

Organizational AI Readiness Maturity Model (AIRMM): A Conceptual Framework Bridging AI Readiness and Maturity Perspectives

Modèle de maturité de la préparation organisationnelle à l'intelligence artificielle (AIRMM) : un cadre conceptuel reliant les perspectives de préparation et de maturité en matière d'IA

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Abstract

Artificial intelligence (AI) adoption requires more than technological availability; it depends on organizational conditions related to strategy, resources, knowledge, culture, data, and processes. Existing AI readiness frameworks primarily identify these conditions, while AI maturity models generally assess the sophistication of AI capabilities and use. This study addresses the conceptual space between these two perspectives by proposing an Organizational AI Readiness Maturity Model (AIRMM). Drawing on organizational readiness theory, AI readiness research, and maturity-model literature, the AIRMM conceptualizes organizational preparedness as a progressive and multidimensional construct. The proposed framework comprises six dimensions—strategic alignment, resources, knowledge, culture, data, and process readiness—and four maturity levels ranging from Fragmented to Institutionalized. Rather than treating organizations as simply ready or not ready, the model assesses the degree to which readiness conditions are developed, formalized, integrated, and institutionalized. The AIRMM contributes to the literature by introducing a developmental perspective on organizational AI readiness and distinguishing readiness maturity from broader AI maturity. As a conceptual framework, it also provides a basis for organizational diagnosis and future empirical validation.

Key words : Intelligence artificielle ; Préparation organisationnelle à l'IA ; Maturité de l'IA ; Modèle de maturité ; Adoption de l'IA.

Résumé

L'adoption de l'intelligence artificielle (IA) ne dépend pas uniquement de la disponibilité des technologies, mais également de conditions organisationnelles liées à la stratégie, aux ressources, aux connaissances, à la culture, aux données et aux processus. Les cadres existants de préparation à l'IA identifient principalement ces conditions, tandis que les modèles de maturité de l'IA évaluent généralement le degré de sophistication des capacités et des usages de l'IA. Cette étude propose de combler l'espace conceptuel entre ces deux perspectives à travers un Modèle de maturité de la préparation organisationnelle à l'intelligence artificielle (AIRMM). S'appuyant sur la théorie de la préparation organisationnelle, les travaux sur la préparation à l'IA et la littérature sur les modèles de maturité, l'AIRMM conceptualise la préparation organisationnelle comme un construit progressif et multidimensionnel. Le cadre comprend six dimensions — alignement stratégique, ressources, connaissances, culture, données et préparation des processus — et quatre niveaux de maturité allant de Fragmenté à Institutionnalisé. Le modèle permet ainsi d'évaluer le degré de développement, de formalisation, d'intégration et d'institutionnalisation des conditions de préparation. Il fournit enfin une base conceptuelle pour le diagnostic organisationnel et de futures validations empiriques.

Mots clés : Intelligence artificielle ; Préparation organisationnelle à l'IA ; Maturité de l'IA ; Modèle de maturité ; Adoption de l'IA.

Introduction

Artificial intelligence (AI) has progressively moved from an emerging technological phenomenon to a strategic consideration for organizations across industries. Advances in machine learning, natural language processing, computer vision, and, more recently, generative AI have substantially expanded the range of organizational activities that can be supported or transformed by AI. Organizations increasingly explore AI for process automation, decision support, customer interaction, knowledge management, forecasting, and innovation. Yet the increasing availability of AI technologies does not necessarily mean that organizations are capable of adopting and integrating them successfully.

AI adoption requires more than access to appropriate technologies. It may require substantial organizational changes involving strategy, resources, data, technological infrastructure, managerial capabilities, employee knowledge, organizational culture, and business processes. Consequently, organizations facing similar technological opportunities may exhibit very different levels of preparedness for AI adoption. Some may possess the technological and organizational foundations necessary to initiate AI projects, whereas others may still lack basic conditions required to move beyond experimentation or intention.

This observation has contributed to the emergence of organizational AI readiness as a distinct research concern. The concept shifts attention from the adoption decision itself toward the organizational conditions that precede and enable such adoption. This distinction is particularly important because an organization can express an intention to adopt AI without necessarily possessing the capabilities, resources, data, knowledge, or organizational alignment required to implement it effectively.

The broader organizational readiness literature provides an important theoretical foundation for this perspective. Weiner (2009) conceptualizes organizational readiness for change as a shared organizational state reflecting both commitment to change and collective capability to implement it. His theoretical contribution emphasizes that readiness is not simply an individual attitude but an organizational condition shaped by the perceived value of change and the organization's confidence in its ability to execute it. This perspective is particularly relevant to AI because AI adoption represents not merely a technological decision but a potentially substantial organizational change.

Building on this broader readiness perspective, Jöhnk et al. (2021) developed one of the first dedicated frameworks for organizational AI readiness. Based on interviews with 25 AI experts and a review of academic and practitioner literature, they identified 18 factors

grouped into five categories: strategic alignment, resources, knowledge, culture, and data. Their contribution is particularly significant because it moves the discussion from generic organizational readiness toward the specific organizational conditions required for AI adoption.

Subsequent research has demonstrated that AI readiness is broader than the dimensions initially identified by Jöhnk et al. Holmström (2022), for example, conceptualizes AI readiness from a digital transformation perspective, emphasizing technologies, activities, boundaries, and goals. Tehrani et al. (2024) further extend the construct through an empirical investigation of multinational corporations, identifying eight dimensions encompassing informational, environmental, infrastructural, participant, process, customer, data, and technological readiness. These contributions indicate that organizational AI readiness is a multidimensional and context-dependent construct rather than a simple technological prerequisite.

At the same time, another stream of literature has developed around organizational maturity models. Maturity models differ from readiness frameworks in that they do not merely identify the conditions associated with a capability; they seek to represent different degrees of development through progressive levels. In this sense, maturity models can help organizations assess their current state, identify capability gaps, and determine potential pathways for improvement. The AI maturity literature has adopted this logic to assess organizational AI capabilities, although existing models vary considerably in their scope, dimensions, levels, and purposes. A systematic review by Sadiq et al. (2021) found that most AI maturity models were developed for specific domains or purposes and that many remained primarily descriptive; the review also highlighted a strong technological orientation among existing models.

The coexistence of these two research streams raises an important conceptual question. AI readiness research explains what organizations need to have in place to be prepared for AI adoption, whereas maturity research explains how organizational capabilities can progress from lower to higher levels of development. What remains less clearly articulated is how the multidimensional conditions identified by AI readiness research can themselves be represented as a progressive maturity construct.

This distinction is particularly important for organizations that are at the beginning of their AI journey. For such organizations, asking whether they are simply "ready" or "not ready" provides limited managerial guidance. An organization may be relatively advanced in

technological infrastructure but remain poorly prepared in terms of data governance, AI skills, strategic alignment, or organizational culture. A useful assessment should therefore capture not only which readiness conditions exist, but also the degree to which those conditions have been developed and institutionalized.

The present study addresses this issue by proposing an Organizational AI Readiness Maturity Model (AIRMM). Rather than introducing another list of AI readiness factors or another general AI maturity model, the study seeks to establish a conceptual bridge between these two literatures. Specifically, it investigates how organizational AI readiness dimensions can be translated into progressive levels of preparedness for AI adoption.

The research question guiding the study is therefore:

How can organizational AI readiness be conceptualized as a progressive maturity model for assessing organizational preparedness for AI adoption?

The study makes three conceptual contributions. First, it extends the organizational AI readiness literature by introducing a developmental perspective to a construct that has predominantly been conceptualized through multidimensional factors. Second, it distinguishes AI readiness maturity from broader AI maturity, thereby focusing specifically on the development of the organizational conditions that enable AI adoption rather than on the sophistication of AI use itself. Third, it proposes a structured basis for organizational diagnosis by linking readiness dimensions to progressive states of development.

The study is intentionally conceptual. Its purpose is to develop a theoretically grounded maturity framework that can subsequently be subjected to empirical validation. This approach is consistent with the observation that maturity models require explicit conceptual foundations and careful development before their empirical assessment.

The remainder of the paper is organized as follows. The next section establishes the conceptual foundations of organizational AI readiness, reviews the main AI readiness frameworks, examines the logic of organizational maturity models, and distinguishes AI readiness maturity from broader AI maturity. The section then develops the theoretical positioning of the proposed framework.

1. Literature Review and Theoretical Framework

1.1. Organizational readiness as a foundation for AI readiness

The concept of organizational readiness originates in the broader literature on organizational change and implementation. Unlike individual readiness, which focuses on an individual's

willingness or ability to undertake change, organizational readiness concerns the collective capacity and commitment of an organization to implement a change.

Weiner (2009) provides an influential theoretical account of organizational readiness for change. He conceptualizes readiness as a shared psychological state in which organizational members are committed to implementing a particular change and collectively confident in their capability to do so. Organizational readiness is consequently influenced by both change commitment and change efficacy, while contextual conditions such as resources, task demands, and situational factors shape the organization's perceived capacity to implement change.

This conceptualization is relevant to AI adoption for two reasons. First, AI adoption can represent a substantial organizational change rather than the simple acquisition of a technological tool. Second, successful implementation depends not only on technological feasibility but also on whether organizational actors recognize the value of AI-related change and believe that the organization possesses the capacity to implement it.

However, general organizational readiness theory does not specify the technological and organizational conditions that are particularly relevant to AI. AI introduces specific requirements related to data, computational infrastructure, technical expertise, algorithmic knowledge, governance, and the integration of AI into organizational processes. This creates the need for an AI-specific conceptualization of readiness.

1.2. Organizational AI readiness: from general readiness to AI-specific conditions

Organizational AI readiness can be understood as the organizational preparedness required to initiate and support AI adoption. The concept therefore occupies a position between general organizational readiness for change and actual AI adoption.

The distinction is important because AI adoption should not be considered an isolated technological event. AI systems interact with organizational structures, processes, people, data, and strategic objectives. An organization may consequently have high general digital maturity while remaining poorly prepared for AI if, for example, its data are inadequate or its employees lack the required knowledge.

Jöhnk et al. (2021) provide a particularly important contribution in this regard. Their interview-based study identifies five categories of organizational AI readiness factors: strategic alignment, resources, knowledge, culture, and data.

Strategic alignment captures the extent to which AI initiatives are connected to organizational objectives and business needs. Resources concern the availability of the financial,

technological, and human resources necessary to pursue AI initiatives. Knowledge encompasses the organization's understanding of AI and its ability to develop or acquire relevant expertise. Culture reflects organizational attitudes, collaboration patterns, and openness toward AI-related change. Data concerns the availability, quality, accessibility, and suitability of data for AI applications.

The importance of this framework lies not only in the dimensions it identifies but also in its assessment-oriented logic. Jöhnk et al. provide illustrative indicators that organizations can use to examine their preparedness. This makes the framework a particularly appropriate starting point for developing a maturity-oriented representation of readiness.

Nevertheless, the framework primarily answers the question:

What organizational conditions are relevant to AI readiness?

It provides less explicit guidance regarding:

What distinguishes an organization with low readiness from one with moderate or advanced readiness within each of these conditions?

This distinction is central to the present study.

1.3. Broadening the conceptualization of AI readiness

The subsequent literature confirms that organizational AI readiness cannot be reduced to the five categories proposed by Jöhnk et al.

Holmström (2022) approaches AI readiness through the lens of digital transformation and proposes four dimensions: technologies, activities, boundaries, and goals. His framework emphasizes that AI readiness depends on how AI technologies interact with organizational activities, organizational boundaries, and strategic objectives. The contribution is therefore less focused on identifying discrete readiness factors and more concerned with understanding how AI can be embedded into the organizational transformation process.

This perspective complements Jöhnk et al. by emphasizing that readiness is not solely a question of possessing resources. An organization may possess advanced technology and skilled employees while still lacking readiness if AI is poorly connected to organizational activities or strategic objectives.

Tehrani et al. (2024) provide another important extension. Their empirical study of multinational corporations identifies eight dimensions of AI readiness: informational, environmental, infrastructural, participant, process, customer, data, and technological readiness. Their framework expands readiness beyond internal organizational resources by incorporating external conditions, stakeholders, processes, information, and customers.

Taken together, these studies demonstrate two characteristics of AI readiness. First, the construct is multidimensional. No single dimension is sufficient to capture organizational preparedness. Second, the construct is systemic. AI readiness emerges from the interaction between technological, organizational, human, informational, strategic, and environmental conditions.

Recent systematic literature also supports this interpretation. Ali and Khan's (2025) review identifies a broad set of recurring AI readiness factors, including IT infrastructure, top management support, resources, organizational capabilities, collaborative culture, compatibility, data quality, and financial resources. This growing evidence base reinforces the need to move beyond narrow technological interpretations of readiness.

The implication for the present study is important: a maturity model should not simply reproduce Jöhnk et al.'s five categories mechanically. It should use them as a conceptual foundation while remaining open to dimensions that subsequent research has demonstrated to be relevant.

1.4. From multidimensional readiness to organizational maturity

While AI readiness research has focused primarily on identifying organizational conditions, maturity research addresses a different analytical problem: the degree to which a capability has been developed.

Maturity models emerged from organizational and process improvement research as mechanisms for representing progressive development. A maturity model generally establishes a limited number of levels, with each level representing a qualitatively different state of capability. The purpose is not merely classification but also diagnosis and improvement: an organization can identify its current state and determine what needs to change to progress toward a more advanced state.

The maturity concept is therefore fundamentally developmental. A capability is not simply present or absent; it can evolve from informal and fragmented practices toward increasingly formalized, integrated, and continuously improved capabilities.

This logic has been applied extensively to digital transformation and, more recently, AI. Sadiq et al. (2021), in their systematic review of AI maturity models, show that existing AI maturity models differ considerably in their objectives, scope, dimensions, methods, and validation approaches. They also report that many models are descriptive and that technological dimensions receive substantial attention.

This observation is significant for the present research. Existing AI maturity models demonstrate the usefulness of progressive assessment, but their primary object is generally AI capability or AI maturity, rather than the maturity of the organizational conditions that precede AI adoption.

The distinction can be represented conceptually as follows:

AI readiness

Does the organization possess the conditions required to undertake AI adoption?

AI maturity

How advanced is the organization's AI capability and use?

AI readiness maturity

How developed and institutionalized are the conditions required for the organization to undertake AI adoption?

The third question constitutes the specific conceptual space addressed by this study.

1.5. Distinguishing AI readiness maturity from AI maturity

The distinction between AI readiness maturity and AI maturity is necessary because the two concepts may otherwise become conflated.

AI maturity generally describes an organization's development in relation to AI capabilities, applications, processes, governance, or strategic use. An organization may therefore achieve a high level of AI maturity after developing and institutionalizing extensive AI capabilities.

AI readiness maturity, in contrast, focuses on the preparedness conditions surrounding the initiation and development of AI adoption. It is particularly relevant to organizations that are at an early or intermediate stage of their AI journey.

This distinction does not imply that readiness ends once adoption begins. Rather, readiness can progressively develop as organizations strengthen the organizational conditions that enable AI initiatives. An organization may therefore move through increasingly advanced states of preparedness while simultaneously progressing toward actual AI adoption.

This perspective also helps explain why a conventional AI maturity model may not be sufficient for organizations that have not yet established significant AI capabilities. Assessing the sophistication of AI applications provides limited guidance to an organization that is still struggling with basic strategic alignment, data quality, skills, infrastructure, or organizational acceptance.

A readiness-oriented maturity model therefore requires a different unit of analysis: the development of enabling conditions rather than the sophistication of AI outcomes or applications.

1.6. Principles for an Organizational AI Readiness Maturity Model

The synthesis of the organizational readiness, AI readiness, and maturity literatures suggests four principles for constructing an AI readiness maturity model.

Principle 1: Multidimensionality

AI readiness should be assessed across multiple dimensions rather than reduced to a single technological or organizational variable. Jöhnk et al. (2021), Holmström (2022), and Tehrani et al. (2024) all support this multidimensional interpretation, despite differences in their frameworks.

Principle 2: Progressivity

Readiness conditions should be represented through progressive states rather than binary indicators. Maturity models are specifically designed to capture such progression by describing qualitative differences between levels of capability.

Principle 3: Institutionalization

Progression should reflect more than the accumulation of resources. Higher maturity should indicate increasing formalization, integration, consistency, and institutionalization of AI-related conditions within organizational practices.

For example, possessing one employee with AI expertise should not be considered equivalent to having an organizational mechanism for developing and maintaining AI capabilities.

Principle 4: Actionability

A maturity model should provide more than a classification. Each level should indicate the organizational characteristics associated with that state and, ideally, the development priorities required to progress toward a subsequent level.

This principle is particularly important because maturity models have been criticized when they remain purely descriptive and fail to provide practical guidance for organizational improvement. Sadiq et al. (2021) highlight precisely this issue in their review of AI maturity models.

1.7. Theoretical positioning of the proposed model

Based on these principles, the proposed Organizational AI Readiness Maturity Model is positioned at the intersection of three bodies of literature.

The first is the organizational readiness literature, which establishes readiness as a collective organizational condition associated with commitment and implementation capability. Weiner's (2009) theory provides the conceptual foundation for understanding readiness as a property of the organization rather than simply an individual attitude.

The second is the organizational AI readiness literature, which specifies the conditions that make readiness meaningful in the context of AI. Jöhnk et al. (2021) provide the principal starting point because their framework is explicitly dedicated to organizational AI readiness and offers an operationally useful set of dimensions. Holmström (2022) and Tehrani et al. (2024) broaden this conceptual foundation by emphasizing the strategic, sociotechnical, environmental, informational, and process-related aspects of AI readiness.

The third is the maturity-model literature, which provides the developmental logic required to transform a set of organizational conditions into progressive states of capability. Rather than treating readiness dimensions as static factors, the maturity perspective allows each dimension to be examined according to the degree to which its underlying practices and capabilities have been developed and institutionalized.

The resulting conceptual logic can therefore be expressed as:

Organizational readiness theory

→ What does it mean for an organization to be ready for change?

AI readiness literature

→ What specific conditions are required for AI adoption?

Maturity-model literature

→ How can organizational capabilities be represented as progressive levels?

Organizational AI Readiness Maturity Model

→ How developed are the conditions that enable an organization to undertake AI adoption?

The proposed model thus does not seek to replace existing AI readiness frameworks or general AI maturity models. Instead, it occupies an intermediate conceptual position between them. Its purpose is to transform the static multidimensional representation of AI readiness into a developmental representation of AI preparedness.

This positioning provides the conceptual basis for developing the maturity dimensions and levels in the following section.

2. Development of the Organizational AI Readiness Maturity Model

2.1. Development approach

The Organizational AI Readiness Maturity Model (AIRMM) proposed in this study is developed through conceptual synthesis rather than empirical derivation. This approach is consistent with the nature of the research problem identified in the previous section: no existing framework currently articulates organizational AI readiness as a progressive maturity construct. Before such a construct can be empirically tested, it must first be theoretically specified.

This approach also follows established guidance on maturity model development. Becker et al. (2009) argue that maturity models should be grounded in a clearly articulated problem definition, build on existing theoretical and empirical knowledge, and follow a structured, iterative design logic rather than an ad hoc accumulation of dimensions and levels. Similarly, de Bruin et al. (2005) emphasize that the early phases of maturity model development should focus on scoping the domain and identifying the relevant dimensions before specifying levels of progression. The development of the AIRMM follows this logic in three steps: (1) scoping the readiness dimensions relevant to AI adoption, (2) defining a generic maturity logic applicable across those dimensions, and (3) integrating dimensions and levels into a structured assessment matrix.

This conceptual approach has an important implication for how the model should be read. The AIRMM is not proposed as a finished diagnostic instrument ready for immediate managerial application. Rather, it is a theoretical artifact intended to organize existing knowledge into a coherent developmental structure, which can subsequently be operationalized and validated empirically — a point returned to in the discussion and conclusion.

2.2. Selecting and integrating readiness dimensions

The dimensional structure of the AIRMM is built on the five categories identified by Jöhnk et al. (2021): strategic alignment, resources, knowledge, culture, and data. This choice is deliberate rather than incidental. Among existing frameworks, Jöhnk et al.'s study remains the most explicitly dedicated to organizational AI readiness, and its factors were derived specifically from expert accounts of what organizations need before undertaking AI initiatives — making it the most direct conceptual match for a readiness-oriented maturity model.

However, Section 1.3 established that subsequent research demonstrates readiness to be broader than these five categories. Two extensions are incorporated on this basis, subject to a single inclusion criterion: a dimension is added only if it captures an organizational condition

that precedes and enables AI adoption, rather than a characteristic of AI use or performance itself.

First, strategic-organizational embeddedness is incorporated from Holmström (2022). His framework shows that readiness cannot be reduced to possessing the right resources or knowledge in isolation; it also depends on whether AI initiatives are connected to organizational activities and boundaries in a coherent way. Rather than introducing "activities," "boundaries," and "goals" as three separate dimensions, this study treats them as an elaboration of Jöhnk et al.'s strategic alignment category, sharpening it to explicitly capture the coherence between AI initiatives and existing organizational structures and processes — not merely the existence of an AI strategy on paper.

Second, process readiness is incorporated from Tehrani et al. (2024). Their study indicates that AI readiness depends partly on whether organizational processes are structured in ways that allow AI to be meaningfully integrated — for instance, whether workflows are documented and standardized enough to support automation or decision support. This condition is not adequately captured by any of Jöhnk et al.'s five categories, which justifies its addition as a distinct dimension rather than folding it into an existing one.

By contrast, other elements identified by Tehrani et al. — informational, environmental, participant, customer, and technological readiness — are treated as manifestations of the existing dimensions rather than as additional ones. Informational and technological readiness, for example, overlap substantially with data and resources; participant readiness overlaps with culture and knowledge. Incorporating them as separate dimensions would inflate the model without adding distinct conceptual content, which would violate the parsimony that maturity models require to remain usable (a concern also raised by Sadiq et al., 2021, regarding the proliferation of AI maturity models with excessive, poorly differentiated dimensions).

This process yields six dimensions for the AIRMM:

Dimension	Core question
Strategic alignment	Is AI adoption coherently connected to organizational objectives, activities, and structures?
Resources	Are the financial, technological, and human resources required for AI initiatives available and allocated?
Knowledge	Does the organization possess or have access to the expertise required to understand and apply AI?
Culture	Do organizational attitudes, norms, and collaboration patterns support AI-related change?

Data	Is data available, accessible, and of sufficient quality to support AI applications?
Process readiness	Are organizational processes sufficiently structured and documented to allow AI integration?

2.3. Defining the maturity levels

Having scoped the dimensions, the AIRMM requires a generic maturity logic that can be applied consistently across all six of them. Following Principle 2 (Progressivity) and Principle 3 (Institutionalization) established in Section 1.6, progression across levels should not be interpreted merely as the accumulation of resources or activities, but as increasing formalization, integration, and institutionalization of readiness-related practices.

The AIRMM adopts a four-level structure. A four-level scale is preferred over more granular alternatives (five or six levels, as seen in some existing AI maturity models) because the object of assessment here is preparedness conditions rather than AI capability sophistication. Readiness conditions are inherently more binary in their early stages — a condition is either largely absent or beginning to emerge — and a coarser scale better avoids the false precision that finer-grained levels can introduce into a still-conceptual model. This choice can be revisited during empirical validation if finer distinctions prove necessary in practice.

The four levels are defined as follows:

Level 1 — Fragmented. Readiness conditions exist, if at all, in isolated and uncoordinated forms. Any relevant activity is initiated informally, typically by individual actors or teams, without organizational sponsorship, documentation, or continuity. There is no shared understanding across the organization of what the dimension requires or why it matters. Conditions at this level are highly dependent on specific individuals and are vulnerable to disruption through staff turnover or shifting priorities.

Level 2 — Emerging. The organization recognizes the relevance of the dimension and begins to take deliberate, though still localized, action. Isolated initiatives are supported by limited resources or informal management attention, but they remain confined to particular units, projects, or individuals rather than being coordinated across the organization. Practices are inconsistent, and no shared standards or repeatable processes yet exist.

Level 3 — Structured. The dimension is addressed through formalized, organization-wide practices. Roles, responsibilities, standards, or processes are explicitly defined and consistently applied across relevant parts of the organization. Readiness conditions no longer depend on individual initiative; they are supported by defined organizational mechanisms, and their existence is recognized and reinforced by management.

Level 4 — Institutionalized. Readiness conditions are fully embedded in organizational governance, culture, and routine practice. They are proactively monitored, periodically reviewed, and continuously improved as part of normal organizational functioning. Practices at this level are not only consistent but adaptive — the organization has established mechanisms for reassessing and updating them as AI-related needs evolve.

This generic scale is intentionally abstract at this stage so that it can be applied uniformly across dimensions with very different substantive content (e.g., data quality versus organizational culture). Section 2.4 operationalizes this scale by specifying what each level means concretely within each of the six dimensions.

2.4. The AIRMM matrix

Table 1 integrates the six dimensions (Section 2.2) with the four maturity levels (Section 2.3) into the AIRMM matrix. Each cell provides an illustrative descriptor of the organizational state associated with that dimension at that level. These descriptors are intended as indicative anchors rather than exhaustive checklists; their function is to make each level tangible and distinguishable from adjacent levels, consistent with Principle 4 (Actionability).

Table 1. The Organizational AI Readiness Maturity Model (AIRMM)

Dimension	Level 1: Fragmented	Level 2: Emerging	Level 3: Structured	Level 4: Institutionalized
Strategic alignment	AI is discussed informally; no connection to organizational objectives	AI initiatives exist but are driven bottom-up, disconnected from strategy	AI strategy is formally defined and linked to business objectives and processes	AI strategy is continuously reviewed and dynamically aligned with evolving organizational goals
Resources	No dedicated budget or personnel for AI	Ad hoc funding or staff time allocated to isolated projects	Dedicated budget, infrastructure, and roles established for AI initiatives	Resource allocation is systematically planned, monitored, and adjusted based on portfolio-level AI needs
Knowledge	AI understanding limited to a few individuals, if any	Pockets of expertise exist in specific teams; no organization-wide capability	Formal training programs and defined AI-related competencies exist across relevant functions	Continuous learning mechanisms and knowledge-sharing structures sustain and evolve AI expertise
Culture	Skepticism, indifference, or fear toward AI; no shared	Growing interest, but attitudes vary widely across	Organization-wide openness to AI is actively cultivated through	AI-related experimentation and learning from failure are embedded as cultural

	narrative	units	communication and leadership support	norms
Data	Data is siloed, undocumented, or of unknown quality	Data quality and access issues are recognized; localized clean-up efforts underway	Formal data governance, quality standards, and access protocols exist across the organization	Data governance is continuously monitored and adapted to evolving AI use cases
Process readiness	Processes are undocumented and highly variable	Some core processes are documented, but standardization is inconsistent	Key processes are documented, standardized, and assessed for AI-integration potential	Processes are systematically redesigned and monitored to accommodate AI-driven change

An organization's overall readiness maturity profile is not necessarily uniform across dimensions. Consistent with the multidimensionality principle (Section 1.6), an organization may be Structured in resources while remaining Fragmented in data governance. The AIRMM is therefore intended to produce a profile across the six dimensions rather than a single composite score — a design choice that preserves diagnostic value, since collapsing dimensions into one index would obscure exactly the kind of unevenness that Section 1.2 identified as a key limitation of binary readiness assessments.

2.5. Illustrative application

To ground the abstract structure of Table 1, consider a hypothetical mid-sized manufacturing firm exploring AI adoption for predictive maintenance. Leadership has expressed strategic interest in AI (moving beyond Level 1 in strategic alignment) and has allocated a modest pilot budget to a single engineering team (Level 2 in resources). However, sensor data across production lines is fragmented across incompatible legacy systems with no documented quality standards (Level 1 in data), while process documentation for maintenance workflows is well established and standardized across all plants, a legacy of prior ISO certification efforts (Level 3 in process readiness). Employees are broadly curious about AI but this curiosity is confined to a handful of engineers rather than reflected in company-wide attitudes (Level 2 in culture), and no formal AI training exists (Level 1 in knowledge).

This profile illustrates the diagnostic value of a multidimensional maturity view: a conventional binary readiness assessment might classify this organization simply as "not ready," or an aggregated score might mask its genuine strength in process standardization. The AIRMM profile instead reveals that the organization's most urgent development priority is not strategic commitment — which already exists — but data governance and AI-specific

knowledge, which lag well behind the organization's process maturity. This is precisely the kind of actionable, dimension-specific guidance that Principle 4 requires, and which a single-score instrument would not provide.

3. Discussion

3.1. Theoretical contributions

The development of the AIRMM offers three contributions, corresponding to those anticipated in the Introduction.

First, the model introduces a developmental perspective to a construct that has so far been conceptualized almost exclusively through static, multidimensional factors. Jöhnk et al. (2021), Holmström (2022), and Tehrani et al. (2024) each specify what conditions matter for AI readiness, but none specify how those conditions vary in degree. By translating six readiness dimensions into a four-level progression, the AIRMM reframes readiness assessment from a checklist exercise ("is this condition present?") into a diagnostic exercise ("how developed is this condition, and what would the next stage of development look like?"). This shift addresses the limitation identified in Section 1.2: that existing frameworks provide limited guidance for distinguishing organizations with low, moderate, or advanced readiness within a given dimension.

Second, the model distinguishes AI readiness maturity from AI maturity, a distinction that Section 1.5 argued is necessary but currently underdeveloped in the literature. Because existing AI maturity models — as Sadiq et al.'s (2021) review shows — are predominantly oriented toward the sophistication of AI capabilities and applications, they offer limited value to organizations that have not yet initiated substantial AI activity. The AIRMM fills this gap by focusing the unit of analysis on enabling conditions rather than AI outcomes, making it applicable to organizations at the earliest stages of their AI journey, where conventional AI maturity models have the least to offer.

Third, the model provides a structured basis for organizational diagnosis by integrating dimensions and levels into a single matrix (Table 1). This integration operationalizes the conceptual bridge announced in the Introduction between the AI readiness literature and the maturity-model literature — a bridge that, to date, has been asserted more often than constructed.

3.2. Managerial implications

Although the AIRMM is developed conceptually, its structure carries several implications for organizations considering or pursuing AI adoption.

The illustrative case in Section 2.5 demonstrates the model's central managerial value: it resists the temptation to summarize organizational preparedness in a single score. A composite readiness index might reward the manufacturing firm's process standardization enough to offset its weak data governance, yielding a misleadingly reassuring "moderate readiness" verdict. The AIRMM's profile format instead directs managerial attention specifically toward the dimensions lagging furthest behind — in that case, data and knowledge — which is consistent with Principle 4 (Actionability) established in Section 1.6.

The model also implies that AI readiness development is not a single organizational initiative but a portfolio of parallel developmental trajectories. An organization does not "become AI ready" as a unitary event; it advances at different rates across strategic alignment, resources, knowledge, culture, data, and process readiness, and these trajectories can be managed and resourced somewhat independently. This has a practical corollary: an organization need not wait until every dimension reaches Level 3 or 4 before pursuing limited AI initiatives, provided the initiative's requirements are matched to the dimensions in which the organization is already sufficiently mature — a more nuanced managerial posture than the binary "ready/not ready" framing criticized in Section 1.2.

Finally, the model's institutionalization logic (Section 2.3) suggests that organizations should treat readiness not as something to be established once, but as a capability requiring ongoing governance. Level 4 in every dimension is characterized by continuous monitoring and adaptation, implying that even organizations that reach advanced readiness states must sustain the mechanisms that produced them, rather than treating readiness as a milestone that, once reached, no longer requires attention.

3.3. Limitations

Several limitations qualify the contributions of this study.

Most importantly, the AIRMM is a conceptual artifact that has not been empirically validated. Its dimensions, levels, and descriptors are derived through theoretical synthesis rather than tested against organizational data. Consequently, claims about the model's practical utility — including the illustrative case in Section 2.5 — should be read as demonstrations of the model's internal logic rather than as evidence of its real-world diagnostic accuracy.

Second, the selection and integration of dimensions in Section 2.2 involved interpretive judgment. While the inclusion criterion was made explicit, other researchers might reasonably weigh the contributions of Holmström (2022) or Tehrani et al. (2024) differently — for instance, by treating process readiness as a subcomponent of resources rather than as a

standalone dimension. The six-dimension structure proposed here should therefore be regarded as one defensible synthesis rather than a definitive taxonomy.

Third, the four-level scale, while justified on parsimony grounds in Section 2.3, has not been tested against organizational reality. It remains possible that certain dimensions — data governance, in particular, given its technical granularity — would benefit from a finer-grained scale than others, a possibility the current uniform four-level structure does not accommodate. Fourth, the model assumes that readiness dimensions can be assessed relatively independently of one another. In practice, dimensions likely interact — for example, weak strategic alignment may constrain the resources allocated to data governance. The AIRMM in its current form does not explicitly model such interdependencies between dimensions.

Conclusion and Future Research Directions

Summary

This study set out to answer the question: how can organizational AI readiness be conceptualized as a progressive maturity model for assessing organizational preparedness for AI adoption? Building on organizational readiness theory (Weiner, 2009), the organizational AI readiness literature (Jöhnk et al., 2021; Holmström, 2022; Tehrani et al., 2024), and the maturity-model literature (Sadiq et al., 2021), the study developed the Organizational AI Readiness Maturity Model (AIRMM) — a six-dimension, four-level framework linking strategic alignment, resources, knowledge, culture, data, and process readiness to a developmental progression from Fragmented to Institutionalized.

In doing so, the study addressed a gap identified in Section 1.4: existing AI readiness frameworks specify what organizational conditions matter, but not how those conditions vary in degree, while existing AI maturity models assess the sophistication of AI capability rather than the preparedness conditions that precede it. The AIRMM occupies the conceptual space between these two streams, treating the development of enabling conditions — rather than AI outcomes — as its unit of analysis.

Future research directions

Several directions follow directly from the limitations identified in Section 3.3.

Empirical validation. The most immediate priority is subjecting the AIRMM to empirical testing. This could proceed in stages consistent with established maturity-model development methodologies (Becker et al., 2009; de Bruin et al., 2005): first, qualitative validation through expert review or case studies to assess whether the level descriptors in Table 1 are

recognizable and discriminating in practice; second, the development of a survey instrument operationalizing each dimension, allowing quantitative assessment of organizations' maturity profiles; and third, testing whether maturity levels derived from the instrument correlate with actual AI adoption outcomes.

Refining the dimensional structure. Future research could examine whether the six-dimension structure proposed here holds across different empirical settings, or whether certain dimensions — process readiness in particular, given its recent addition to the readiness literature — should be further subdivided or merged. Cross-industry or cross-country studies would be particularly valuable, given that the illustrative case in Section 2.5 was drawn from a single organizational context.

Testing dimension interdependencies. As noted in Section 3.3, the current model treats dimensions as largely independent. Future work could investigate whether progression in one dimension enables or constrains progression in others — for instance, whether a minimum level of strategic alignment is a precondition for advancing data governance, rather than the two developing in parallel as the current model implicitly assumes.

Refining the granularity of levels. Future research could test whether a uniform four-level scale is appropriate across all dimensions, or whether some dimensions — such as data, which spans technical and governance considerations — warrant a more granular scale than others.

Longitudinal application. Because the AIRMM is explicitly developmental, its greatest practical value may lie in longitudinal use: tracking how an organization's dimensional profile evolves over time, rather than producing a single point-in-time assessment. Future research could explore how organizations actually progress between levels, and whether progression follows a consistent sequence across dimensions or varies by organizational context.

Concluding remark

Organizational AI readiness has been extensively studied as a multidimensional construct, and organizational AI maturity has been extensively studied as a developmental one. This study has argued that neither framing, on its own, adequately serves organizations at the early stages of their AI journey — the former because it cannot distinguish degrees of preparedness, the latter because it presumes a level of AI activity these organizations have not yet reached. The AIRMM is offered as a conceptual bridge between these two perspectives: a way of asking not only what an organization needs before adopting AI, but how far it has come in developing what it needs.

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