A Systematic Literature Review on Organizational Readiness for Artificial Intelligence Adoption Based on the TOE Framework

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***Abstract*—Artificial intelligence (AI) is increasingly being integrated into organizational processes, reshaping how organizations operate, compete, and make decisions. However, despite growing interest, many organizations face challenges in adopting AI effectively due to insufficient readiness. Prior research on organizational AI readiness has produced diverse and sometimes inconsistent conceptualizations, particularly with respect to definitions, readiness factors, and analytical approaches. To consolidate these dispersed insights, this study undertakes a structured review of the literature to synthesize organizational AI readiness factors through the lens of the Technology–Organization–Environment (TOE) framework. The review applies a transparent and replicable screening and selection process, consistent with PRISMA principles, to analyze peer-reviewed journal articles on organizational AI adoption and readiness. Through a multi-stage coding process, 124 readiness-related indicators were identified and subsequently consolidated into 35 factors, which were further synthesized into 12 core readiness themes mapped across the technological, organizational, and environmental dimensions of the TOE framework. The results indicate that organizational AI readiness is not a standalone condition, but a multidimensional and interdependent construct shaped by the alignment of technological capabilities, organizational structures and competencies, and external environmental conditions. By providing a structured synthesis of organizational AI readiness factors, this study clarifies the multidimensional nature of readiness and highlights cross-dimensional interdependencies within the TOE framework. The findings contribute theoretical clarity to the AI readiness literature and offer a consolidated foundation for future empirical studies and practical readiness assessments in organizational settings.**

***Keywords*—Artificial intelligence readiness; organizational readiness; TOE framework; systematic literature review; AI adoption**

I. INTRODUCTION

Artificial Intelligence (AI) has become a critical driver of organizational transformation, influencing how organizations create value, optimize operations, and support decision-making [1], [2]. In the past decade, the integration of AI across industries—from manufacturing and finance to agriculture and public services—has demonstrated its potential to enhance efficiency, accuracy, and decision-making quality [3], [4]. However, despite the recognized benefits, AI adoption at the organizational level remains uneven due to the complexity of readiness conditions required for successful implementation [5], [6].

Organizational readiness for AI adoption extends beyond technological availability and reflects a multidimensional capability involving infrastructure, human competencies, financial commitment, governance mechanisms, cultural alignment, and external conditions [7], [8]. The effectiveness of AI initiatives depends on how well organizations align these internal and external enablers to support transformation [9]. Accordingly, readiness assessment plays a critical role prior to AI investment to reduce the risks of implementation failure, limited utilization, or ethical challenges [10].

Among established innovation adoption theories, the Technology–Organization–Environment (TOE) framework [11] provides a comprehensive perspective for examining how technological capabilities, organizational characteristics, and environmental conditions jointly influence adoption behavior [12]. Although prior AI adoption studies have applied TOE to explore specific drivers (e.g., [6], [13], [14]), these findings have rarely been synthesized into a coherent and unified structure of organizational AI readiness. Existing research tends to fragment the discussion across isolated dimensions or sectors, leading to inconsistencies in how readiness factors are defined, categorized, and measured [15], [16].

While foundational theories such as the Technology–Organization–Environment framework originate from earlier literature, this review predominantly synthesizes empirical AI adoption and readiness studies published between 2015 and 2025, ensuring the contemporary relevance of its findings.

Moreover, while the literature has grown rapidly, few reviews have systematically mapped how TOE dimensions interrelate to influence AI readiness holistically. Earlier reviews have primarily emphasized either technological or organizational enablers, overlooking the moderating role of the environment [5]. Therefore, a Systematic Literature Review (SLR) is needed to consolidate the growing body of knowledge and identify theoretical and empirical patterns regarding AI readiness within the TOE framework.

While prior systematic literature reviews have examined artificial intelligence adoption from technological, organizational, or sector-specific perspectives, most existing reviews remain either descriptively oriented or focused on isolated determinants of adoption. They typically emphasize drivers and barriers without synthesizing readiness as a multidimensional organizational capability, nor do they systematically integrate cross-theoretical perspectives within a unified analytical structure. As a result, existing SLRs provide limited guidance on how technological, organizational, and environmental readiness dimensions interact to shape organizational preparedness for AI adoption.

This study addresses this gap by conducting a theory-integrative systematic literature review that explicitly positions organizational AI readiness within the Technology–Organization–Environment (TOE) framework, while incorporating insights from Dynamic Capability and Institutional perspectives. By synthesizing empirical findings across these lenses, this review goes beyond prior SLRs to conceptualize AI readiness as a systemic and capability-oriented construct rather than a static pre-adoption condition. Specifically, this study produces: 1) a consolidated taxonomy of organizational AI readiness factors, 2) twelve core readiness constructs structured across the TOE dimensions, and 3) a conceptual foundation that can support future development of standardized AI readiness assessment frameworks.

Prior review studies have examined artificial intelligence adoption from organizational and managerial perspectives. Conceptual and agenda-setting reviews, such as Dwivedi et al. [5], discuss broad challenges, opportunities, and managerial implications of AI adoption. More recent systematic literature reviews employ the Technology–Organization–Environment (TOE) framework to analyze adoption and readiness determinants. For example, Ayinaddis [17] examines AI adoption dynamics across SMEs and large firms, while Ali and Khan [18] review organizational readiness factors influencing AI adoption decisions. However, these reviews primarily apply TOE as a classificatory lens to organize adoption or readiness determinants. In contrast, this study advances the literature by explicitly conceptualizing organizational AI readiness as an integrative and capability-oriented construct. By synthesizing the TOE framework with dynamic capability and institutional perspectives, this review shifts the analytical focus from factor identification to readiness as a systemic and evolving organizational capability shaped by cross-dimensional interdependencies.

Building on this positioning, this study conducts a decade-long synthesis (2015–2025) of peer-reviewed journal articles focusing on AI adoption through the TOE perspective. The review is structured around three research questions (RQs):

- How has the TOE framework been applied in AI adoption research at the organizational level?
- What are the key organizational readiness factors influencing AI adoption based on TOE dimensions?
- How are the interdependencies among TOE dimensions conceptualized in AI adoption readiness studies?

By addressing these questions, this study makes a significant contribution to both theory and practice. Theoretically, it advances the understanding of organizational readiness as a multi-dimensional construct within the TOE framework. Practically, it provides an evidence-based foundation for organizations and policymakers to design structured readiness assessments and strategies for AI adoption.

II. Methodology

This study adopts a systematic review strategy to identify, evaluate, and synthesize academic research addressing organizational readiness for Artificial Intelligence (AI) adoption within the Technology–Organization–Environment (TOE) framework. To ensure methodological rigor, transparency, and replicability, the review process was structured in accordance with established reporting standards for systematic literature reviews, including PRISMA [19]. The process was adapted from established practices in information systems research [20], [21].

A. Research Design and PICOC Framework

The design of this review was guided by the PICOC framework, which supports methodological clarity in systematic literature reviews by specifying the Population, Intervention, Comparison, Outcome, and Context dimensions [22].

In this review, the population comprised organizations that have adopted, or are in the process of adopting, AI technologies. The intervention dimension captured studies examining AI implementation frameworks, readiness assessment models, or organizational adoption approaches. Since the review did not seek to compare intervention groups, the Comparison element was not applied. The Outcome was defined as the identification of factors influencing AI readiness across the three TOE dimensions—technological, organizational, and environmental [11]. The Context covered organizational-level studies across sectors and regions, thereby capturing cross-industry and cross-national insights.

The application of PICOC ensured that the review maintained conceptual precision and excluded studies unrelated to organizational-level adoption, such as those focused on consumer behavior or algorithmic performance. This alignment enhanced both the relevance and internal validity of the synthesis.

B. Search Strategy

The literature search was performed using the Scopus database, which was selected due to its extensive coverage of peer-reviewed journals in management, computer science, and information systems. The database search was executed on October 14, 2025 (20:47 WIB) using a structured keyword combination designed to capture studies on AI adoption and organizational readiness within the TOE perspective, as follows:

"Artificial Intelligence" AND Adoption AND (TOE OR (Technology AND (Organization OR Organisation) AND Environment))

The search was limited to the period 2015–2025, reflecting a decade of maturity in both AI research and organizational readiness discourse [5]. To maintain scientific rigor, the inclusion was restricted to journal articles in their final publication stage, written in English, and classified as articles (not conference papers or reviews).

After applying these initial filters, 190 records were retrieved. Non-article publications—such as conference papers (46), book chapters (11), reviews (9), books (1), and articles in press (16)—were excluded. This refinement ensured that only high-quality, peer-reviewed journal outputs were retained for systematic screening.

C. Inclusion and Exclusion Criteria

To maintain conceptual relevance and methodological rigor, explicit inclusion and exclusion criteria were applied during the screening process. Table I summarizes the inclusion and exclusion criteria applied during the review.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Exclusion Criteria
Studies were included if they: a) addressed AI adoption or readiness at the organizational level, b) were theoretically aligned with the TOE framework or compatible constructs, c) provided empirical or conceptual insights relevant to organizational readiness.	Conversely, studies were excluded if they: a) focused solely on technical AI models or algorithms, b) investigated individual or consumer adoption behavior, c) lacked theoretical grounding in TOE or related frameworks, or d) were written in languages other than English.

After screening, 52 papers met the preliminary inclusion conditions. A subsequent full-text review identified 12 papers that did not sufficiently address organizational-level readiness, leading to a final corpus of 40 studies used for synthesis.

D. PRISMA Flow and Screening Process

The selection of studies followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, which structures systematic reviews through four sequential phases: The study selection process progressed through sequential phases encompassing record identification, relevance screening, full-text eligibility assessment, and final inclusion [19]. This process ensured methodological transparency and reproducibility throughout the review.

During the Identification phase, records were retrieved from the Scopus database based on the query and criteria defined in Section 2.2. After applying initial filters for language, document type, and publication status, a total of 190 journal records were identified for potential inclusion. As confirmed in the database export, no duplicate or automated removals were required prior to screening.

In the Screening stage, titles and abstracts of all 190 records were examined to determine their relevance to AI adoption and readiness at the organizational level. This stage resulted in the exclusion of 138 studies, primarily consisting of non-journal documents (e.g., conference proceedings, book chapters, reviews) and non-English publications. Consequently, 52 studies were retained for full-text assessment.

At the Eligibility phase, the full texts of these 52 studies were successfully retrieved for in-depth evaluation. Each paper was reviewed to confirm its theoretical alignment with the Technology–Organization–Environment (TOE) framework or compatible perspectives (e.g., RBV, DCV, Institutional Theory). Twelve studies were excluded at this stage for reasons such as a purely technical orientation (n = 4), lack of organizational or managerial focus (n = 5), or incomplete conceptual detail (n = 3).

Following the screening and eligibility assessment, a total of 40 peer-reviewed journal articles satisfied all selection criteria and were retained for qualitative synthesis. These studies constitute the final corpus analyzed through open, axial, and selective coding in Section III. The overall workflow, including the number of records removed, screened, and retained at each stage, is illustrated in Fig. 1, which presents the PRISMA flow diagram of the study selection process.

E. Data Extraction and Thematic Synthesis

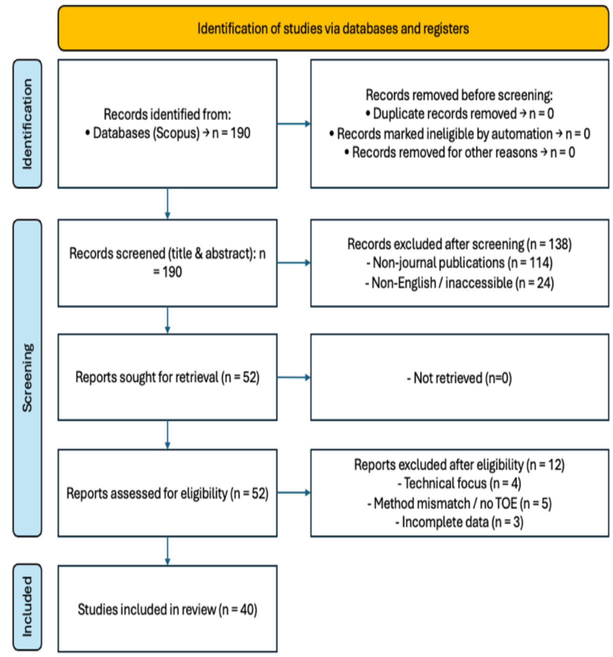

Fig. 1. PRISMA flow diagram of the study selection process.

A structured data extraction template was designed to capture consistent information from each study, including bibliographic details (authors, year, journal, country), type of AI technology and sectoral application, theoretical foundation (TOE or derivative), identified readiness factors per TOE dimension, and major findings and implications. The extracted data were analyzed using thematic synthesis, allowing for the identification and grouping of readiness factors under the three TOE dimensions. Subsequent cross-analysis was performed to examine interdependencies among these dimensions, consistent with the methodological guidance of Tranfield [21]. Through this process, the review produced an integrative synthesis of 40 studies, highlighting trends, methodological gaps, and opportunities for future research on organizational AI readiness.

III. RESULTS

A. Overview of Reviewed Studies

The systematic review encompassed forty peer-reviewed journal articles published between 2021 and 2025 that focus on organizational readiness for Artificial Intelligence (AI) adoption. As illustrated in Fig. 2, publication output increased substantially over the review period, rising from two studies in 2021 to seventeen studies in 2025. After a modest rise in 2022 and a slight dip in 2023, the trend accelerated sharply in 2024–2025, reflecting the growing strategic relevance of AI readiness within organizational digital transformation agendas. This temporal pattern indicates a shift from early exploratory investigations toward more structured empirical validation and framework refinement.

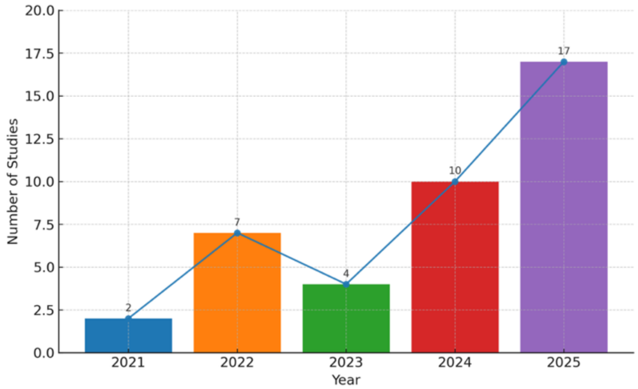

Fig. 2. Publication trend of AI readiness studies.

From a geographical perspective, the reviewed studies are distributed across multiple regions, although the distribution remains uneven. As shown in Fig. 3, the majority of reviewed studies originated from Europe (35%) and Asia (30%), where AI readiness research is often situated within policy-driven digitalization and institutional modernization contexts, where AI readiness has been explored within policy-driven digitalization and institutional modernization frameworks [23], [24], [25], [26]. Studies from North America (25%) emphasized resource-based and dynamic capability perspectives [4], [5], [16], while smaller shares originated from Africa (5%) and the Middle East (5%), often focusing on contextual barriers, policy readiness, and infrastructural challenges [27], [28], [29]. This geographical pattern indicates a strong research concentration in high-income and policy-advanced regions, with limited representation from emerging economies.

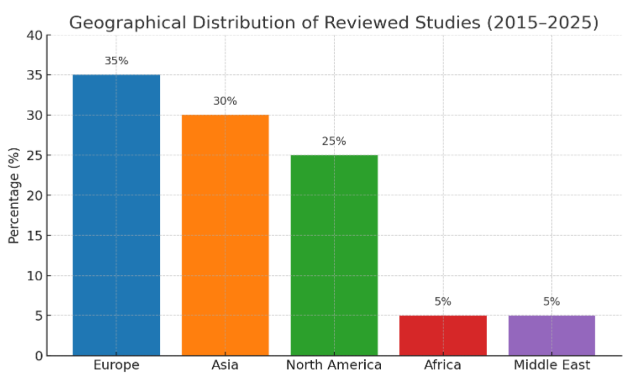

Fig. 3. Geographical distribution of reviewed studies.

With respect to industrial orientation, Fig. 4 indicates that most studies focused on manufacturing (20%), public administration (17.5%), and financial services (15%), reflecting sectors leading in automation, data-driven governance, and innovation [24], [30], [31]. Other contexts, including agriculture (10%), healthcare (10%), services (7.5%), and education (5%), were comparatively less explored but demonstrate emerging academic attention as AI adoption expands beyond high-tech industries [32], [33], [34], [35]. This sectoral diversity highlights that AI readiness is increasingly understood as a cross-sectoral organizational capability, applicable across both public and private sectors with varying degrees of digital maturity.

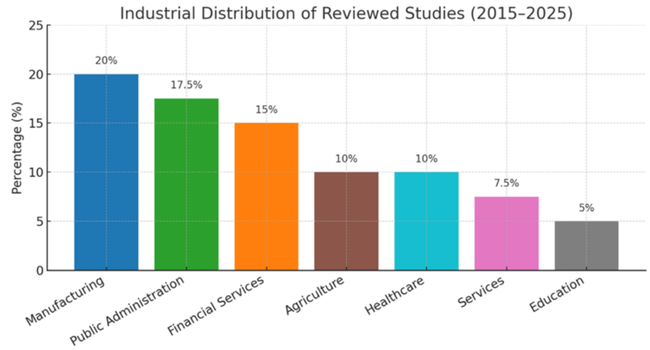

Fig. 4. Industrial distribution of reviewed studies.

From a methodological perspective, quantitative approaches (45%) constitute the largest proportion of the reviewed studies, with studies primarily employing survey-based analysis and structural equation modeling to test readiness determinants under the Technology–Organization–Environment (TOE) framework [7], [31], [36]. Qualitative studies (30%)—such as case studies and semi-structured interviews—provided an in-depth understanding of organizational dynamics, leadership, and governance in AI adoption [6], [24], [37]. A smaller proportion of mixed-method research (15%) combined statistical validation with contextual insights [16], [38], while conceptual papers (10%) contributed to the refinement of AI readiness constructs [39], [40].

Overall, the descriptive synthesis indicates that the field has developed empirical diversity, while remaining geographically and methodologically uneven. Most studies remain concentrated in high-income regions and quantitative paradigms, while cross-sectoral, longitudinal, and developing-country analyses remain limited. These gaps highlight the need for future research that broadens contextual coverage and examines AI readiness development within diverse institutional and economic settings.

B. Theoretical Foundations in AI Readiness Studies

The synthesis of the reviewed studies confirms that the Technology–Organization–Environment (TOE) framework [11] continues to function as the primary theoretical lens for analyzing organizational readiness for AI adoption. This continued relevance stems from its capacity to integrate technological, organizational, and environmental determinants within a unified analytical structure that explains adoption behavior beyond purely technical or managerial considerations [5], [7], [38].

Approximately 95 per cent of all reviewed articles employed TOE either independently or in combination with complementary theories. The integration trend reflects a conceptual broadening of readiness from deterministic adoption toward dynamic capability and institutional perspectives. Around 20 per cent of studies combined TOE with the Resource-Based View (RBV) to emphasize internal resources and capability orchestration [7], [23]. Another 15 per cent paired TOE with the Dynamic Capability View (DCV) to capture organizational agility and transformation processes [16], [37]. The Institutional Theory (≈10 per cent) appeared mainly in public-sector contexts to highlight regulatory alignment and legitimacy pressures [24], [36]. Meanwhile, behavioral models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (≈7 per cent) were applied to integrate individual-level acceptance factors into organizational readiness [40], [41].

Together, these theoretical combinations indicate that AI readiness research is shifting from static adoption logic toward a multi-level capability perspective that connects technology, organization, and environment in an adaptive ecosystem. Table II presents the distribution of theoretical frameworks applied in AI readiness studies, summarizing how TOE is used both independently and in combination with complementary theories across the reviewed literature.

The dominance of TOE and its frequent integration with RBV, DCV, Institutional Theory, and TAM/UTAUT suggests that contemporary AI readiness studies increasingly adopt hybrid theoretical models. These combinations enable the operationalization of readiness not merely as a structural condition but as a dynamic capability responsive to institutional and human factors within digital transformation ecosystems.

C. Thematic Synthesis of Readiness Factors

To identify the core dimensions of organizational readiness for Artificial Intelligence (AI) adoption, a three-stage thematic coding process was conducted—open coding, axial coding, and selective coding—using the Technology–Organization–Environment (TOE) framework as the analytical lens. The TOE structure was defined a priori to classify readiness factors; it served as a guiding taxonomy rather than a coded outcome.

During the open coding stage, a total of 124 readiness-related statements were extracted from 40 Scopus-indexed journal articles published between 2015 and 2025. Each statement represented a specific condition, enabler, or organizational characteristic influencing AI adoption. Of these, 120 statements were classified into the three TOE dimensions—Technology (40), Organization (40), and Environment (40)—while four meta-level codes (Layer RBV, UTAUT (Individual), Mediating Construct, Moderating Variable) were identified as theoretical supplements and excluded from the readiness classification.

Through axial coding, semantically similar open codes were consolidated and standardized into 35 intermediate readiness categories distributed across the three TOE dimensions (15 technological, 12 organizational, and 8 environmental). These categories captured interrelationships among internal and external readiness factors. Finally, selective coding integrated these categories into 12 final readiness themes, with four readiness constructs identified within each TOE dimension. As summarized in Table III, this stepwise synthesis—from 124 open codes to 35 axial categories and finally 12 selective readiness constructs—illustrates the structured process of theoretical condensation applied in this study.

The technological dimension captures the internal enablers that support AI deployment, such as infrastructure, data, and innovation capability. The organizational dimension represents leadership, culture, and resource capabilities that drive AI transformation. Meanwhile, the environmental dimension reflects regulatory, market, and social conditions that facilitate or constrain adoption. As detailed in Table IV, these 12 readiness themes reflect the final synthesis of conceptual categories derived from the 40 reviewed studies, organized within the TOE framework.

TABLE II. THEORETICAL FRAMEWORKS APPLIED IN AI READINESS STUDIES

Framework Combination	Analytical Focus / Conceptual Contribution	Representative Studies	% of Included Studies (n = 40)
TOE only	Baseline model integrating technological, organizational, and environmental readiness determinants. Serves as the dominant lens for organizational AI adoption.	[5], [32]	47.5 % (19 studies)
TOE + RBV (Resource-Based View)	Highlights internal resources and capability orchestration as strategic enablers of AI readiness. Focuses on value creation from existing assets.	[23], [7], [38]	20 % (8 studies)
TOE + DCV (Dynamic Capability View)	Emphasizes organizational agility, learning, and reconfiguration to sustain readiness under digital transformation.	[16], [42], [43]	15 % (6 studies)
TOE + Institutional Theory	Addresses legitimacy, regulation, and coercive pressures influencing AI readiness—particularly in public and regulated domains.	[24], [36], [44]	10 % (4 studies)
TOE + TAM / UTAUT	Integrates individual-level acceptance, perceived usefulness, and behavioral intention within organizational readiness contexts.	[41], [40]	7.5 % (3 studies)

TABLE III. SUMMARY OF CODING STAGES (OPEN–AXIAL–SELECTIVE) AND DISTRIBUTION ACROSS TOE DIMENSIONS

Coding Stage	Description of Process	Result	TOE Dimensions
Open Coding	Extraction of readiness-related concepts and determinants from 40 Scopus-indexed studies (2015–2025). Each indicator represents a discrete aspect of AI readiness.	124 open codes	Technology: 40 Organization: 40 Environment: 40 Non-TOE (meta): 4
Axial Coding	Consolidation of conceptually similar open codes into standardized readiness categories within each TOE dimension.	35 axial categories	Technology: 15 Organization: 12 Environment: 8
Selective Coding	Integration of axial categories into final readiness constructs describing organizational preparedness for AI adoption.	12 final readiness themes	Technology: 4 Organization: 4 Environment: 4

TABLE IV. SUMMARY OF SELECTIVE CODING THEMES ACROSS THE THREE TOE DIMENSIONS

TOE Dimension	Selective Theme (Readiness Construct)	Description / Core Meaning	Representative Studies
Technological Readiness	System Capability	Availability and reliability of IT/AI infrastructure, interoperability, and automation capacity enabling AI operation.	[26], [38], [40]
	Data & Analytics Readiness	Availability, governance, and security of organizational data supporting AI-driven analytics and decision-making.	[35], [25], [45]
	Technology Usability	Perceived usefulness, ease of use, and compatibility facilitating system integration and adoption.	[34], [46]
	Innovation Capability	Organizational ability to experiment with and integrate new AI tools, fostering digital agility and innovation.	[47], [48]
Organizational Capability	Strategic & Managerial Support	Leadership commitment, managerial capability, and strategic orchestration of resources for AI initiatives.	[38], [42]
	Human & Structural Readiness	Competence of human resources, training, and financial readiness supporting AI transformation.	[35], [31], [28]
	Cultural & Governance Alignment	Alignment of innovation culture, ethical leadership, and IT governance with AI objectives.	[42], [49], [28]
	Knowledge & Learning	Capacity for organizational learning, absorptive capability, and knowledge sharing sustaining AI competence.	[38], [50]
Environmental Readiness	Regulatory & Policy Context	National policies, regulations, and compliance standards promoting AI legitimacy.	[24], [51]
	Market Dynamics	Competitive pressure and industry turbulence driving AI adoption decisions.	[31], [46], [52], [53], [54], [55], [56]
	Collaborative Ecosystem	External partnerships, vendor support, and stakeholder collaboration fostering AI implementation.	[55], [53], [57], [58], [52], [25]
	Social Legitimacy & Ethics	Public trust, ethical acceptance, and social legitimacy influencing AI adoption readiness.	[52], [58], [59]

TABLE V. SUMMARY OF READINESS THEMES IDENTIFIED THROUGH THE SYSTEMATIC REVIEW

TOE Dimension	Core Readiness Themes	Core Conceptual Meaning
Technological Readiness	1. System Capability	Availability and reliability of AI infrastructure, interoperability, and automation systems forming the technological foundation.
	2. Data & Analytics Readiness	Data quality, accessibility, and governance supporting machine learning and analytics integration.
	3. Technology Usability	Perceived usefulness, ease of use, and compatibility of AI systems enhancing adoption.
	4. Innovation Capability	Capacity to integrate, experiment, and evolve with new AI tools and technologies.
Organizational Capability	5. Strategic & Managerial Support	Leadership commitment, managerial capability, and strategic orchestration of AI resources.
	6. Human & Structural Readiness	Workforce competence, training, and financial support enabling AI initiatives.
	7. Cultural & Governance Alignment	Innovation culture, ethics, and governance alignment with AI objectives.
	8. Knowledge & Learning	Organizational learning capacity, absorptive ability, and knowledge-sharing culture.
Environmental Readiness	9. Regulatory & Policy Context	Government regulations, standards, and policies legitimizing AI use.
	10. Market Dynamics	Competitive and market pressures driving AI transformation.
	11. Collaborative Ecosystem	Vendor support, external partnerships, and inter-organizational collaboration.
	12. Social Legitimacy & Ethics	Public trust, ethical norms, and social acceptance of AI implementation.

To consolidate these findings, Table V provides an overview of the final twelve core readiness themes as the outcome of the systematic literature review. Each construct represents an empirically supported component of organizational AI readiness that can later be operationalized into measurable indicators for quantitative assessment.

In summary, Table III to Table V collectively present the complete thematic synthesis from the coding process. Table III outlines the progressive abstraction stages, Table IV elaborates the thematic content of each dimension, and Table V consolidates the 12 final readiness constructs as the conceptual outcome of the SLR. This hierarchical structure provides both empirical transparency and theoretical coherence, forming the basis for the next stage of framework development and quantitative instrument design.

D. Cross-Dimensional Patterns and Interdependencies

A cross-dimensional analysis of the three TOE domains reveals that AI readiness is a systemic and interdependent construct, rather than a collection of isolated factors. The twelve core readiness themes identified in Section III C (see Table III to Table V) interact dynamically across technological, organizational, and environmental boundaries, indicating that improvements in one dimension often depend on reinforcing conditions in the others. Three dominant patterns of interaction emerged from the synthesis:

1) Technology–organization synergy: Technological capabilities such as infrastructure robustness, data quality, and AI tool maturity serve as essential enablers, yet they do not automatically ensure readiness without corresponding organizational commitment and competencies. Leadership support, resource allocation, and skilled personnel determine whether technological potential can be translated into business value [38], [6]. This interaction aligns with the Dynamic Capability View, which posits that technological enablers must be integrated with organizational routines and strategic management processes to create adaptive advantage [16], [42].

In essence, technology provides capability, while organization provides direction.

2) Organization–environment alignment: Institutional and regulatory contexts shape organizational governance, ethics, and risk management, reinforcing the principles of responsible AI adoption [24], [36]. External pressures—such as evolving regulations, market competition, and societal expectations—stimulate internal strategic agility and reform initiatives, linking organizational culture and leadership to broader environmental expectations [60], [61]. This alignment demonstrates how institutional legitimacy and regulatory compliance become catalysts for sustainable AI readiness.

External legitimacy drives internal adaptation.

3) Technology–environment dependence: Environmental conditions—comprising vendor collaboration, industry standards, and ecosystem maturity—directly influence technological readiness. These relationships accelerate innovation diffusion, promote interoperability, and reduce implementation risk through shared knowledge and technical standards [62], [63]. Such dependencies emphasize that AI readiness extends beyond a single firm; it requires a network-oriented and policy-supported ecosystem to sustain large-scale technological transformation.

Technological advancement flourishes in collaborative ecosystems.

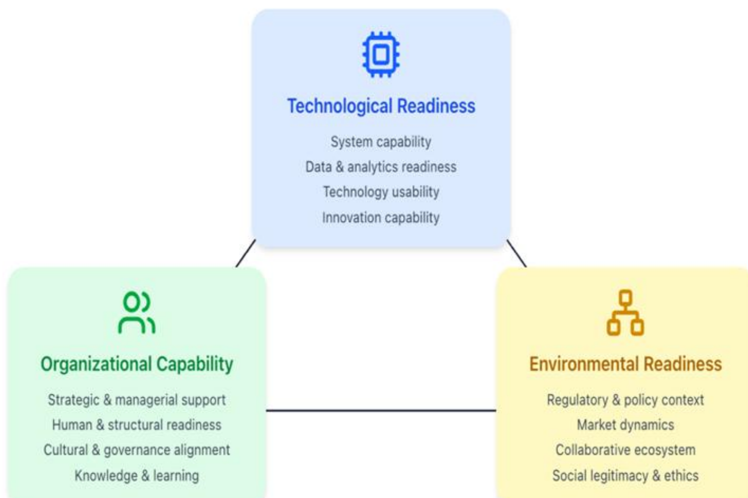

Fig. 5. Conceptual map of interdependencies among TOE dimensions.

Arrows between Technological and Organizational Readiness indicate internal synergy between capability and leadership [see Fig. 5]. Arrows connecting Organizational and Environmental Readiness show alignment between strategy, governance, and external expectations. Arrows linking Technological and Environmental Readiness highlight dependence on industry standards, vendor networks, and regulatory support. Together, these relationships form a systemic readiness model, depicting AI adoption as an ecosystem-driven capability embedded in multi-level interactions.

E. Summary of Findings

The systematic review of forty peer-reviewed studies revealed a comprehensive picture of how organizations develop readiness for Artificial Intelligence (AI) adoption. Through a three-stage thematic synthesis—open, axial, and selective coding—124 readiness-related indicators were identified, refined into 35 standardized categories, and ultimately consolidated into twelve core readiness themes organized within the Technology–Organization–Environment (TOE) framework. These twelve core readiness themes capture the multidimensional conditions that jointly determine an organization's preparedness to adopt, manage, and sustain AI transformation.

Technological readiness provides the capacity to act through infrastructure, data quality, usability, and innovation enablers that make AI implementation technically feasible. Organizational capability defines the ability to adapt and lead through strategic commitment, human competence, and governance mechanisms that enable effective transformation. Meanwhile, environmental readiness sets the context to legitimize and sustain AI initiatives by shaping regulatory alignment, market competition, collaboration networks, and public trust [7], [44], [64].

As summarized in Table VI, these findings demonstrate that successful AI adoption requires alignment and mutual reinforcement among the three TOE dimensions. AI readiness thus functions as an integrative organizational capability—a systemic configuration in which technology, organization, and environment co-evolve to enable sustainable AI transformation.

TABLE VI. CONCEPTUAL CONSOLIDATION OF AI READINESS DIMENSIONS

TOE Dimension	Primary Readiness Focus	Strategic Interpretation / Core Implication
Technological Readiness	• System Capability • Data & Analytics Readiness • Technology Usability • Innovation Capability	Represents the organization's technical foundation—the digital infrastructure, data governance, and innovation capacity that provide the *ability to act* and support AI functionality.
Organizational Capability	• Strategic & Managerial Support • Human & Structural Readiness • Cultural & Governance Alignment • Knowledge & Learning	Reflects internal leadership, competencies, culture, and learning systems that transform technological potential into operational and strategic performance.
Environmental Readiness	• Regulatory & Policy Context • Market Dynamics • Collaborative Ecosystem • Social Legitimacy & Ethics	Defines the external environment—regulatory frameworks, competitive forces, partnerships, and social trust—that legitimize and sustain AI adoption at the ecosystem level.

IV. DISCUSSION

This discussion synthesizes the review findings by explicitly addressing the three research questions of the study. Rather than treating technological, organizational, and environmental readiness as independent dimensions, the analysis reveals how prior studies conceptualize AI readiness as an interdependent and systemic organizational capability. The following discussion interprets these patterns in relation to RQ1–RQ3 and highlights their theoretical and practical implications.

A. Evolution of Theoretical Foundations

Across the reviewed literature, the Technology–Organization–Environment (TOE) framework [11] remains the principal theoretical lens for examining organizational readiness for AI adoption. Its enduring appeal lies in its ability to integrate technological, organizational, and environmental determinants into a single systemic model that explains adoption behavior beyond purely technical or managerial boundaries [5], [7], [65]. By linking these three dimensions, TOE positions readiness as a multidimensional construct that aligns internal capability with external opportunity, providing a balanced analytical view of how organizations prepare for technological transformation.

Over time, the field has undergone a theoretical broadening. Earlier studies published between 2015 and 2019 predominantly applied TOE in a deterministic manner, conceptualizing readiness as a pre-adoption condition indicating whether organizations possessed sufficient capability to adopt AI [66], [67]. From 2020 onward, researchers increasingly reconceptualized readiness as a dynamic organizational capability, embedding the TOE framework within complementary perspectives such as the Resource-Based View (RBV) [68] and the Dynamic Capability View (DCV) [69]. In this hybridization, readiness is no longer treated as a binary condition but as an evolving capability that enables organizations to sense technological opportunities, seize them strategically, and reconfigure internal structures in response to environmental turbulence [65], [16], [70].

Parallel developments have further enriched TOE through the adoption of Institutional Theory [75], emphasizing that readiness is also influenced by external legitimacy pressures, regulatory conformity, and ethical accountability [64], [71], [72].

At the micro level, the Technology Acceptance Model (TAM) [73] and the Unified Theory of Acceptance and Use of Technology (UTAUT) extend the discussion by linking user-level adoption behaviors to organizational and institutional readiness [66], [74]. Together, these integrations demonstrate that readiness operates across nested levels—from individual cognition to institutional governance—connecting micro, meso, and macro dimensions of capability formation.

Collectively, this convergence marks a paradigmatic shift from viewing readiness as a deterministic predictor of adoption to conceptualizing it as a strategic, adaptive, and socially embedded capability. The TOE framework, augmented by the RBV [68], DCV [69], and Institutional Theory [75], now functions as an integrative meta-framework that connects technological affordances, organizational competencies, and environmental legitimacy within complex socio-technical systems. This theoretical evolution substantiates the continued use of TOE as the conceptual core of AI readiness research—its flexibility enabling consistent yet context-sensitive analysis across sectors, organizational scales, and AI applications.

This pattern indicates that TOE is increasingly used not merely as a classificatory framework but as a foundational structure for organizing organizational readiness constructs in AI adoption research.

B. Dominant Readiness Factors and Thematic Patterns

The thematic synthesis derived from open, axial, and selective coding identified twelve core readiness themes distributed across the technological, organizational, and environmental dimensions of AI adoption.

Together, these themes form a consolidated structure of readiness constructs applicable across industries and organizational contexts, providing the conceptual foundation for future assessment frameworks and maturity models. The findings indicate that technological readiness is the most extensively examined dimension, with particular emphasis on infrastructure maturity, data governance, interoperability, and cybersecurity [76], [77], [66]. Unlike traditional IT readiness, AI readiness extends beyond digital infrastructure toward datacentric capabilities such as accessibility, analytical accuracy, and model reliability [7], [78].

Accordingly, technological readiness represents a necessary, yet insufficient, condition for successful AI-driven transformation—it provides the technical foundation, but organizational and environmental mechanisms ultimately determine whether technological potential can be realized [79], [16].

Organizational readiness reflects a combination of managerial, structural, and cultural capacities that enable and sustain transformation processes. The synthesis highlights four dominant constructs: strategic and managerial support, human and structural readiness, cultural and governance alignment, and knowledge and learning [80], [72], [81], [70]. Leadership and strategic alignment consistently appear as pivotal determinants, reinforcing theories of vision-driven transformation within strategic management literature [69], [16]. Furthermore, the growing integration of ethical governance and responsible AI practices demonstrates that readiness also involves legitimacy and trust, not merely competence or resource sufficiency.

Environmental readiness refers to the institutional, market, and societal conditions that influence and constrain organizational AI adoption. Its four major constructs include regulatory and policy context, market dynamics, collaborative ecosystem, and social legitimacy and ethics [64], [82], [83]. External collaboration and policy alignment have become increasingly vital, especially in public-sector and cross-sector ecosystems where interoperability and compliance determine adoption success [84], [85]. These findings reinforce the view that AI readiness extends beyond internal organizational capabilities and is embedded within a broader socio-technical and institutional ecosystem, shaped by institutional frameworks and inter-organizational relationships.

Integrating these twelve core readiness themes confirms that AI readiness operates as a multidimensional organizational capability, combining technological enablement, managerial adaptability, and environmental alignment. This holistic perspective moves the field beyond deterministic adoption models, positioning readiness as a dynamic equilibrium between technological potential, organizational capacity, and environmental legitimacy—an equilibrium that defines an organization's sustained ability to transform through AI.

Taken together, these readiness factors suggest that AI adoption success is less dependent on isolated technological assets and more contingent on the alignment of technological capability, managerial orchestration, and environmental legitimacy.

C. Cross-Dimensional Interdependencies

Cross-dimensional analysis across the TOE framework demonstrates that the twelve core readiness themes are inherently interdependent instead of analytically isolated, forming a systemic and recursive structure rather than a set of discrete categories. Technological readiness without corresponding organizational capability rarely leads to meaningful transformation [6], [80], while strong leadership and financial investment remain ineffective without high-quality data and reliable AI infrastructure [77], [76]. Environmental readiness—particularly regulatory clarity, policy alignment, and stakeholder trust—moderates the effectiveness of both technological and organizational readiness, demonstrating that adoption success depends on the degree of contextual alignment [64], [67], [71].

Such interdependencies align with the concept of mutual shaping in socio-technical theory, which emphasizes the co-evolution of technologies, organizational structures, and institutional contexts.

Empirical evidence reinforces this view: effective AI adoption requires not only robust infrastructure and data systems but also adaptive governance mechanisms that respond dynamically to ethical, regulatory, and market conditions [16], [72], [83]. Accordingly, readiness should not be perceived as a collection of independent domains but as a coupled system of enablers, whose collective value emerges through interaction and interdependence across all TOE dimensions.

From a theoretical perspective, these cross-dimensional dynamics align with the Dynamic Capability View (DCV), which conceptualizes readiness as a higher-order capability that enables organizations to integrate, build, and reconfigure technological and managerial resources in response to environmental turbulence [69], [80]. From a managerial standpoint, enhancement in one dimension (e.g., technology) must be complemented by synchronized investments in other areas (e.g., human skills, governance, and partnerships). This multi-domain coherence reflects the organizational alignment required for AI-driven transformation, ensuring that technological, human, and institutional components evolve cohesively.

Fig. 5 illustrates this systemic interplay among technological, organizational, and environmental readiness dimensions, visualizing how reciprocal relationships sustain overall readiness maturity. Collectively, these patterns reinforce the conceptualization of AI readiness as a socio-technical system capability—an emergent property arising from balanced maturity, continuous alignment, and coordinated evolution across the TOE framework.

This finding directly addresses RQ3 by demonstrating that AI readiness is conceptualized in the literature as a co-evolving system, where weaknesses in one TOE dimension may constrain the effectiveness of others.

D. Theoretical and Practical Implications

From a theoretical standpoint, this review advances TOE-based research by shifting the analytical focus from a deterministic adoption model toward a capability-oriented and ecosystem-level perspective.

These theoretical implications are directly derived from the cross-dimensional synthesis of readiness constructs identified in Section A to C. By integrating insights from the Resource-Based View (RBV) and the Dynamic Capability View (DCV), readiness is redefined as a dynamic organizational capability—reflecting an organization's ability to sense opportunities, seize technological potential, and transform internal processes in response to environmental constraints [69], [16]. This reconceptualization advances theory by positioning readiness not as a static precondition for adoption but as a continuous process of adaptation, learning, and institutional alignment within socio-technical systems.

The integration of Institutional Theory further extends the TOE framework's boundary by embedding normative, regulatory, and ethical dimensions into the readiness construct. AI adoption entails socio-ethical implications requiring compliance, accountability, and legitimacy [64], [72], [83]. Consequently, readiness now encompasses a form of moral capability—the organizational capacity to align technological innovation with societal expectations and governance norms. This theoretical enrichment broadens the TOE framework's explanatory power, providing a more holistic understanding of how AI readiness functions as a multi-level and socially embedded capability in digitally transforming environments.

From a practical standpoint, the synthesized findings provide actionable guidance for organizations as well as policymakers. Organizations should design balanced readiness strategies that integrate technological, organizational, and environmental investments rather than focusing narrowly on infrastructure or human capital. This includes establishing robust data governance mechanisms, fostering AI ethics and transparency frameworks, and nurturing ecosystem partnerships that accelerate responsible innovation [7], [79].

For policymakers, the findings highlight the need to build enabling regulatory environments and cross-sectoral collaborations that minimize readiness disparities across industries, sectors, and economies [85], [86]. Such alignment between internal organizational practices and external institutional support is essential to ensure equitable and sustainable AI diffusion.

In synthesis, this review positions AI readiness as both a theoretical bridge between information systems and strategic management research and a practical instrument for guiding digital transformation strategies in the era of intelligent technologies. These practical implications reflect the interdependent nature of technological, organizational, and environmental readiness dimensions identified in the review. Table VII summarizes the theoretical contributions and practical implications derived from this study.

TABLE VII. SUMMARY OF THEORETICAL AND PRACTICAL IMPLICATIONS

Perspective	Key Contributions / Implications	Representative Sources
Theoretical	• Reframes TOE from a deterministic adoption model to a capability-based, dynamic, and ecosystemic framework. • Integrates RBV and DCV to define readiness as a higher-order organizational capability for sensing, seizing, and transforming. • Embeds Institutional Theory to capture legitimacy, ethics, and governance as integral components of readiness. • Expands TOE into a multi-level socio-technical framework connecting micro (user), meso (organizational), and macro (institutional) levels.	[69], [16], [64], [72]
Practical	• Guides organizations to pursue integrated readiness strategies across technological, organizational, and environmental domains. • Emphasizes data governance, AI ethics, and transparency as enablers of responsible innovation. • Encourages ecosystem partnerships and inter-sectoral collaborations to strengthen readiness maturity. • Informs policymakers to establish enabling regulations and reduce readiness gaps across industries and economies.	[79], [7], [86], [85]

E. Field Maturity and Research Gaps

The temporal trend observed between 2015 and 2025 shows that AI readiness research has evolved from conceptual exploration to empirical consolidation, signaling a field that is maturing yet uneven in scope and depth. Europe and Asia dominate the literature, accounting for over 60% of publications, reflecting regions with strong institutional and policy support for digital transformation [64], [65]. However, this geographic concentration also introduces contextual bias, as only a limited number of studies examine readiness in developing or low-income economies [27], [72]. Future research should therefore broaden its contextual coverage to enhance cross-regional generalizability and uncover readiness dynamics in underrepresented environments.

Methodologically, nearly half of the studies (around 45%) employ quantitative, cross-sectional designs that capture static relationships among TOE variables. Few investigations adopt longitudinal or mixed-method approaches capable of tracing the evolution of readiness or its performance outcomes over time [7], [16]. Moreover, limited research has connected readiness assessment to benefit realization frameworks, such as Benefits Management [87] or the Generic IT/IS Business Value model [88]. The absence of such linkages constrains the field's ability to demonstrate how readiness translates into tangible organizational value, leaving a critical bridge between measurement and impact underdeveloped.

Conceptually, AI readiness studies have yet to fully integrate human, ethical, and environmental sustainability as integral dimensions of preparedness. As AI technologies increasingly influence organizational decision-making, future studies must embed responsible AI principles, socio-ethical governance, and sustainability considerations into readiness constructs [89], [83]. This integration would extend current frameworks beyond technical and managerial boundaries, positioning readiness as a foundation for ethical, inclusive, and context-sensitive AI transformation.

Taken together, the evidence suggests that the AI readiness field is transitional moving from descriptive to dynamic and integrative paradigms. While theoretical maturity is advancing, significant opportunities remain to expand contextual diversity, strengthen methodological rigor, and link readiness to measurable value creation. Overall, this synthesis positions AI readiness as a multi-level, evolving capability embedded within socio-technical and institutional systems, requiring continuous adaptation to ensure responsible and sustainable digital transformation.

V. Conclusion

This systematic literature review synthesizes forty peer-reviewed studies published between 2015 and 2025 to examine how organizational readiness for Artificial Intelligence (AI) adoption is conceptualized within the Technology–Organization–Environment (TOE) framework. By consolidating fragmented readiness concepts into twelve core readiness themes across technological, organizational, and environmental dimensions, this study demonstrates that AI readiness constitutes a multidimensional, capability-oriented construct rather than a static precondition for adoption. The findings clarify the structural boundaries of organizational AI readiness and establish an integrated conceptual foundation to support future empirical research and readiness assessment initiatives.

Despite the systematic approach adopted in this review, several limitations should be acknowledged. The analysis was limited to English-language journal articles indexed in Scopus and relied on heterogeneous conceptualizations of readiness across the reviewed studies. In addition, the review focused on organizational-level readiness and did not examine post-adoption stages such as value realization. Future research may build on these findings by prioritizing longitudinal research designs, developing standardized readiness measurement models, and examining how organizational readiness translates into performance outcomes and sustained AI-enabled value.

Ultimately, this study reconceptualizes organizational AI readiness from a checklist of adoption prerequisites into an evolving and interdependent capability shaped by the alignment of technological, organizational, and environmental dimensions. This perspective provides a critical foundation for linking readiness assessment with strategic decision-making and long-term, responsible AI-driven transformation in complex organizational contexts.

Acknowledgment

This study benefited from the analytical and visualization assistance of OpenAI's ChatGPT (GPT-5), which was used to support literature synthesis, reference organization, and ensure narrative consistency and analytical clarity. All AI-assisted inputs were reviewed and validated by the author to ensure academic accuracy and integrity. All interpretations, analyses, and conclusions presented in this study remain solely the author's responsibility.

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