to organizational readiness:** Few maturity models adequately capture organizational capacity for change, cultural readiness or human capital development requirements[9]. The human dimension of AI adoption—including skills gaps, change resistance and the need for new organizational roles-is frequently marginalized despite empirical evidence of its critical importance. Leadership capability for AI-driven transformation, a crucial enabler of success, often receives minimal treatment[10].
- **Inadequate coverage of data and governance dimensions:** While data quality is foundational for AI success, many models provide limited guidance on assessing data maturity specifically in AI contexts. Moreover, the governance frameworks embedded in current models often lack the sophistication required for managing AI-specific risks including model bias, explainability and algorithmic accountability[11]. Ethical governance and responsible AI considerations are frequently treated as separate from operational maturity rather than as integrated dimensions.
- **Limited attention to ecosystem and external factors:** Most models treat the enterprise in isolation, failing to adequately account for external partnership ecosystems, supplier readiness, regulatory environments and industry-specific requirements[12]. The increasing prevalence of AI delivered through cloud services and third-party integrators suggests that maturity assessment must extend beyond organizational boundaries.
- **Unclear progression pathways:** Many existing models identify maturity levels but provide insufficiently detailed guidance on transitioning between levels, creating confusion about improvement roadmaps[13]. The practical steps required to move from one maturity level to the next often remain vague or abstract.
- **Limited empirical validation:** A significant proportion of proposed AI maturity models lack rigorous empirical validation through real-world application[12]. Many remain theoretical constructs without demonstrated effectiveness in guiding organizational transformation.

3. Proposed Enhanced AI Maturity Model: Multi-Dimensional Framework

3.1. Model architecture and dimensions

In response to identified shortcomings, we propose an Enhanced AI Maturity Model (E-AIMM) structured across seven integrated dimensions, each assessed across five maturity levels (Initial, Developing, Defined, Managed, Optimized). This structure aligns conceptually with CMMI while extending well beyond its scope to encompass AI-specific requirements.

3.1.1. Dimension 1: Strategic alignment and governance

This dimension assesses the degree to which AI initiatives are explicitly aligned with organizational strategy and supported by robust governance frameworks[9]. Key assessment areas include:

- Explicit AI strategy formulation and integration with business objectives
- Board-level and executive sponsorship for AI initiatives
- Clear governance structures for AI decision-making
- Risk management frameworks specific to AI applications

- Regulatory compliance and policy alignment
- Ethical AI governance and responsible use frameworks

Maturity progression moves from ad-hoc AI projects with limited strategic connection (Initial) through recognized strategic importance but fragmented governance (Developing), to formalized AI strategies with integrated governance (Defined), managed AI portfolios with measurable business outcomes (Managed) and finally to predictive and continuously optimized AI strategy aligned across the enterprise (Optimized).

3.1.2. Dimension 2: Data and information architecture

Building on the recognition that data quality is foundational, this dimension specifically addresses data readiness for AI. Assessment areas include:

- Data governance frameworks and quality management
- Data availability, accessibility and integration capabilities
- Privacy and security controls for AI applications
- Master data management and metadata standards
- Data architecture supporting AI/ML requirements
- Data lineage and traceability capabilities
- Data valuation and business intelligence integration

3.1.3. Dimension 3: Technological capabilities and infrastructure

This dimension assesses the technical foundation supporting enterprise AI implementation[7]. Key areas include:

AI/ML platform infrastructure and cloud capabilities

Model development, testing and deployment processes

DevOps and MLOps maturity

Integration with enterprise applications and systems

Scalability and performance management

Security and compliance automation

Edge computing and IoT integration

3.1.4. Dimension 4: Talent, skills and organizational culture

Recognizing the critical importance of human capital, this dimension assesses organizational capacity for AI-driven transformation. Assessment areas include:

- Talent acquisition and retention for AI roles
- Training and continuous learning programs
- AI literacy across the organization
- Organizational culture supporting innovation and experimentation
- Change management capabilities
- Diversity and inclusion in AI teams
- Performance incentive alignment with AI outcomes

3.1.5. Dimension 5: Product and service innovation

- This dimension evaluates how effectively AI is being embedded in products, services and business models [1]. Key areas include:
- AI-enabled product features and capabilities
- Service innovation and new business models
- Customer experience enhancement through AI
- Personalization and recommendation capabilities
- Predictive and prescriptive analytics integration
- Platform-based business model evolution
- Continuous product learning and adaptation

3.1.6. Dimension 6: Organizational processes and operations

This dimension assesses AI integration into core business processes. Assessment areas include:

- Process automation and optimization
- Decision support and autonomous decision-making
- Operational efficiency improvements
- Quality assurance and compliance automation
- Resource optimization
- Supply chain and logistics AI applications
- Real-time monitoring and anomaly detection

3.1.7. Dimension 7: External ecosystem and market responsiveness

Recognizing the networked nature of modern enterprises, this dimension assesses the organization's ability to leverage external partnerships and respond to market dynamic. Key areas include:

- Partnership and ecosystem management
- API-led connectivity and service integration
- Customer-centric AI capabilities
- Competitive intelligence and market responsiveness
- Industry collaboration and standards participation
- Platform economy participation
- Dynamic capability development

3.2. Maturity levels and progression

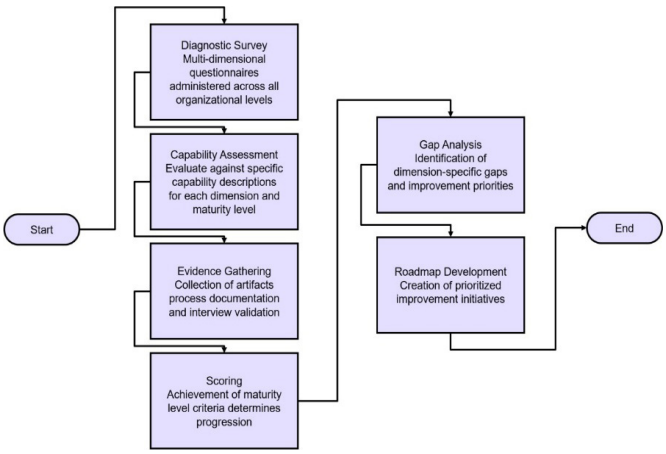
Each dimension is assessed across five maturity levels:

- **Level 1 - Initial (Ad Hoc):** AI activities are sporadic, reactive to immediate needs, with minimal planning or coordination. Success depends on heroic individual efforts rather than established processes.
- **Level 2 - Developing (Repeatable):** AI initiatives follow basic processes and show awareness of AI's strategic potential. Basic skills exist, but approaches lack consistency across the organization. Some documented successes with replicable approaches beginning to emerge.
- **Level 3 - Defined (Standardized):** AI strategies are formally documented and integrated with business planning. Standardized processes exist for AI development and deployment. Skilled teams are established and learning from projects is captured.
- **Level 4 - Managed (Measured):** AI initiatives are managed with metrics and data-driven decision making. Quantitative targets exist and are tracked. Infrastructure is optimized and continuous improvement processes are established. Risk management is active and systematic.
- **Level 5 - Optimized (Advanced):** AI capabilities are continuously optimized based on market feedback and emerging technologies. The organization anticipates and adapts to change proactively. Innovation is embedded

throughout and the organization leads industry standards in AI adoption.

3.3. Assessment methodology

Assessment follows a structured process. The following diagram shows steps for the proposed methodology:



- **Diagnostic survey:** Multi-dimensional questionnaires administered to representatives across all organizational levels
- **Capability assessment:** For each dimension and maturity level, specific capability descriptions provide clear evaluation criteria
- **Evidence gathering:** Collection of artifacts, process documentation and interview validation
- **Scoring:** Achievement of maturity level criteria determines progression
- **Gap analysis:** Identification of dimension-specific gaps and improvement priorities
- **Roadmap development:** Creation of prioritized improvement initiatives

3.4. AI maturity heatmap

With the dimensionality and maturity levels each organization should be able to assess its AI maturity using an AI Maturity Heatmap. The AI Maturity Heatmap would be a 2X2 metric that provides dimensionalities in the vertical columns and Maturity levels in the horizontal level.

	Governance	Data Architecture	Technology	Org Culture	Innovation	Process C Operations	Ecosystem
Initial							
Developing							
Defined							
Managed							
Optimized							

Organizations can assess their existing maturity state and target maturity state and based on the aspirational state align initiatives to set the roadmap.

4. Comparison with Industry Standards: CMMI and TOGAF

4.1. CMMI (Capability Maturity Model Integration)

CMMI represents the most established maturity model framework in software and systems development. Its contributions to structured process improvement are substantial and its five-level maturity structure has proven effective across diverse domains.

4.1.1. Alignment with CMMI: The proposed E-AIMM adopts CMMI's fundamental structure of five maturity levels and the concept of measured, progressively improving capabilities[3]. The governance and process dimensions of E-AIMM explicitly incorporate CMMI principles, particularly regarding process discipline and measurement. Recent research applying CMMI to AI governance demonstrates the framework's relevance[6]. Comparative analyses of maturity model approaches provide additional validation[15].

Key Differences:

Aspect	CMMI	**E-AIMM**
Scope	Software and systems development processes	Enterprise-wide AI transformation
Primary Focus	Process maturity and capability	Multidimensional transformation including culture, strategy, ecosystem
Data Emphasis	Implicit in software development	Explicit, foundational dimension
Governance	Process governance and quality	Governance + AI ethics + risk + compliance
Talent Dimension	Staffing and training (process area)	Comprehensive talent strategy dimension
Innovation Focus	Continuous improvement within processes	Radical innovation and business model change
Ecosystem Consideration	Limited (supplier management only)	Explicit dimension covering partnerships and market responsiveness
Business Alignment	Implicit through organizational context	Explicit strategic alignment dimension

CMMI's strength lies in providing rigorous process discipline, which remains essential for AI development. However, CMMI was designed for environments where requirements can be relatively well-specified and where process discipline directly correlates with quality. AI systems, particularly those involving machine learning, operate in conditions of greater uncertainty and require simultaneous innovation in business models organizational structures and technology stacks[16].

The E-AIMM extends CMMI principles by explicitly incorporating dimensions that CMMI treats only implicitly, if at all. Strategic alignment, for example, receives minimal attention in CMMI, yet represents a critical determinant of AI project success. Similarly, the talent dimension in CMMI focuses narrowly on staffing and training for established roles, whereas E-AIMM requires comprehensive assessment of skills development organizational culture and change management.

4.2. TOGAF (The Open Group Architecture Framework)

TOGAF represents the leading enterprise architecture framework, addressing the systematic design and management of enterprise information systems and infrastructure. It provides structured guidance for architecture development through its Architecture Development Method (ADM).

4.2.1. Alignment with TOGAF: The E-AIMM incorporates TOGAF's systematic approach to architecture development and its recognition of multiple architecture domains: business, information, applications and technology[9]. The Technological Capabilities and Infrastructure dimension of E-AIMM aligns closely with TOGAF's technology architecture domain, while the Strategic Alignment dimension resonates with TOGAF's emphasis on business architecture.

The integration of AI within enterprise architecture frameworks has been explicitly addressed in recent research [17], demonstrating the necessity of extending traditional TOGAF approaches to encompass AI-specific considerations including model governance, data architecture for AI and intelligent automation. Recent frameworks further demonstrate how TOGAF principles apply to AI-driven enterprise transformation[18].

4.2.2. Key differences:

Evaluation Criterion	TOGAF	CMMI	E-AIMM
Primary Objective	Architect enterprise transformation	Improve organizational process capability	Assess and accelerate enterprise AI maturity
Core Strength	Holistic alignment of business, data, applications and technology	Process discipline, quality and repeatability	AI strategy, governance and enterprise-scale AI adoption
Strategic Perspective	Enterprise-wide architecture planning	Operational excellence	AI-driven business transformation
Architectural Depth	Very High	Low	Moderate
Business–Technology Alignment	Excellent	Moderate	High
Governance Focus	Architecture governance	Process governance	AI governance, ethics and model lifecycle
Support for AIs GenAI	Limited; requires extensions	Minimal	Native capability
Support for Agentic AI	Not explicitly addressed	None	Emerging focus
Transformation Guidance	Structured through ADM	Process improvement roadmap	AI capability evolution roadmap
Primary Limitation	Developed before the AI era; lacks guidance for autonomous systems	Process-centric with limited strategic or architectural guidance	AI-focused but lacks the architectural breadth and governance depth of mature EA frameworks
Best Fit	Enterprise-wide digital transformation	Organizations seeking operational maturity	Enterprises scaling AI capabilities responsibly
Research Perspective	Remains the benchmark for enterprise architecture but requires modernization for AI-native enterprises.	Valuable for improving execution capability, yet insufficient as a strategic transformation framework.	Addresses the AI capability gap but should complement—not replace—an enterprise architecture framework.

TOGAF excels at providing structured approaches to complex IT architecture challenges and establishing governance over technology assets. Its systematic method for architecture development-defining baselines, target states and transition roadmaps-provides valuable patterns that E-AIMM assessment incorporates.

However, TOGAF's primary limitation in the AI context stems from its traditional IT infrastructure focus. While recent extensions to TOGAF incorporating AI considerations demonstrate the need, the framework fundamentally approaches architecture from an infrastructure and systems integration perspective rather than from an organizational transformation perspective. AI maturity extends far beyond infrastructure considerations to encompass strategic decision-making organizational culture evolution, business model innovation and ecosystem dynamics[19].

4.3. Synthesized framework: Bridging CMMI, TOGAF and E-AIMM

Organizations implementing enterprise AI benefit from integrating insights from CMMI, TOGAF and E-AIMM: From CMMI, adopt: - Rigorous process discipline for AI development and deployment - Measurement-based management of AI initiatives - Emphasis on organizational process assets and lessons learned - Quantitative quality management.

From TOGAF, adopt: - Systematic architecture governance and standards - Structured approach to defining target states and transition plans - Integration of business, information, application and technology architectures - Stakeholder alignment and communication mechanisms.

From E-AIMM, adopt: - Explicit multidimensional assessment across strategic organizational, technological and ecosystem dimensions - Recognition of talent and cultural transformation requirements - Business model innovation and value creation focus

- Acknowledgment of external partnership ecosystems - Governance frameworks specific to AI risks and ethical considerations

5. Implementation Guidance and Practical Application

5.1. Assessment process

Organizations implementing E-AIMM should follow a structured assessment approach:

- **Phase 1:** Preparation - Identify assessment sponsors and steering committee - Define assessment scope and boundaries - Select assessment team with diverse expertise - Communicate objectives and process to stakeholders
- **Phase 2:** Current State Assessment - Administer diagnostic

surveys across organization - Conduct structured interviews with key stakeholders - Review existing documentation, projects and capabilities - Gather evidence for each dimension

- **Phase 3:** Analysis and Scoring - Score current capabilities against dimension-specific maturity criteria - Create capability matrix showing current state across dimensions - Identify strengths and critical gaps - Validate findings with stakeholders
- **Phase 4:** Roadmap Development - Prioritize improvement initiatives based on strategic importance and dependencies - Define transition steps from current to target maturity - Identify required investments in talent, infrastructure and capabilities - Establish success metrics and accountability
- **Phase 5:** Implementation and Monitoring - Execute prioritized improvement initiatives - Establish governance and monitoring mechanisms - Track progress against roadmap - Conduct periodic reassessment.

5.2. Case study application

Consider a traditional manufacturing enterprise seeking to establish enterprise-wide AI capabilities. Assessment across E-AIMM dimensions would reveal:

- **Strategic alignment (Level 2):** Emerging AI strategy but limited board engagement; siloed initiatives
- **Data architecture (Level 1):** Legacy systems, poor data integration, limited governance
- **Technological capabilities (Level 2):** Pilot projects underway, but no integrated MLOps infrastructure
- **Talent (Level 1):** Few AI specialists, limited training programs, culture skeptical of automation
- **Product innovation (Level 1):** No AI-enabled products, early exploration of possibilities
- **Operations (Level 2):** Automation in isolated processes, limited intelligent decision-making
- **Ecosystem (Level 1):** Limited partnerships, primarily internal capability focus

This assessment immediately reveals that technical infrastructure improvements alone would be insufficient without simultaneous development across strategic alignment, data architecture, talent development and organizational culture. A roadmap addressing these interdependencies would likely prioritize:

- Executive alignment on AI strategy (Strategic Alignment)
- Data governance and master data management (Data Architecture)
- Targeted recruitment and training (Talent)
- First AI-enabled product prototype (Product Innovation)
- MLOps infrastructure (Technology)
- Pilot automation projects (Operations)
- Partnership identification (Ecosystem)

The interdependencies between these initiatives would be explicitly managed, recognizing that progress in one dimension enables advancement in others.

6. Discussion: Critical Implementation Considerations

6.1. Organizational context variation

The E-AIMM framework requires adaptation based on organizational context including:

- **Industry and sector:** AI applications and maturity requirements vary significantly between financial services, manufacturing, healthcare and other sectors[9].
- **Organization size:** SMEs face different capability development challenges than large enterprises.
- **Existing technology maturity:** Organizations with advanced cloud and data infrastructure face different acceleration paths than those with legacy systems.
- **AI strategy orientation:** Organizations pursuing product innovation require different maturity paths than those focused on operational efficiency.

6.2. Temporal dynamics

AI maturity is not static. The framework should explicitly acknowledge:

- **Technology evolution:** Rapid advancement in AI capabilities creates moving targets for maturity assessment
- **Competitive dynamics:** Market pressures create urgency for acceleration that must be balanced against sustainable capability development
- **Organizational learning:** Capabilities developed for initial AI applications must evolve for successive waves of AI innovation

6.3. Ethical and responsible AI integration

While governance dimension addresses responsible AI, implementation requires explicit attention to:

- **Bias and fairness:** Systematic assessment of AI system fairness across protected characteristics
- **Explainability and transparency:** Requirements for model interpretability across different stakeholder groups
- **Privacy and security:** Particularly critical in AI contexts involving personal data [21]
- **Accountability mechanisms:** Clear assignment of responsibility for AI system behavior

7. Limitations and Future Research Directions

7.1. Model limitations

The proposed E-AIMM has several acknowledged limitations:

- **Complexity:** The seven-dimension framework is more complex than some existing models, potentially creating assessment burden
- **Measurement challenges:** Quantifying maturity across dimensions with subjective elements (culture, governance, ecosystem) presents challenges
- **Context sensitivity:** Generic assessment criteria may require significant customization for specific industries and organization types
- **Validation status:** Empirical validation through large-scale application remains ongoing

7.2. Future research directions

Promising areas for future development include:

- **Sector-Specific models:** Development of industry-specific maturity frameworks building on E-AIMM principles
- **Quantitative metrics:** Development of robust quantitative measures for currently subjective dimensions
- **Accelerated maturity pathways:** Research into strategies for organizations to rapidly advance maturity levels
- **Technology-specific considerations:** Explicit frameworks for different AI technologies
- **Small and medium enterprise adaptations:** Simplified models applicable to resource-constrained organizations[22]
- **International and cultural factors:** Consideration of how cultural contexts influence AI maturity progression

8. Conclusion

The acceleration of AI adoption across enterprises has created urgent need for comprehensive, multidimensional frameworks to assess organizational readiness and guide systematic transformation. Existing maturity models, while valuable contributions, inadequately address the full scope of organizational change required for successful enterprise AI implementation.

The proposed Enhanced AI Maturity Model addresses critical shortcomings by:

- **Expanding beyond technology:** Explicitly incorporating strategic organizational, cultural and ecosystem dimensions alongside technical capabilities.
- **Recognizing multidimensionality:** Acknowledging that AI maturity advances progressively across multiple interdependent dimensions.
- **Addressing talent and culture:** Elevating human capital and organizational culture from implicit considerations to explicit assessment dimensions.
- **Governance and ethics:** Embedding responsible AI governance as foundational rather than supplementary.
- **Business value focus:** Centering assessment on value creation and business outcomes rather than process compliance alone.

Comparison with established frameworks (CMMI and TOGAF) demonstrates that while these models provide valuable foundations, AI transformation requires extended frameworks that simultaneously address process discipline (CMMI), architectural governance (TOGAF) and organizational transformation (E-AIMM).

Organizations implementing this framework should recognize that AI maturity represents an ongoing journey rather than a destination. The framework provides structured guidance for assessing current capabilities, identifying improvement priorities and managing the complex transformations required for successful enterprise AI adoption.

As AI technologies continue to evolve and organizational approaches mature, maturity frameworks themselves must evolve. The E-AIMM provides a foundation upon which future refinements can build, incorporating insights from ongoing implementation experiences, emerging technologies and evolving best practices.

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