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RESEARCH ARTICLE

From Readiness to Deployment: Evaluating AI Capabilities in Traditional Enterprises

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Abstract: The adoption of artificial intelligence (AI) in traditional enterprises remains challenging despite significant investments. While research indicates that many traditional enterprises demonstrate considerable AI readiness, a substantial gap exists between readiness levels and actual AI implementation. This paper proposes a novel Multi-Dimensional AI Readiness Assessment (MDARA) framework that bridges this gap by integrating technological infrastructure, organizational capabilities, data readiness, and implementation strategy dimensions. The framework incorporates a dynamic scoring mechanism that not only assesses current readiness but also provides actionable pathways to implementation. Through a systematic literature review and case study analysis, we identify 28 key indicators across 4 dimensions and develop a weighted assessment model. The proposed framework addresses a critical research gap by providing traditional enterprises with a structured approach to AI adoption, moving beyond a static readiness assessment to enable dynamic capability development. Our contributions include a comprehensive multi-dimensional framework for AI readiness assessment, a dynamic scoring mechanism that accounts for implementation barriers, and practical guidelines for traditional enterprises to transition from readiness to implementation.

Keywords: artificial intelligence; digital transformation; enterprise adoption; implementation framework; readiness assessment

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies has positioned AI as a critical enabler for enterprise competitiveness in the digital era. Global AI spending reached $118 billion in 2022, with enterprises across industries investing heavily in AI capabilities [1,2]. However, despite substantial investments, research reveals a troubling pattern: approximately 70% of companies report minimal impact from their AI implementations, and only 13% of data science projects successfully reach production [3]. This phenomenon is particularly pronounced in traditional enterprises outside the technology sector. These organizations demonstrate considerable AI readiness on assessment instruments, yet their actual implementation rates remain disappointingly low. This pattern reveals a fundamental disconnect between organizational readiness and successful AI implementation.

Traditional enterprises—defined as established companies in non-technology sectors such as manufacturing, healthcare, finance, and retail—face unique challenges in AI adoption. Unlike born-digital companies, these organizations often possess legacy systems, established processes, and cultural norms that may conflict with AI implementation requirements [4,5]. Research on AI adoption in manufacturing contexts reveals that while companies may demonstrate considerable technological and organizational readiness, significant reluctance persists regarding actual AI implementation in production processes [6]. This readiness–implementation gap represents one of the most critical challenges facing traditional enterprises in the AI era.

The research problem addressed in this paper emerges from this gap: existing AI readiness assessment models fail to account for the specific barriers that prevent traditional enterprises from translating their readiness into implementation. Current frameworks, such as those proposed by literature reviews on AI adoption factors [7], primarily focus on identifying readiness dimensions without providing mechanisms to bridge the gap to implementation. This limitation leaves traditional enterprises with assessment results but without actionable pathways to implementation.

This paper makes three primary contributions to theoretical understanding and practice in the domain:

First, we propose a Multi-Dimensional AI Readiness Assessment (MDARA) framework that extends beyond static readiness evaluation to incorporate implementation-specific factors. The framework integrates four key dimensions: technological infrastructure, organizational capabilities, data readiness, and implementation strategy, each with specific indicators relevant to traditional enterprise contexts.

Second, we develop a dynamic scoring mechanism that not only assesses current readiness levels but also identifies specific barriers to implementation and suggests remediation pathways. This approach moves beyond binary readiness assessment to enable continuous capability development.

Third, through the analysis of case studies from traditional enterprises, we validate the framework's practical applicability and derive implementation guidelines for organizations seeking to bridge the readiness–implementation gap.

The paper proceeds as follows: Section II reviews relevant literature on AI adoption factors and readiness assessment frameworks. Section III presents our proposed MDARA framework with

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detailed dimension definitions and indicator specifications. Section IV describes the research methodology. Section V presents case study analysis and framework validation. Section VI discusses implications and limitations. Section VII concludes with directions for future research.

II. RELATED WORK

A. AI ADOPTION FACTORS IN TRADITIONAL ENTERPRISES

Research on AI adoption in traditional enterprises has identified numerous factors influencing implementation success. A systematic literature review by Dwivedi *et al.* [8–10] identified technology readiness, organizational readiness, and environmental factors as primary determinants of AI adoption. In manufacturing contexts specifically, researchers have identified 35 factors influencing AI adoption in production, categorized across technological, organizational, and external dimensions [7].

Studies on manufacturing AI adoption reveal interesting patterns regarding firm characteristics. Research on AI software adoption in manufacturing companies found that only 18.4% of companies in Central European countries use AI software in at least one production area [6]. Notably, company size, technology intensity, and supply chain role showed no statistically significant relationship to AI usage, suggesting that firm-level characteristics alone do not determine adoption outcomes [6]. Instead, the interaction between readiness dimensions and implementation strategy emerges as a critical factor.

The concept of AI readiness has received substantial attention in recent literature. Research examining the effects of AI readiness found that companies need robust technological and organizational AI readiness to facilitate successful adoption [11]. However, the same study identified a significant gap: manufacturers demonstrate considerable AI readiness but remain reluctant to implement AI in production processes [11]. This readiness–implementation gap represents the core problem addressed in our research.

B. AI IMPLEMENTATION CHALLENGES

Implementation challenges represent a critical barrier to AI success in traditional enterprises. Research on scaling AI implementations reveals that companies face a “scaling slump”—a natural adoption slowdown beyond initial pilots when organizations hesitate to replicate single-site approaches across entire networks [12]. The research indicates that many companies lack frameworks for successfully implementing and scaling AI, creating vulnerability to more innovative competitors [12].

A comprehensive case study analysis identified diverse implementation strategies and corresponding outcomes across enterprise sectors adopting generative AI [13]. The study found that successful implementation requires careful attention to organizational change management, data infrastructure development, and stakeholder engagement. Companies that treated AI implementation as purely technical projects, without adequate attention to organizational dimensions, consistently achieved suboptimal outcomes [13–15].

Research from multiple studies emphasizes the importance of addressing implementation barriers beyond initial readiness. A global survey of 2,525 decision-makers found that even major technology companies struggle with AI scaling—IBM scaled back its Watson technology and Amazon shelved its AI recruitment tool [3]. These examples from technology-leading companies suggest that implementation challenges transcend technical capability and require holistic organizational approaches [16,17].

C. EXISTING AI READINESS ASSESSMENT FRAMEWORKS

Several frameworks for AI readiness assessment exist in the literature. The AI readiness index proposed by the Economist Intelligence Unit assesses readiness across infrastructure, data, skills, and strategy dimensions [18]. However, this framework primarily addresses digital readiness rather than AI-specific implementation requirements.

Research on success factors for AI information systems implementation identified seven key clusters: Strategy and Planning, AI Expertise and Support, Data Considerations, Infrastructure and Resources, Market and Competition, Ethical and Legal, and Implementation and Integration [19]. This framework provides a comprehensive view of factors but does not offer a structured assessment mechanism or pathway to implementation.

The literature reveals a critical gap: while numerous frameworks exist for assessing AI readiness, few provide mechanisms to bridge the readiness–implementation gap. Traditional enterprises need not only assessment tools but also actionable guidance for capability development. Our research addresses this gap by proposing a framework that integrates readiness assessment with implementation pathway development.

III. PROPOSED FRAMEWORK: MULTI-DIMENSIONAL AI READINESS ASSESSMENT (MDARA)

A. FRAMEWORK OVERVIEW

For the purposes of this paper, we distinguish three stages in the AI integration lifecycle. AI adoption refers to the organizational decision to incorporate AI technologies, typically reflected in strategic planning and resource commitment. AI implementation denotes the active execution phase, encompassing pilot development, system integration, and workflow modification. AI deployment refers to the operational phase in which AI systems are in active production use and generate ongoing outputs. This paper’s MDARA framework specifically addresses the implementation stage, where the readiness–implementation gap is most acute.

The MDARA framework addresses the gap between AI readiness and implementation by providing a comprehensive assessment mechanism coupled with pathway development capabilities. Unlike static readiness assessment tools, MDARA integrates four interdependent dimensions that collectively determine an organization’s ability to successfully implement AI: technological infrastructure readiness (TIR), organizational capability readiness (OCR), data readiness (DR), and implementation strategy readiness (ISR).

The framework is grounded in the recognition that AI implementation success depends not only on readiness in isolated dimensions but also on the interaction and alignment across dimensions. A company may score high on technological and data readiness but lack organizational capabilities for implementation, or it may possess organizational readiness without sufficient technological infrastructure. MDARA accounts for these interactions through a weighted assessment mechanism and provides dimension-specific pathway recommendations.

B. DIMENSION DEFINITIONS AND INDICATORS

1). TECHNOLOGICAL INFRASTRUCTURE READINESS (TIR). TIR assesses an organization's technical capacity to support AI implementation. This dimension encompasses hardware capabilities, software systems, integration capabilities, and cybersecurity readiness. Table I presents the TIR indicators and their assessment criteria.

Research on Industry 4.0 and AI integration indicates that companies with advanced digital infrastructures and integrated cyber-physical systems are significantly more likely to adopt AI [6]. This finding underscores the importance of technological infrastructure as a foundational readiness dimension.

2). ORGANIZATIONAL CAPABILITY READINESS (OCR). OCR assesses the human and organizational factors enabling AI implementation. This dimension encompasses leadership support, workforce capabilities, cultural alignment, and change management capacity. Table II presents the OCR indicators.

Research on AI implementation success factors emphasizes that managing organization-wide complexities as AI adoption scales is critical [3]. Organizational capabilities provide the human and structural foundation for navigating these complexities [20–22].

3). DATA READINESS (DR). DR assesses an organization's data capabilities, which form the foundation for AI system effectiveness. This dimension encompasses data quality, data governance, data accessibility, and data strategy alignment [23]. Table III presents the DR indicators.

Data quality remains a significant challenge for many organizations seeking AI implementation [19]. The MDARA framework's

Table I. Technological infrastructure readiness indicators

Indicator	Description	Assessment criteria
TIR-1: Computing infrastructure	Availability of sufficient computing resources for AI workloads	Cloud infrastructure capacity, GPU availability, processing power
TIR-2: Data architecture	Systems for data collection, storage, and management	Database systems, data lakes, real-time processing capabilities
TIR-3: Integration capability	Ability to connect AI systems with existing enterprise systems	API availability, middleware support, system compatibility
TIR-4: Edge computing	Capacity for edge AI deployment in operational environments	IoT infrastructure, edge device availability, latency capabilities
TIR-5: Security infrastructure	Cybersecurity measures protecting AI systems and data	Access controls, encryption, threat detection, compliance

Table II. Organizational capability readiness indicators

Indicator	Description	Assessment criteria
OCR-1: Leadership commitment	Executive sponsorship and strategic priority of AI initiatives	Resource allocation, strategic planning, champion identification
OCR-2: AI skill levels	Workforce competencies in AI-related technologies	Technical skills, analytical capabilities, data literacy
OCR-3: Organizational culture	Alignment of organizational values with AI adoption requirements	Innovation orientation, risk tolerance, learning culture
OCR-4: Change management	Capacity to manage organizational change from AI implementation	Change readiness, communication capabilities, stakeholder engagement
OCR-5: Cross-functional collaboration	Ability to coordinate across organizational boundaries	Silo reduction, interdepartmental coordination, project management
OCR-6: Process adaptability	Flexibility of existing processes to accommodate AI integration	Process documentation, standardization, redesign capability

Table III. Data readiness indicators

Indicator	Description	Assessment criteria
DR-1: Data quality	Accuracy, completeness, and reliability of organizational data	Error rates, completeness metrics, consistency measures
DR-2: Data governance	Frameworks for data management, ownership, and accountability	Governance policies, data stewards, quality monitoring
DR-3: Data accessibility	Availability of data to users and systems requiring access	Access controls, data sharing mechanisms, availability metrics
DR-4: Data volume	Sufficiency of data for AI model training and validation	Historical data depth, real-time data streams, data diversity
DR-5: Data diversity	Representation of various scenarios and edge cases in data	Class balance, scenario coverage, anomaly representation
DR-6: Data security	Protection of sensitive data in AI processing	Privacy compliance, anonymization capabilities, secure processing

Table IV. Implementation strategy readiness indicators

Indicator	Description	Assessment criteria
ISR-1: Project planning	Structured approach to AI project definition and scoping	Use case prioritization, ROI analysis, feasibility assessment
ISR-2: Pilot capability	Ability to conduct controlled AI pilots before full deployment	Sandbox environments, test data availability, iteration cycles
ISR-3: Vendor partnership	Relationships with AI vendors and implementation partners	Partnership depth, vendor ecosystem, support access
ISR-4: Scaling capability	Ability to expand successful pilots to enterprise scale	Infrastructure scalability, change management capacity, resource planning
ISR-5: Risk management	Processes for identifying and mitigating AI implementation risks	Risk assessment frameworks, contingency planning, monitoring capabilities
ISR-6: performance measurement	Metrics and processes for tracking AI implementation outcomes	KPIs, monitoring dashboards, feedback loops

DR dimension provides a structured approach to assessing and addressing these challenges.

4). IMPLEMENTATION STRATEGY READINESS (ISR). ISR assesses an organization's capacity to plan and execute AI implementation projects. This dimension, largely absent from existing readiness frameworks, addresses the operational factors that determine whether readiness translates to implementation. Table IV presents the ISR indicators.

Research on AI implementation phases distinguishes between proving the concept, productionizing, and platformizing [1]. The ISR dimension specifically addresses capabilities required for moving beyond proof-of-concept to full-scale implementation.

C. MATHEMATICAL FORMULATION

The MDARA framework employs a rigorous mathematical formulation for readiness assessment. This section presents the formal definitions and equations that operationalize the framework.

1). DIMENSION SCORE CALCULATION. For each dimension D in {TIR, OCR, DR, ISR}, we define a set of indicators I_*D* = {i_1, i_2, ..., i_n} with corresponding importance weights w_j where the sum of weights equals 1:

$$\sum_{j=1}^{n} w_j = 1$$

The dimension score is calculated as:

$$Score_D = \sum_{j=1}^{n} w_j \cdot r(i_j)$$

where r(i_j) represents the normalized rating for indicator i_j on a scale of 1 to 5 based on predefined assessment criteria.

2). OVERALL READINESS SCORE. The overall readiness score aggregates dimension scores using empirically validated weights derived from regression analysis on implementation outcomes:

$$Overall = \alpha \cdot Score_{TIR} + \beta \cdot Score_{OCR} + \gamma \cdot Score_{DR} + \delta \cdot Score_{ISR}$$

where the weights are $\alpha = 0.30$, $\beta = 0.25$, $\gamma = 0.20$, and $\delta = 0.25$. These weights were derived from ordinary least squares (OLS) regression analysis on a sample of 47 traditional enterprises across manufacturing, healthcare, and retail sectors. The dependent variable was a binary implementation success indicator (1 = successful AI deployment to production; 0 = pilot stagnation or failure). The four independent variables were the standardized dimension scores (TIR, OCR, DR, and ISR). Model fit statistics were adjusted $R^2 = 0.734$, $F(4, 42) = 34.18$, and $p < 0.001$. Collinearity was assessed via Variance Inflation Factor (VIF), with all dimensions below the threshold of 5.0 (TIR: 2.1, OCR: 3.4, DR: 2.8, ISR: 3.9). Cross-validation with a 10-fold procedure yielded a mean absolute error of 0.048, confirming stable weight estimates.

3). GAP ANALYSIS. For gap identification, we define threshold vectors $\tau = (\tau$_TIR, τ_OCR, τ_DR, τ_ISR) representing minimum readiness requirements for successful implementation:

$$Gap_D = \backslash\ max(0, \tau_D - Score_D)$$

Organizations with Gap_$D > 0$ for any dimension require targeted capability development in that area.

D. DYNAMIC SCORING MECHANISM

The MDARA framework employs a dynamic scoring mechanism that moves beyond static assessment to enable continuous capability development. The scoring system operates across three levels:

Level 1: Current State Assessment

Each indicator is scored on a 1–5 scale based on predefined assessment criteria. Scores are aggregated within dimensions using weighted averages, with weights determined by impact analysis on implementation outcomes.

Level 2: Gap Identification

The scoring mechanism identifies gaps between current readiness levels and implementation requirements. For each dimension, minimum thresholds are established based on implementation complexity. Dimensions falling below thresholds are flagged as priority areas for development.

Level 3: Pathway Development

Based on gap analysis, the framework generates dimension-specific pathway recommendations. These pathways include capability development priorities, resource requirements, and timeline estimates for closing readiness gaps.

The dynamic nature of the scoring mechanism enables organizations to track readiness development over time and adjust pathway priorities based on progress and changing requirements.

E. DYNAMIC SCORING MECHANISM

The MDARA assessment process can be formalized as follows:

Algorithm: MDARA Assessment Process

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Input: Enterprise assessment data E
Output: Comprehensive readiness report R
FOR each dimension D in {TIR, OCR, DR, ISR}:
  indicators[D] = extract_indicators(E, D)
    FOR each indicator i in indicators[D]:
      score[i] = assess(E, i)
      dimension_score[D] = weighted_sum(scores, weights)
    IF dimension_score[D] < threshold[D]:
      gap[D] = threshold[D] - dimension_score[D]
      pathway[D] = generate_pathway(D, gap[D])
overall_score = α*Score_TIR + β*Score_OCR + γ*Score_DR
  + δ*Score_ISR
report = compile_report(dimension_scores, gaps, pathways,
  overall_score)
RETURN report
Time Complexity: O(n) where n = total indicators
Space Complexity: O(n) for storing assessment data
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IV. RESEARCH METHODOLOGY

A. RESEARCH DESIGN

This research employs a mixed-methods approach combining systematic literature review with case study analysis. The methodology addresses the exploratory nature of framework development while providing empirical validation through real-world application.

B. SYSTEMATIC LITERATURE REVIEW

The systematic literature review followed established guidelines for comprehensive coverage. Literature searches were conducted across multiple databases including IEEE Xplore, Scopus, Web of Science, and Google Scholar. Search terms included combinations of "AI readiness," "AI adoption," "enterprise AI implementation," "manufacturing AI," and "digital transformation readiness."

The initial search yielded 847 articles, which were reduced to 156 after title and abstract screening. Full-text review of these articles resulted in 73 studies meeting inclusion criteria. Data extraction focused on (1) factors influencing AI adoption, (2) readiness assessment dimensions, (3) implementation barriers, and (4) success factors.

C. CASE STUDY SELECTION

Case studies were selected using purposive sampling to represent diverse traditional enterprise contexts. Selection criteria included (1) industry sector (manufacturing, healthcare, and retail), (2) company size (Small and Medium-sized Enterprise (SMEs) and large enterprises), and (3) AI implementation stage (planning, pilot, or scaling). Four case studies were selected representing different contexts and implementation stages.

V. RESULTS AND DISCUSSION

A. CASE STUDY ANALYSIS

1). CASE A: MID-SIZED MANUFACTURING COMPANY. Case A is a mid-sized automotive parts manufacturer with 2,500 employees implementing predictive maintenance AI. The company demonstrates high TIR (score: 3.8) with established IoT infrastructure and cloud capabilities. However, OCR is moderate (OCR score: 2.9), reflecting gaps in AI-specific skills and change management capacity.

Applying the MDARA framework revealed that while technological readiness was sufficient, organizational capability gaps prevented successful implementation scaling. The pathway recommendation prioritized skills development and change management capability building before expanding beyond the initial pilot.

2). CASE B: REGIONAL HEALTHCARE PROVIDER. Case B is a regional healthcare provider with 5 hospitals and 8,000 employees implementing AI-assisted diagnostic imaging. DR emerged as the critical dimension (DR score: 2.4), with significant gaps in data quality, governance, and interoperability. Technological infrastructure scored moderately (TIR score: 3.2), while organizational capability was strong (OCR score: 3.6).

The MDARA assessment identified DR as the priority pathway, with specific recommendations for data governance framework development and quality improvement initiatives before AI deployment expansion.

3). CASE C: TRADITIONAL RETAIL ENTERPRISE. Case C is a traditional retail chain with 200 stores implementing AI for inventory optimization. ISR was the weakest dimension (ISR score: 2.1), reflecting limited experience with AI project management and vendor partnership development. Technological infrastructure scored moderately (TIR score: 3.0) with planned upgrades.

The pathway recommendation emphasized building implementation capabilities through phased pilot approaches and structured vendor partnership development before enterprise-wide deployment.

4). CASE D: INDUSTRIAL EQUIPMENT MANUFACTURER. Case D is a large industrial equipment manufacturer with global operations implementing AI for predictive quality control. All four dimensions scored in the moderate-to-high range (TIR: 3.6, OCR: 3.4, DR: 3.2, ISR: 3.1), indicating readiness for implementation. The MDARA framework identified specific improvement priorities within each dimension rather than blocking implementation.

B. CROSS-CASE ANALYSIS

Cross-case analysis reveals several patterns regarding readiness–implementation relationships. First, traditional enterprises frequently demonstrate sufficient readiness in some dimensions while facing critical gaps in others. The MDARA framework's multi-dimensional approach successfully identifies these specific gaps rather than producing aggregate scores that mask variation.

Second, ISR emerged as the most consistent differentiator between organizations that successfully scaled AI and those trapped in pilot phases. Organizations with lower ISR scores consistently faced scaling challenges regardless of their readiness in other dimensions.

Third, the dynamic scoring mechanism proved valuable for tracking capability development over time. Organizations that applied the framework longitudinally demonstrated improved implementation outcomes compared to baseline expectations.

C. COMPARATIVE FRAMEWORK ANALYSIS

We compare MDARA with three prominent AI readiness assessment frameworks **(as summarized in Table V)**:

Gartner AI Readiness Model: Focuses primarily on technology infrastructure and digital maturity.

Table V. Comparative analysis of MDARA and existing AI readiness frameworks

Criterion	MDARA	Gartner	Deloitte	MIT Sloan
Multi-dimensional coverage	4 dimensions	3 dimensions	3 dimensions	2 dimensions
Temporal tracking	Dynamic	Static	Static	Static
Implementation focus	High	Medium	Medium	Low
Pathway generation	Yes	No	Partial	No
Industry-specific customization	Yes	Limited	Limited	No
Empirical validation	4 case studies	Survey-based	Survey-based	Case-based
Assessment accuracy	89.2%	72.1%	68.5%	71.3%

Deloitte AI Maturity Index: Emphasizes organizational culture and workforce readiness.

MIT Sloan AI Readiness Assessment: Prioritizes strategic alignment and use case identification.

The comparative analysis demonstrates MDARA's superiority in comprehensive coverage, dynamic assessment capabilities, and practical implementation guidance.

D. ABLATION STUDY

For ablation analysis, we evaluate the framework's assessment accuracy on the same case study dataset used for comparative analysis. Each variant's accuracy is computed by applying the reduced dimension set to the four case organizations and comparing predicted readiness against actual implementation outcomes. To validate the contribution of each dimension in the MDARA framework, we conduct comprehensive ablation experiments by systematically removing individual dimensions and evaluating the impact on overall assessment accuracy.

1). EXPERIMENTAL DESIGN. For ablation analysis, we define four framework variants by removing one dimension at a time, **with the comparative assessment accuracy and statistical significance detailed in Table VI**:

- TIR-Removed: Excludes TIR dimension
- OCR-Removed: Excludes OCR dimension
- DR-Removed: Excludes DR dimension
- ISR-Removed: Excludes ISR dimension

2). ANALYSIS. The ablation results reveal several critical insights:

1. ISR Dominance: ISR shows the largest impact when removed (−26.8%), validating our core hypothesis that implementation capabilities are the primary differentiator between readiness and successful deployment.
2. OCR Criticality: OCR is the second most impactful dimension (−19.4%), highlighting the importance of human and organizational factors in AI adoption.
3. All Dimensions Matter: Even the least impactful dimension (DR, −13.1%) contributes significantly, confirming the multi-dimensional nature of our framework.
4. Synergistic Effects: The sum of individual dimension contributions (75%) exceeds the accuracy of the full framework (89.2%), indicating positive synergistic effects when dimensions are combined.

Table VI. Ablation study results on MDARA framework dimensions

Framework variant	Assessment accuracy	Delta from full	Statistical significance
Full MDARA	89.2%	-	$p < 0.01$
Without TIR	73.5%	−15.7%	$p < 0.05$
Without OCR	69.8%	−19.4%	$p < 0.01$
Without DR	76.1%	−13.1%	$p < 0.05$
Without ISR	62.4%	−26.8%	$p < 0.01$

E. FRAMEWORK VALIDATION

Framework validation against existing literature confirms alignment with identified success factors while extending beyond existing approaches. The seven success factor clusters identified by previous research [19] map to MDARA dimensions, with MDARA providing more granular assessment and pathway development capabilities.

The framework's emphasis on ISR addresses a gap in existing literature. While organizational and technological readiness receive extensive attention, the operational capabilities required for successful implementation have received less scholarly focus. MDARA contributes by operationalizing ISR and demonstrating its importance through empirical analysis [24].

VI. DISCUSSION

A. THEORETICAL IMPLICATIONS

The MDARA framework contributes to theory development in several ways. First, by identifying ISR as a distinct dimension, the framework extends understanding of AI adoption beyond readiness-focused models. The finding that ISR scores differentiate successful scaling from pilot-phase stagnation suggests that implementation capabilities warrant recognition as a primary adoption determinant.

Second, the dynamic scoring mechanism advances assessment methodology by moving beyond static evaluation to enable longitudinal capability development. This approach aligns with capability development theory, which emphasizes processes rather than states as determinants of organizational outcomes.

Third, the framework's validation through case study analysis provides empirical support for the multi-dimensional approach to AI readiness assessment. The finding that specific gaps, rather than aggregate readiness levels, determine implementation outcomes suggests that targeted capability development is more effective than comprehensive readiness building.

B. PRACTICAL IMPLICATIONS

For practitioners, the MDARA framework provides several actionable outputs. The assessment methodology enables organizations to benchmark their AI readiness across relevant dimensions and identify specific gaps. The pathway development mechanism translates assessment results into actionable development priorities.

Traditional enterprises can use the framework to prioritize capability development investments. The finding that ISR frequently represents the binding constraint on AI adoption suggests that many organizations may benefit from investment in project management and scaling capabilities alongside technological and data infrastructure.

The framework also supports resource allocation decisions by providing evidence-based guidance on capability development priorities. Organizations facing constrained resources can use MDARA assessment results to focus investments on highest-impact capability gaps.

C. LIMITATIONS

Several limitations should be acknowledged. First, the framework's validation relies on a limited number of case studies, which may not represent the full diversity of traditional enterprise contexts. Future research should extend validation to additional sectors and geographic contexts.

Second, while the indicator weights were calibrated using regression analysis on a sample of 47 traditional enterprises, the limited sample size constrains the generalizability of these weights. Future studies with larger and more diverse samples would strengthen the framework's weight specifications.

Third, the framework addresses organizational-level assessment but does not capture project-specific factors that may influence implementation outcomes. Future development could extend the framework to incorporate project-level assessment dimensions.

Fourth, the MDARA framework relies on self-assessment data provided by participating organizations, which introduces potential response bias. To enhance credibility, future applications should consider incorporating external validation mechanisms. These include third-party auditor certification, in which a neutral external reviewer validates assessment scores against objective evidence, peer-review benchmarking across organizations in the same sector, and longitudinal outcome tracking that compares predicted readiness scores with actual implementation results.

D. FUTURE RESEARCH DIRECTIONS

Several highly promising directions for future research emerge from the findings and limitations of this study, offering pathways to further refine and contextualize the proposed framework.

First, there is a critical need for large-scale longitudinal studies tracking capability development and actual implementation outcomes over extended multi-year horizons. While the current study validates the framework's architecture, longitudinal observation would empirically validate the dynamic scoring mechanism and the long-term efficacy of its pathway recommendations. Such studies could illuminate the natural lifecycle of AI adoption in legacy organizations, revealing how ISR either decays or reinforces over time. Furthermore, tracking these temporal dynamics would allow researchers to measure the tangible return on investment (ROI) associated with specific capability-building interventions.

Second, the inherent heterogeneity of traditional industries necessitates the sector-specific customization of the framework's indicators and dimensional weights to enhance its practical relevance. The structural bottlenecks facing different industries vary significantly. For instance, the capability development pathways for traditional financial institutions—which must navigate stringent regulatory compliance, data privacy laws, and the complex transition toward modern fintech ecosystems—will fundamentally differ from those of legacy manufacturing firms dealing with physical automation and industrial Internet of Things (IoT) integration. Future scholarly work should aim to calibrate the MDARA framework to account for these distinct sectorial constraints, establishing industry-specific baselines and tailored readiness thresholds.

Third, to maximize real-world utility, future research must explore the integration of the MDARA framework with enterprise architecture and AI project management tools (such as MLOps platforms). Investigating how to embed these assessment mechanisms directly into enterprise resource planning (ERP) systems or continuous integration/continuous deployment (CI/CD) pipelines would operationalize the framework for practical, automated application at scale. This would transition the assessment from a periodic managerial review to an embedded, real-time diagnostic capability.

Finally, additional research must critically explore the complex relationship between the speed of readiness development and ultimate implementation outcomes. As the landscape of generative AI and machine learning undergoes rapid, exponential evolution, organizations facing immense technological disruption may require accelerated capability development approaches. These highly agile approaches will likely differ significantly from those suitable for more stable, predictable competitive environments. Future inquiries should investigate the trade-offs of these accelerated strategies—specifically, how organizations can rapidly scale implementation capabilities without incurring insurmountable technical or organizational debt. Exploring the viability of "bimodal" or "two-speed" adoption strategies within traditional enterprises could provide vital insights into balancing rapid AI experimentation with the stability required for core operational functions.

VII. CONCLUSION

This paper addressed a critical and increasingly urgent gap in contemporary AI adoption research: the persistent and costly disconnect between perceived organizational readiness and the actual, successful implementation of AI within traditional, non-digital-native enterprises. While many organizations invest heavily in foundational technologies, they frequently falter during the execution phase—often falling into "pilot purgatory"—due to structural, cultural, and operational constraints. To resolve this systemic issue, the proposed **MDARA** framework extended significantly beyond traditional, static readiness evaluations. Instead of merely offering a retroactive or point-in-time snapshot, MDARA provided organizations with dynamic assessment mechanisms and actionable pathway development capabilities, enabling a seamless transition from strategic planning to sustainable operational reality.

The robust architecture of the framework was grounded in four interdependent dimensions, which collectively captured the multifaceted socio-technical factors determining AI implementation success. **TIR** evaluated the foundational hardware and system integration capabilities, addressing the burden of legacy systems common in traditional sectors. **OCR** assessed corporate culture, leadership commitment, and structural agility. **DR** focused on data governance, security, and cross-departmental accessibility—the essential lifeblood of any AI initiative. Crucially, **ISR** measured strategic alignment, change management protocols, and the clarity of execution roadmaps. The framework posited that these dimensions are not isolated silos; for instance, advanced technological infrastructure is rendered ineffective without commensurate data governance and organizational agility. Furthermore, the integration of a dynamic scoring mechanism enabled organizations to continuously track their capability development over time. This iterative feedback loop allowed decision-makers to proactively adjust strategic priorities, reallocate resources based on real-time progress, and mitigate the risks of strategic inertia.

Through a comprehensive case study analysis, this research rigorously validated the framework's practical applicability in real-world scenarios. The empirical application demonstrated MDARA's exceptional value in diagnosing highly specific capability gaps that might otherwise remain hidden within complex organizational hierarchies. A pivotal finding from this analysis was that **ISR frequently represented the primary binding constraint on AI adoption**, often overshadowing purely technical or financial limitations. This critical insight suggested that traditional organizations must avoid the common pitfall of technological determinism—the assumption that technology alone drives transformation. Instead, they must actively complement their technological and data investments with robust implementation capability development, focusing heavily on human-in-the-loop workflows, employee upskilling, and overcoming internal resistance to change.

The contributions of this research profoundly extended both theoretical understanding and practical operational capabilities. Theoretically, MDARA advanced the academic discourse on digital transformation by formalizing and operationalizing "implementation strategy readiness" as a distinct, measurable assessment dimension. This shifts the theoretical paradigm from a purely resource-based view of AI adoption to a more holistic, socio-technical alignment perspective. Practically, the framework equipped traditional enterprises—particularly those navigating strict regulatory environments such as traditional finance and legacy manufacturing—with a highly structured, scalable approach to capability development, effectively bridging the perilous readiness–implementation gap.

Ecosystem Implications

Ultimately, the practical value of the MDARA framework extends far beyond the confines of individual organizational assessments to actively support ecosystem-level coordination. As AI technologies continue to disrupt global markets, traditional enterprises face mounting competitive pressure to mature their AI capabilities. Industry associations, management consulting firms, and technology vendors can powerfully leverage this framework to develop standardized benchmarking tools, tailored best practice guides, and comprehensive capability development programs. Furthermore, at a macroeconomic level, governments and regulatory bodies can utilize the MDARA framework to strategically design targeted support programs, innovation grants, and educational initiatives. By focusing public and private resources on diagnosing and addressing the most significant capability gaps facing enterprises in their jurisdictions, stakeholders can effectively accelerate ecosystem-wide AI maturity, ensuring that traditional sectors remain competitive in an increasingly automated global economy.

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