

A conceptual framework for AI Maturity Assessment in Technology Supply Chains

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ABSTRACT

Artificial Intelligence (AI) has become a fundamental part of technological supply chains which now use AI for better demand prediction, fraud prevention, risk assessment and efficiency improvement. Organizations face a problem with AI assessment because they currently operate in multiple supply chain environments yet need an assessment method which lacks standardization and specific industry guidelines. The current AI maturity frameworks focus only on business organizations which makes them unsuitable for measuring technology supply chain systems because they fail to account for dependencies and data exchange and system compatibility issues. The research introduces a new conceptual framework which enables organizations to assess their AI maturity through a dedicated framework for technology supply chains. The framework introduces a multi-dimensional structure which includes data readiness and model capability and infrastructure scalability and governance and ethics and interoperability and risk and resilience and organizational capability. The evaluation process assesses these dimensions through a five-level maturity continuum which starts from basic adoption and ends with complete automated AI implementation.

The study establishes a complete assessment system which includes measurable performance indicators and assessment scoring system to conduct structured evaluations and performance comparisons. The framework becomes more understandable through its demonstration in real-world financial technology applications and cloud ecosystem operations and healthcare data systems. The implementation guide provides organizations with a step-by-step process to develop their artificial intelligence capabilities while reducing operational and systemic dangers. The research introduces a scalable assessment tool which assesses AI maturity in technology supply chains to benefit researchers and industry professionals. The proposed framework addresses a critical gap in current literature and provides a foundation for future empirical validation and industry standardization.

Keywords: Artificial Intelligence Maturity, Technology Supply Chains, AI Governance, Data Interoperability, Supply Chain Analytics, Maturity Assessment Framework, AI Risk and Resilience

1. INTRODUCTION

The implementation of Artificial Intelligence (AI) functions as a key element which drives changes throughout current digital systems especially in technology supply chains which support financial operations and cloud computing systems and data-driven services. Modern supply chains function as complex networks which interlink multiple data providers and platform operators and algorithm developers who provide services to end users. Artificial Intelligence enables organizations to perform essential tasks which include detecting fraud in real time conducting predictive analysis and making automated decisions and optimizing their systems. The complete implementation of artificial intelligence systems into technological supply chains creates multiple operational challenges which must be overcome. Supply chain artificial intelligence systems function through multiple organizations because they depend on different data types and use various external systems and their entire network. The current system creates difficulties which include problems with data sharing between different systems and issues regarding the dependability of models and challenges with managing operations and the risk of major system failures.

Organizations require AI maturity evaluation because they increasingly rely on AI systems which operate in interconnected AI ecosystems.

The existing AI maturity models serve organizations by showing their current operational abilities while providing insights into their future growth potential. The majority of frameworks follow an enterprise-focused approach that examines organizations' internal strengths which include their data systems and employee resources and their capacity to implement models. The models provide useful insights but they do not capture the complete operational needs of technology supply chains which depend on cross-organizational relationships and data sharing systems and the risks that result from AI system interconnections. The current situation lacks common methods to assess AI maturity in environments where multiple users work together to enhance system operation. This paper addresses this gap by proposing a conceptual framework for AI maturity assessment specifically designed for technology supply chains. The framework establishes a multi-dimensional model which includes both technical requirements and organizational demands of AI implementation together with the supply chain ecosystem interdependencies that exist in the system. The framework establishes multiple evaluation pathways which show how AI capabilities develop through different stages in complex systems that operate across multiple locations.

The study presents a practical assessment methodology which uses measurable indicators and a structured scoring system to evaluate its assessment framework. The framework demonstrates its relevance and applicability through use cases that show its operation in financial technology and cloud-based AI systems and healthcare data supply chains. The organization should follow the proposed implementation roadmap to achieve AI maturity which includes protection against governance risks and risk management and system integration problems. The paper presents three main contributions to scientific knowledge. The first contribution extends AI maturity as a concept which now includes technology supply chains beyond its original scope of enterprise assessment. The second contribution presents a structured multi-dimensional framework which enables better understanding of AI deployment challenges in environments with multiple actors. The assessment methodology and implementation roadmap provide practical guidance which connects theoretical concepts with real-world applications.

2. LITERATURE REVIEW AND CONCEPTUAL BACKGROUND

2.1 AI in Technology Supply Chains

The modern supply chains of technology-driven systems which operate with multiple data sources and remote processing capabilities use Artificial Intelligence (AI) as their primary technological driver for operational transformation. The multiple functions of AI technology include demand forecasting and fraud detection and predictive maintenance and vendor risk assessment. The financial technology and cloud computing and healthcare sectors use these applications because they need to process real-time data for their decision-making tasks (Ivanov & Dolgui, 2020; Wamba et al., 2020). The technology supply chains function as interconnected networks which connect data providers with platform operators and service consumers, in contrast to traditional supply chains. The AI systems built in these systems operate through continuous data sharing which takes place between different organizations, while using both cloud-based systems and third-party application programming interfaces (APIs) as their primary data-sharing methods. The internal capabilities of a system determine its performance, yet the system's external components need to function well to guarantee reliable system output (Kshetri, 2021).

The distributed design of the system with its interconnected components creates new difficulties for AI system management and assessment. The supply chain experiences disruptions when upstream data sources fail or platform services go down because these issues affect the entirety of the system. The evaluation of AI maturity in these environments needs an expanded framework that includes both organizational relationships and all system interactions.

Existing AI and Digital Maturity Models

Organizations have used maturity models for many years to measure their capabilities and to develop their digital transformation strategies. The Capability Maturity Model Integration (CMMI) and other traditional frameworks which exist before it work to establish standardized processes and help organizations achieve progress (Paulk et al., 1993). Recent digital maturity models now evaluate enterprise technological adoption and data utilization and

innovation potential using their existing methods (Westerman et al., 2012). Organizations need AI maturity models to prepare themselves for assessing their AI readiness and building their AI capabilities. The models perform assessments on four main areas which include data infrastructure and algorithmic sophistication and talent availability and governance structures (Davenport & Ronanki, 2018; Fountaine et al., 2019). These frameworks help organizations understand their internal AI abilities. However, the frameworks focus on single businesses and fail to handle the complex nature of AI usage which occurs when multiple parties work together. The current models used in research studies fail to include external dependencies because they focus exclusively on different organizational boundaries. AI systems in technology supply chains require data and services from various external sources, which creates an urgent need for organizations to establish proper interoperability and coordination controls. The existing maturity frameworks do not provide solutions for cross-platform integration and data exchange standards and shared governance mechanisms. The systems provide an incomplete understanding of AI maturity which exists within distributed ecosystems.

Challenges in AI-Driven Supply Chain Ecosystems

AI integration into technology supply chains creates multiple implementation and assessment hurdles for organizations. The primary challenge for organizations arises from data fragmentation because organizations produce and archive data through different systems that use distinct formats and standards. (Chen et al. 2012) state that data integration becomes difficult because of inconsistent data patterns which decrease AI model performance. Interoperability represents a critical situation because different platforms and services need to work together without problems during their use. AI systems face restrictions because of multiple interface problems and different data structure requirements which decrease both their operational capacity and processing speed. Organizations face governance problems because they must secure data privacy while meeting security needs and following various jurisdictional regulatory frameworks (Kshetri 2021). The landscape becomes more complex because of model-related risks. AI systems experience trust and reliability issues because they suffer from bias problems and model drift and lack of explainability (Amershi et al. 2019). The interconnected nature of supply chains leads to more severe risks because any error at one point will affect the entire system. The monitoring system needs effective evaluation methods because localized failures between different regions create a significant risk which impacts the entire system. The absence of standardized approaches to assess AI maturity exacerbates these challenges. Organizations need a complete framework to assess their AI abilities and weaknesses because it enables them to find and rank their development areas.

2.4 Research Gap

The supply chains of technology companies have started to adopt AI technologies more frequently yet there is no standard method to evaluate AI maturity in these supply chain environments. Existing models primarily focus on internal organizational capabilities and do not account for the distributed nature of supply chain ecosystems that depend on multiple entities. The crucial components of interoperability and cross-entity data dependencies and systemic risk remain mostly unexamined. The gap between theories and practical uses is restricted by this gap. The research needs frameworks that study multiple systems which exist beyond normal business operations. The industry faces obstacles with its benchmark evaluations along with its risk control processes and its strategic development activities.

2.5 Positioning of This Study

The paper presents a new framework which evaluates AI maturity for technology supply chains because the current evaluation methods have critical deficiencies. The framework uses multiple dimensions to assess AI capabilities through its three main elements which include technical and organizational and inter-organizational elements. The proposed framework extends current maturity models through its evaluation of data readiness and system interoperability and organizational governance and system resilience to risks. The research presents an evaluation system with a detailed implementation guide which demonstrates practical use of theoretical concepts. The research study will serve as a theoretical framework for AI maturity research while providing a practical resource for organizations that work in intricate technology environments.

3. CONCEPTUAL FOUNDATIONS

3.1 Defining AI Maturity

AI maturity measures how well an organization or system uses artificial intelligence capabilities to meet its strategic and operational goals through their entire development and deployment and integration and management process. The process involves establishing AI-based systems which organizations need to develop their full operational capacity to maintain these systems through ongoing development and performance improvement (Davenport & Ronanki, 2018; Fountaine et al., 2019). Existing research studies use data availability and technological infrastructure and talent and organizational alignment as dimensions to measure AI maturity. The definitions used here limit their application to enterprise-level capabilities which fail to address the complexities that arise from distributed systems which depend on multiple interrelated components. AI adoption and AI capability and AI maturity represent three separate concepts which show some relationships to each other. AI adoption refers to the initial implementation of AI technologies within specific processes or functions. AI capability requires organizations to develop the technical and organizational skills that enable them to construct and operate AI systems. AI maturity develops to an advanced state when organizations use AI to handle various system operations which drive ongoing improvement and development across multiple system components. AI maturity according to technology supply chains needs to expand its scope from internal process improvement to encompass all organizational collaborations which create a more complex and multi-dimensional system.

3.2 Technology Supply Chains as Socio-Technical Systems

The technology supply chains operate differently from the conventional supply chains because they depend on digital infrastructure and data streams and platform-based system connections. The supply chains operate through their different elements which include data sources and cloud computing platforms and AI model creators and user-facing software applications. The systems can be understood as socio-technical systems because technical systems and human systems of organization exist in deep connection (Bostrom & Heinen, 1977). The value creation process in these environments depends on organizations using data and algorithms and infrastructure systems which work together without interruption. The interconnected systems lead to security weaknesses because of their design. The usage of third-party services together with external data dependencies and shared platform systems establishes intricate risk patterns which do not appear in systems that maintain centralized control (Ivanov & Dolgui, 2020). The technology supply chain decision-making process becomes more automated through AI systems which reduce the need for human control while increasing demands for system dependability and operational transparency. Organizations need to develop new strategies which assess performance metrics and risk assessment procedures through their testing of network systems which experience frequent total breakdowns. The socio-technical approach to technology supply chains reveals that organizations require maturity assessment systems which need to evaluate their technical strengths and their capacity to coordinate operations.

3.3 Interdependencies and Systemic Risk in AI Ecosystems

The main feature which distinguishes AI-based systems in supply chain operations shows that their different parts maintain strong relationships with one another. AI systems operate through three connected parts which include their data sources and processing systems and output delivery methods which create both value and risk elements. Systemic risk represents a primary threat to these systems because supply chain disturbances in one area create domino effects which impact the whole network. Upstream data errors create model output mistakes which then lead to incorrect decision-making in the downstream process. The failure of cloud systems together with API services results in multiple AI systems becoming nonoperational at the same time (Kshetri, 2021). AI systems create operational dangers together with specific dangers which stem from their models. The high-stakes field of finance together with the high-stakes field of healthcare show particular concern about these threats because their incorrect predictions produce severe outcomes (Amershi et al., 2019). The interconnected nature of these risks demonstrates that AI maturity testing needs to happen at system level assessment instead of single element evaluation. The complete framework requires assessment systems which measure supply chain resilience and supply chain robustness and supply chain risk distribution.

3.4 Dimensions of AI Capability in Distributed Environments

The assessment of AI maturity in technology supply chains requires the identification of fundamental elements which determine AI capability in distributed systems. Previous studies established that successful AI implementation relies on three essential elements which encompass technical aspects along with organizational components and governance mechanisms (Davenport & Ronanki, 2018; Fountaine et al., 2019). AI systems depend on two critical elements because organizations require both data readiness and proper infrastructure to operate their systems. Organizations need high-quality data that works well with their systems because it helps improve their model performance while their infrastructure needs to handle both deployment and immediate data processing. The organizational components of AI implementation include talent management along with leadership development and strategic business operations. Additional dimensions emerge in global supply chains which extend beyond basic operational requirements. Interoperability refers to the capacity of systems to share and use data which serves as a fundamental factor that impacts system performance. Organizations need governance mechanisms because they serve as crucial tools to achieve compliance requirements and handle risks and maintain trustworthiness among different organizational entities. The study's proposed multi-dimensional framework establishes its theoretical foundation through these specific dimensions of study. The framework combines technical elements with organizational components and inter-organizational elements to deliver a complete evaluation of AI development across sophisticated systems.

3.5 Conceptual Basis for the Proposed Framework

This study uses systems thinking to define AI technology maturity in supply chains according to the previous discussion. The proposed framework is grounded in three key principles: First, AI maturity requires organizations to develop four essential elements which include data and technology and governance and organizational capabilities. Second, it is evolutionary, progressing through distinct stages from initial adoption to full optimization. Third, it exists as an ecosystem-dependent entity which derives its structure from the social interactions between various participants who work within the supply chain system. The framework structure found in Section 4 uses these principles to create dimensions and maturity levels which measure the advanced stages of artificial intelligence implementation across various operational settings. The framework establishes a connection between theoretical concepts and real-world assessment requirements to establish a method for assessing practical applications.

4. PROPOSED AI MATURITY FRAMEWORK FOR TECHNOLOGY SUPPLY CHAINS

4.1 Framework Overview

The researchers developed a multi-dimensional AI maturity framework which applies to technology supply chains. The framework developed by the researchers shows how AI-enabled ecosystems function through their decentralized operational model which requires multiple actors to work together. The framework consists of two main structure components which include: (1) AI capability dimensions which define essential elements needed for successful AI implementation and (2) maturity levels which show how AI systems progress from their early stages to full autonomous operation. The framework uses both technical and organizational assessment methods to measure AI maturity because it includes technology supply chain inter-organizational relationships that operate between different organizations. The framework achieves three major design objectives which include: The system needs to assess multiple capability levels through its multiple assessment dimensions. The system needs to assess multiple capability levels through its multiple assessment dimensions. The system needs to assess multiple capability levels through its multiple assessment dimensions.

4.2 Core Dimensions of AI Maturity

The proposed framework consists of seven key dimensions that collectively define AI maturity in technology supply chains.

4.2.1 Data Readiness

Data readiness refers to the availability, quality, integration, and accessibility of data required for AI model development and deployment. In technology supply chains, this includes not only internal datasets but also external data sources obtained from upstream partners and third-party providers.

High maturity in this dimension is characterized by:

- Standardized data formats
- Real-time data integration
- Strong data governance practices
- Low maturity environments, by contrast, are marked by fragmented, inconsistent, and siloed data.

4.2.2 Model Capability

The model capability demonstrates three essential aspects of AI models which include their operational performance capabilities and their testing results. The assessment encompasses four primary elements which include predictive accuracy and system resilience and user explanation capabilities and system adaptability to different operational environments. Advanced maturity levels in this dimension include: Use of advanced machine learning techniques Continuous model monitoring and retraining Explainable AI mechanisms

4.2.3 Infrastructure and Scalability

The dimension assesses all technological components that enable AI systems which include cloud computing resources and data processing systems and MLOps operational frameworks. Technology supply chains depend on scalability because their systems must process extensive data together with immediate data processing requirements. High maturity is indicated by: Cloud-native architectures Automated deployment pipelines Scalable and resilient infrastructure

4.2.4 Governance and Ethical AI

Governance refers to the policies and standards which establish controls that guarantee responsible and lawful AI usage. The system handles data privacy and regulatory compliance while implementing bias mitigation measures together with audit functionality. Governance in distributed supply chains requires organizations to collaborate with different stakeholders throughout their operational network. Mature systems demonstrate: Formal governance frameworks Transparent decision-making processes Continuous compliance monitoring

4.2.5 Interoperability and Integration

Interoperability is a defining feature of technology supply chains and refers to the ability of systems to exchange and utilize data seamlessly across platforms and organizations.

This dimension includes:

- API standardization
- Cross-platform compatibility
- Data exchange protocols
- High maturity is achieved when AI systems are fully integrated across the supply chain, enabling seamless data flow and coordinated decision-making.

4.2.6 Risk and Resilience

This dimension addresses the ability of AI systems to manage and mitigate risks, including operational failures, cyber threats, and model-related risks such as bias and drift.

In interconnected environments, resilience is critical to prevent cascading failures.

Indicators of high maturity include:

- Real-time monitoring systems
- Robust failure recovery mechanisms

- Proactive risk assessment strategies

4.2.7 Organizational and Human Capability

AI maturity requires technical expertise and organizational readiness and human expertise. This dimension measures three components: skilled personnel availability and leadership support and AI implementation into decision-making. High maturity organizations exhibit: Strong AI talent pipelines Cross-functional collaboration Alignment between AI initiatives and business strategy.

4.3 AI Maturity Levels

The framework defines five progressive levels of AI maturity, reflecting the evolution from basic adoption to fully optimized systems.

Level 1: Ad Hoc

Minimal AI usage

Isolated experiments

Lack of structured data and infrastructure

Level 2: Emerging

Initial AI adoption in specific functions

Basic data infrastructure

Limited integration across systems

Level 3: Operational

AI systems deployed in production

Standardized processes

Moderate integration and governance

Level 4: Integrated

AI fully embedded across supply chain processes

Strong interoperability across platforms

Coordinated governance across organizations

Level 5: Optimized / Autonomous

Self-improving AI systems

Real-time decision-making across the supply chain

High resilience and minimal human intervention

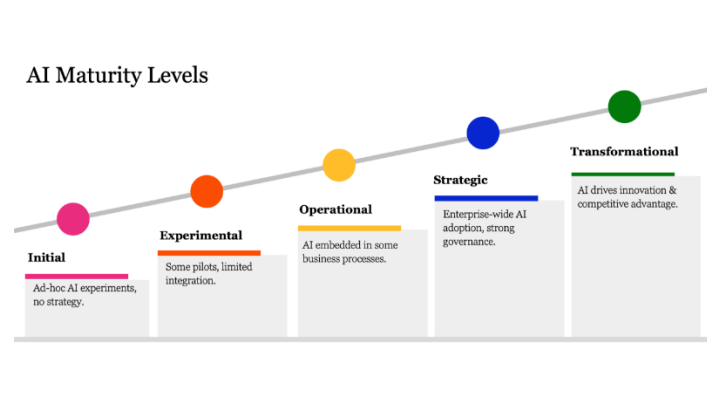


Figure 1. General AI maturity model

4.4 AI Maturity Matrix

The matrix structure emerges from combining dimensions with maturity levels to assess each dimension across five different maturity levels. The matrix provides three main functions which include: The system evaluates strengths and weaknesses through multiple dimensions Organizations can use the system for benchmarking purposes The system helps organizations develop specific improvement plans The matrix defines each maturity state through its respective cell which includes both qualitative and quantitative assessment elements. The Data Readiness Level 3 Operational rating shows that internal datasets have been standardized but external data integration remains restricted.

4.5 Framework Characteristics and Differentiation

The framework proposed in this study establishes multiple fundamental distinctions from present AI maturity assessment frameworks. The framework uses an ecosystem-based approach which requires organizations to assess their interconnections with other organizations. The traditional framework requires organizations to develop their internal strengths without considering their external interdependencies. The framework defines risk and resilience as essential elements because organizations need to handle interconnected environments which lead to systemic risk. The framework requires assessment of AI maturity through interoperability which acts as an essential yet frequently neglected component. The framework establishes a dual purpose of delivering both academic depth and real-world usability through its combination of fundamental theories and evaluation methods which can be used in practice.

4.6 Operationalization of the Framework

The framework can be operationalized through a structured assessment process which enables its practical application. Organizations begin by evaluating their current state across each dimension using predefined indicators. The assessment process assigns scores according to the maturity level characteristics which the assessment process evaluates. The combined scores create an overall AI maturity profile for assessment. The resulting profile enables: Gap analysis Strategic planning Progress tracking over time The operational method converts the framework from its theoretical form into a useful instrument which supports decision-making and performance enhancement.

5. ASSESSMENT METHODOLOGY

5.1 Overview of the Assessment Approach

The study implements its AI maturity framework through a structured assessment method which evaluates AI abilities throughout technology supply chains. The assessment method differs from traditional maturity assessments because it evaluates organizational capacity with the actual operations of organizations and their interdependencies which represent the shared structure of AI ecosystems (Kshetri, 2021; Ivanov & Dolgui, 2020). The methodology transforms the conceptual framework into a repeatable assessment system which organizations use to measure their performance against benchmarks and identify missing capabilities for making strategic choices. The system includes three main elements which together create the complete assessment process: (1) dimension-specific indicators, (2) a

standardized scoring mechanism, and (3) an aggregation model for overall maturity evaluation. The method establishes assessment criteria through qualitative evaluations together with numerical data which validates the need to examine technical performance together with organizational and governance elements during AI evaluation (Davenport & Ronanki, 2018; Fontaine et al., 2019).

5.2 Dimension-Specific Indicators

Each dimension of the proposed framework is operationalized through a set of indicators that capture the organization’s level of AI capability. These indicators are designed to reflect both internal system performance and the degree of integration with external entities within the supply chain.

Consistent with prior studies on digital and AI maturity, indicators are defined to cover data, technology, governance, and organizational readiness (Davenport & Ronanki, 2018; Westerman et al., 2012). However, this framework extends these dimensions by incorporating interoperability and systemic risk considerations specific to distributed environments.

The key indicators for each dimension include:

Data Readiness: data quality, completeness, standardization, and real-time accessibility across internal and external sources. High-quality data has been consistently identified as a critical driver of AI performance (Chen et al., 2012).

Model Capability: predictive performance, robustness, explainability, and adaptability to dynamic data conditions. Continuous monitoring and retraining are essential for maintaining model effectiveness in evolving environments (Amershi et al., 2019).

Infrastructure and Scalability: availability of cloud-based infrastructure, automated data pipelines, and MLOps practices that support deployment, monitoring, and scaling of AI systems.

Governance and Ethical AI: existence of formal governance frameworks, regulatory compliance, bias mitigation strategies, and auditability of AI-driven decisions.

Interoperability and Integration: ability to exchange and utilize data across systems through standardized APIs, data formats, and cross-platform compatibility. This dimension is particularly critical in multi-actor supply chains (Kshetri, 2021).

Risk and Resilience: mechanisms for detecting, managing, and mitigating risks, including system failures, cyber threats, and model-related risks such as bias and drift.

Organizational and Human Capability: availability of skilled personnel, leadership support, and integration of AI into decision-making processes. Organizational alignment has been shown to be a key determinant of AI success (Fontaine et al., 2019).

These indicators may be evaluated using a combination of quantitative metrics (e.g., model accuracy, system latency) and qualitative assessments (e.g., governance maturity, strategic alignment), enabling a comprehensive evaluation of AI maturity.

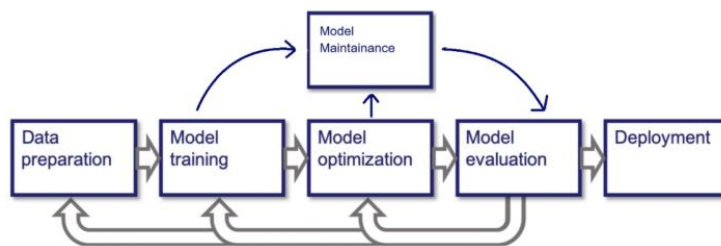


Fig 2: AI/ML lifecycle illustrating data preparation, model training, deployment, and continuous monitoring processes

5.3 Scoring Mechanism

The system evaluates each indicator through its established five-level scale which matches the maturity levels described in Section 4. Organizations follow established maturity modeling practices which require them to develop their capabilities through predefined stages (Paulk et al., 1993). Scoring Scale 1 – Ad Hoc: minimal or inconsistent practices with no formal structure 2 – Emerging: initial adoption with limited standardization 3 – Operational: established processes with moderate effectiveness 4 – Integrated: coordinated, optimized, and cross-functional systems 5 – Optimized: advanced, adaptive, and continuously improving capabilities The score for each dimension is calculated as the average of its associated indicators:

$$D_i = \frac{1}{n} \sum_{j=1}^n s_{ij}$$

where D_i represents the maturity score for dimension i , s_{ij} represents the score of indicator j , and n is the number of indicators within that dimension.

To obtain an overall assessment, dimension scores are aggregated using a weighted model:

$$\sum_{i=1}^k w_i D_i$$

where w_i represents the relative importance of each dimension and k is the total number of dimensions. This weighting mechanism allows organizations to tailor the assessment based on domain-specific priorities. For example, in financial technology environments, greater emphasis may be placed on governance and risk management, whereas cloud-based ecosystems may prioritize scalability and interoperability.

The resulting composite score provides a quantitative representation of AI maturity, enabling benchmarking, performance tracking, and identification of capability gaps across the supply chain.

6. APPLICATION SCENARIOS

6.1 Overview of Application Contexts

The section shows practical application of the proposed AI maturity framework through its testing in three different technology supply chain environments which include financial technology ecosystems, cloud-based AI platforms and healthcare data systems. The domains of this study require assessment because they contain high data volumes which create complex relationships and their operations face both internal hazards and external compliance requirements (Kshetri, 2021; Ivanov & Dolgui, 2020). The study uses the framework to show organizations how to evaluate their current maturity status while they discover their existing capability deficiencies and develop their strategic improvement priorities for different but connected operational environments.

6.2 Financial Technology Supply Chains

The financial technology sector depends on artificial intelligence systems to handle various functions like fraud detection and credit assessment and transaction oversight. The system functions through its connection to various stakeholders which include payment processing companies and banking institutions and external data suppliers and government agencies. The two main factors that determine success in this environment require organizations to maintain data readiness while their models achieve operational capacity to process actual transaction data at high precision and quick processing speed. Different organizations face difficulties when they try to work together because their data systems and technology platforms have different standards. The possibility of financial loss and operational interruptions which arise from system vulnerabilities and cybersecurity attacks drives organizations to focus on risk management and resilience building. The framework which organizations implement helps them assess three areas: The extent of real-time data integration across payment systems The robustness and explainability of fraud detection models The effectiveness of governance mechanisms in ensuring regulatory compliance For example, a fintech organization operating at an Operational (Level 3) maturity may have effective fraud detection models deployed in

production but lack full integration with external data providers, limiting its ability to detect emerging threats. Organizations need to achieve higher maturity levels through building better systems which allow different entities to work together with each other.

6.3 Cloud-Based AI Ecosystems

Modern technology supply chains depend on cloud-based AI ecosystems which provide infrastructure and platforms and services to enable enterprises to implement artificial intelligence at large scales. The ecosystem operates through multiple vendors who provide cloud services and develop APIs and create application integration solutions. In such environments, infrastructure and scalability and interoperability are dominant dimensions. Organizations must ensure that AI systems can scale efficiently while maintaining seamless integration across platforms. The use of standardized APIs and cloud-native architectures is essential for enabling data exchange and system coordination. The proposed framework allows organizations to assess: The maturity of MLOps practices, including deployment and monitoring The degree of cross-platform integration and API standardization The resilience of infrastructure to handle system failures and demand fluctuations Organizations at higher maturity levels demonstrate fully integrated, cloud-native AI systems with automated pipelines and real-time scalability. The operational procedures of lower maturity systems use separate tools which require staff to work manually, thus decreasing their productivity while creating potential threats to their business operations.

6.4 Healthcare Data Supply Chains

The field of healthcare data ecosystems stands as the most challenging and sensitive area which scientists can apply artificial intelligence. The patient data supply chain starts from hospitals and diagnostic laboratories and continues through insurance providers and digital health platforms and ends with patient data usage. The strict regulatory requirements and the need to protect patient information make governance and ethical AI and data readiness essential in this situation. Healthcare systems face major interoperability problems because their existing systems use outdated technology and different data standards. The framework enables evaluation of: Organizations need to follow data protection regulations and they must implement ethical AI practices Healthcare providers need to share their data which creates better patient care The AI systems need to show their diagnostic and predictive capabilities through transparent methods. A healthcare system at the Emerging (Level 2) maturity level has started using AI for diagnostic support but it lacks both standardized data integration and strong governance systems. Organizations need to establish better data interoperability systems which will improve their governance systems and make their model operations more visible.

6.5 Cross-Domain Insights

Applying the framework across these domains reveals several common insights. First, interoperability and data integration consistently emerge as critical challenges, regardless of industry. Second, risk and governance considerations play a central role in high-stakes environments such as finance and healthcare. Third, achieving higher levels of AI maturity requires not only technological advancement but also organizational alignment and cross-entity coordination.

These observations reinforce the importance of adopting a multi-dimensional and ecosystem-aware approach to AI maturity assessment. The proposed framework provides a structured means of capturing these complexities, enabling organizations to navigate the challenges of AI deployment in technology supply chains.

7. IMPLEMENTATION ROADMAP FOR AI MATURITY ADVANCEMENT

The technological supply chains need a systematic method which combines data systems and infrastructure and governance and organizational capabilities to achieve their target of advancing AI maturity. The research presents a phased implementation roadmap which matches the maturity levels described in Section 4 to help organizations progress from their initial AI usage to complete system optimization and resilience. The approach establishes strong alignment with previous research which demonstrates that organizations must match their technical abilities to their business procedures and strategic goals to achieve AI transformation success (Davenport & Ronanki, 2018; Fontaine et al., 2019). Organizations at their initial maturity level operate their systems with disconnected data

systems and basic infrastructure and nonexistent governance. The initial priority is therefore to establish a strong foundation by improving data quality and developing basic data pipelines and identifying high-impact use cases such as fraud detection or predictive analytics because this process requires establishing these elements. The organization must create core AI competencies through skill development because human expertise constitutes the essential element for successful AI implementation (Chen et al., 2012). The organization needs to establish standardized processes which can be repeated to advance its operations beyond its current ad hoc research activities.

The organization needs to develop its capabilities which will help them achieve their operational goals. The process includes three main activities which involve bringing machine learning models into operational settings and using MLOps for model lifecycle management and creating standardized procedures for data integration. The initial policies for governance practices begin to emerge at this point which establishes rules for data management and compliance and ethical AI practices. Organizations need to achieve complete operational integration of AI systems which should operate throughout their internal processes and their technology supply chain partner networks. The current state of the system uses standardized APIs to improve data sharing between different parties who work together. Organizations require governance frameworks which can manage data privacy issues and regulatory compliance needs and shared responsibility requirements across different organizations. Organizations need to create strong monitoring systems which allow them to control risks because their AI systems work together with other systems across multiple locations (Kshetri, 2021).

Organizations reach their most advanced level when they establish AI systems which show peak efficiency through their ability to grow and change and withstand challenges. The systems enable immediate data analysis together with decision-making capabilities which depend on automatic model updates and ongoing system performance enhancements. The organization enacts advanced risk management techniques which protect system integrity while it improves its governance procedures to tackle new ethical and legal requirements. AI systems at this point can function in either semi-autonomous or fully autonomous operation modes which allow automated self-optimizing supply chain management (Ivanov & Dolgui, 2020). All AI maturity development phases require organizations to establish strategic alignment together with governance systems which guarantee successful progression. AI projects need to operate according to business goals which company leaders across various departments need to support. The organization needs to develop governance systems which match technological progress because modern systems become more intricate and dangerous. Technology supply chains face special difficulties because their performance depends on multiple parties while responsibility gets divided between different companies. The organization needs to incorporate continuous improvement together with risk reduction into all stages of its implementation work. AI systems work within active environments which experience data pattern changes together with new technologies and regulatory changes. Organizations need to use an iterative framework which requires ongoing assessment together with user feedback and system adjustments through their development process. The system maintains its operational performance through maintained AI capabilities which meet both internal organizational requirements and external ecosystem changes.

8. DISCUSSION

The proposed AI maturity framework provides a structured approach to understanding and evaluating AI capabilities within technology supply chains. By extending maturity assessment beyond organizational boundaries, this study highlights the importance of considering interdependencies, interoperability, and systemic risk in AI-enabled ecosystems. These factors are increasingly critical as organizations rely on distributed infrastructures and external data sources to support real-time decision-making.

One of the key insights from this work is that AI maturity is not solely determined by technological sophistication but by the degree of integration across technical, organizational, and inter-organizational dimensions. While many organizations have made significant progress in developing advanced AI models, limitations in data integration, governance, and cross-platform interoperability often constrain their overall maturity. This imbalance underscores the need for a holistic assessment approach that captures the full spectrum of AI capabilities.

The framework also emphasizes the trade-offs inherent in AI maturity advancement. For instance, increasing automation and autonomy can improve efficiency and scalability but may introduce additional risks related to

transparency, accountability, and control. Similarly, greater integration across supply chain partners enhances data sharing and coordination but raises concerns regarding data privacy and security. These trade-offs must be carefully managed to ensure that AI systems deliver sustainable value without compromising reliability or trust.

In comparison to existing maturity models, the proposed framework offers a more comprehensive perspective by explicitly incorporating ecosystem-level considerations. This positions the framework as a valuable tool for both researchers and practitioners seeking to understand the complexities of AI deployment in modern technology environments.

9. IMPLICATIONS

The results of this research study produce substantial effects for academic studies, business operations, and governmental regulations. The academic field receives an extension of AI maturity research through this study because it establishes a supply chain view of the concept. The research study extends existing literature about AI governance and digital transformation and socio-technical systems by demonstrating how inter-organizational relationships develop AI capabilities. The framework functions as a basis which future studies will use to test and enhance maturity assessment models through actual field investigations. The framework developed in this study provides organizations with an effective method to evaluate and enhance their AI capabilities according to industry requirements. Organizations can achieve their goals through better financial results and operational performance improvements when they identify their strengths and weaknesses in various assessment areas. The ability to operate between different systems and maintain operational stability should be treated as essential business functions because financial technology and cloud services and healthcare industries face complex situations with multiple system components. The framework establishes a requirement for standardized methods which organizations need to implement for managing artificial intelligence systems and evaluating their maturity across different technological ecosystems. Policymakers need to solve issues about sharing data and following regulations and using ethical artificial intelligence because artificial intelligence systems are now used by organizations across different countries and their boundaries. The proposed model can guide the creation of standards and guidelines which help AI-driven systems achieve transparency and accountability and system interoperability.

10. LIMITATIONS AND FUTURE WORK

The research study has made valuable contributions, but it contains multiple research limitations. The first limitation of the proposed framework exists because the modern system lacks real-world validation through empirical testing. The framework depends on established research and real-world knowledge, but researchers must evaluate its effectiveness across various sectors and organizational settings. The assessment framework needs multiple indicators because the selected dimensions need better coverage of all AI maturity elements required for specialized domains. Organizations need to establish their own customized solutions because different industries enforce specific regulatory and technical standards that require individual solutions. The assessment method uses a weighting mechanism that organizations can customize to their needs, which creates an assessment method that contains both flexible elements and elements that depend on the specific needs of each organization. Researchers should investigate data-driven methods, which enhance weighting systems, to develop methods that assess various organizations through improved comparison techniques. The research should concentrate on testing the framework through actual case studies and extensive research that uses case studies. The proposed indicators will undergo refinement through quantitative analysis, which will also evaluate their effectiveness in predicting AI performance and organization success. The industry-specific maturity benchmarks will strengthen the framework's practical application, which will lead to increased usage by organizations.

CONCLUSION

This study presents a conceptual framework for assessing AI maturity in technology supply chains, addressing a critical gap in existing literature. Unlike traditional maturity models that focus on internal organizational capabilities, the proposed framework adopts a multi-dimensional and ecosystem-oriented perspective, capturing the complexities of AI deployment in distributed and interdependent environments.

By integrating dimensions such as data readiness, model capability, infrastructure, governance, interoperability, risk, and organizational capability, the framework provides a comprehensive approach to evaluating AI maturity. The inclusion of a structured assessment methodology and implementation roadmap further enhances its practical relevance, enabling organizations to systematically advance their AI capabilities.

The findings underscore the importance of aligning technological innovation with governance, risk management, and cross-organizational coordination. As AI continues to transform technology supply chains, the ability to assess and manage maturity will become increasingly essential for achieving sustainable and resilient systems.

Overall, this work contributes to both theory and practice by offering a scalable and actionable model for AI maturity assessment. It lays the foundation for future research and provides a valuable tool for organizations seeking to navigate the evolving landscape of AI-driven ecosystems.

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