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A Conceptual Framework for Ai-Driven Industrial Management: Integrating Dynamic Capabilities and Organizational Readiness

Ho Thi Ha
School of Economics and Finace, Thu Dau Mot University

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ABSTRACT: Artificial intelligence (AI) is increasingly positioned as a central lever of industrial management, yet a large share of AI initiatives in manufacturing and operations settings fail to move beyond pilot stage. Existing explanations draw mainly on technology-adoption models, which treat AI implementation as a discrete adoption decision rather than as an ongoing organizational process. This conceptual paper addresses that limitation by integrating dynamic capabilities theory with the construct of organizational readiness for change to explain how industrial firms convert AI investment into sustained managerial and operational advantage. Following an integrative conceptual-article approach, the paper compares dynamic capabilities theory against competing lenses (the resource-based view, the technology-organization-environment framework, and technology-acceptance models), justifies an integrative choice, and develops a framework in which the microfoundations of dynamic capabilities (sensing, seizing, and transforming) operate through organizational readiness (change valence, change efficacy, and change commitment) to shape AI-driven industrial management capability and, in turn, operational and managerial performance outcomes. Six theory-grounded propositions are advanced, alongside a construct-definition table and a conceptual model. The framework contributes to the literature by repositioning organizational readiness as a dynamic, renewable capacity embedded within the seizing and transforming microfoundations rather than as a static precondition for adoption, and by offering industrial managers a process-based diagnostic for sequencing AI capability development. Limitations, boundary conditions, and an agenda for empirical validation, including multi-case and survey-based tests, are discussed.

KEYWORDS: artificial intelligence; industrial management; dynamic capabilities; organizational readiness for change; Industry 4.0; conceptual framework

1. INTRODUCTION

Artificial intelligence (AI) has moved from a peripheral analytics tool to a core input for industrial management, including production planning, predictive maintenance, quality control, supply chain orchestration, and managerial decision-making (Davenport & Ronanki, 2018; Frank et al., 2019). Industrial firms operating under Industry 4.0 conditions are expected to use AI not merely to automate discrete tasks but to reconfigure how operational and managerial decisions are made under uncertainty (Ghobakhloo, 2020). Survey and practitioner evidence consistently suggests that the practical returns from AI investment in industrial settings fall short of expectations: initiatives frequently stall after proof-of-concept, and organizations that do report gains are commonly those that pair AI investment with parallel changes in structure, skills, and decision routines rather than treating AI as a stand-alone technology purchase (Fountaine et al., 2019). This pattern indicates that the central constraint on AI-driven industrial management is organizational rather than purely technical.

The dominant theoretical lenses used to study AI implementation in industrial and organizational contexts are adoption-centric. Frameworks such as the technology-organization-environment (TOE) model (Tornatzky & Fleischer, 1990) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) explain the antecedents of a firm's or an individual's decision to adopt a technology, typically at a single point in time. These models are well suited to explaining initiation, but they are less suited to explaining the sustained, iterative process by which an industrial organization senses new AI opportunities, reconfigures routines and resources around them, and repeats this process as AI capabilities and competitive conditions evolve (Warner & Wäger, 2019). Conversely, dynamic capabilities theory (Teece et al., 1997; Teece, 2007) explains how firms build, integrate, and reconfigure resources to address changing environments, but the theory's microfoundations remain abstract with respect to the internal organizational conditions, such as employee commitment and change efficacy, that determine whether a firm's sensing and seizing routines actually translate into implemented change (Warner & Wäger, 2019). Organizational readiness for change theory (Armenakis et al., 1993; Weiner, 2009) directly addresses these internal conditions but has been developed mainly in general change-management and health-services contexts, with limited integration into the strategic-capability literature and limited application to AI-driven industrial settings (Jöhnk et al., 2021).

The result is a conceptual gap of three related kinds. First, a theoretical gap: dynamic capabilities theory and organizational readiness theory are typically applied in separate literatures and have rarely been integrated into a single explanatory framework for AI-driven organizational change (Warner & Wäger, 2019; Weiner, 2009). Second, a contextual gap: much of the empirical AI-readiness literature is drawn from healthcare, public-sector, and general digital-transformation settings, with comparatively limited theorization specific to industrial management, where safety-critical operations, capital-intensive assets, and shop-floor workforce dynamics create distinctive readiness conditions (Chatterjee et al., 2021; Jöhnk et al., 2021). Third, a mechanism gap: existing AI-adoption studies identify readiness and capability as relevant antecedents but rarely specify the mediating or sequential mechanism by which capability-building processes generate readiness, and readiness in turn converts capability into performance (Mikalef & Gupta, 2021).

This paper addresses these gaps by developing an integrative conceptual framework that positions organizational readiness for change as the internal mechanism through which dynamic capabilities are converted into AI-driven industrial management capability and, ultimately, operational and managerial performance outcomes. The framework is guided by two research questions:

RQ1: How do the microfoundations of dynamic capabilities (sensing, seizing, and transforming) explain the development of AI-driven industrial management capability?

RQ2: How does organizational readiness for change condition or mediate the relationship between dynamic capabilities and AI-driven industrial management capability and performance outcomes?

The paper offers three contributions. Theoretically, it integrates two literatures, dynamic capabilities and organizational readiness for change, that have developed largely in parallel, and it repositions readiness as a renewable, capability-embedded construct rather than a static precondition to be assessed once before implementation. Conceptually, it introduces AI-driven industrial management capability as a distinct, definable construct with a working definition and proposed measurement logic, addressing calls for clearer construct boundaries in the AI-capability literature (Mikalef & Gupta, 2021). Practically, it offers industrial managers a process-based, sequential diagnostic, rather than a one-time readiness checklist, for planning AI initiatives.

2. RESEARCH METHOD

2.1 Rationale for a conceptual Design

Because the objective is theory integration rather than hypothesis testing, this paper follows established guidance for designing conceptual articles in management research, which treats conceptual papers as a distinct scholarly genre with its own methodological standards rather than as a substitute for empirical rigor (Jaakkola, 2020). Consistent with this guidance, the paper is explicit about (a) the boundary conditions of the phenomenon addressed, (b) the theoretical lenses considered and the justification for the ones selected, and (c) the logic connecting each proposition to its underlying theory and supporting evidence, so that the propositions are falsifiable in subsequent empirical work.

2.2 Scope and boundary conditions

The framework is scoped to formal industrial organizations, defined as firms whose core value-creating activities involve manufacturing, process industries, or asset-intensive operations management, that are undertaking AI-based initiatives in planning, production, maintenance, quality, or supply chain management. The unit of analysis is the organization (firm or business unit), not the individual technology user, which distinguishes the framework's scope from individual-level technology-acceptance research. The framework is agnostic to firm size and national context in its general form, but Section 4.3 discusses conditions, including firm size and institutional environment, under which its propositions are expected to hold more or less strongly.

2.3 Literature Domains and Integration Logic

Three literature domains were reviewed to inform construct selection and proposition development: (a) dynamic capabilities and capability microfoundations, (b) organizational readiness for change and related change-management constructs, and (c) AI and Industry 4.0 adoption and capability research in industrial and operations settings. Consistent with an integrative-synthesis approach to literature use in conceptual articles (Jaakkola, 2020), search logic combining the following term groups was used to identify anchor and supporting sources, without claiming the systematic, PRISMA-type completeness appropriate to a systematic review:

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("artificial intelligence" OR "machine learning" OR "AI adoption")
AND ("dynamic capabilit*" OR "sensing" OR "seizing" OR "reconfiguring")
AND ("organizational readiness" OR "readiness for change" OR "change readiness")
AND ("industrial management" OR "manufacturing" OR "operations management" OR "Industry 4.0")
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Sources were prioritized in the following order: (1) foundational theoretical works establishing the constructs used (e.g., Teece et al., 1997; Armenakis et al., 1993); (2) peer-reviewed empirical or conceptual studies applying these constructs to digital transformation, AI, or Industry 4.0 contexts; and (3) practitioner evidence used only to motivate the practical significance of the problem, not to justify theoretical claims.

2.4 Theoretical lens selection

Table 1 compares four candidate lenses against the paper's explanatory requirements: an ability to explain *organizational-level* (not only individual-level) phenomena, an ability to explain *process and change over time* (not only a discrete adoption decision), and an ability to explain the *internal organizational conditions* that determine whether capability translates into implemented change.

Table 1. Comparison of Candidate Theoretical Lenses

Theory	Core proposition	Level of analysis	Explains process/time?	Explains internal readiness conditions?	Limitation for this framework
Resource-based view (RBV)	Valuable, rare, inimitable, non-substitutable resources generate sustained advantage	Organization	Largely static	No	Explains *what* resources matter but not how firms renew them under changing technology

Technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990)	Technological, organizational, and environmental context jointly shape adoption	Organization	Weak; adoption framed as a decision point	Partially (organizational context)	Explains adoption antecedents but not the ongoing capability-building process after adoption
Technology-acceptance models (e.g., UTAUT; Venkatesh et al., 2003)	Individual usage intention is driven by performance expectancy, effort expectancy, and social/facilitating factors	Individual	Weak	No (individual attitudes, not organizational routines)	Unit of analysis mismatch with firm-level industrial management outcomes
Dynamic capabilities theory (Teece et al., 1997; Teece, 2007)	Firms sense opportunities, seize them through resource reconfiguration, and transform organizational structures accordingly	Organization	Strong; explicitly processual	Weak; microfoundations underspecify internal change conditions	Requires a complementary construct to explain internal implementation conditions
Organizational readiness for change (Armenakis et al., 1993; Weiner, 2009)	Collective readiness (valence, efficacy, commitment) determines whether members support and sustain change	Organization/team	Moderate	Strong	Explains implementation conditions but not opportunity recognition or resource reconfiguration

Although the RBV, the TOE framework, and technology-acceptance models each capture part of the phenomenon, none jointly explains both the *process* by which industrial firms build AI capability over time and the *internal conditions* that determine whether that process succeeds. Dynamic capabilities theory is therefore adopted as the primary process lens because it is explicitly organizational, processual, and reconfiguration-oriented, and it has already been extended productively to digital transformation contexts (Warner & Wäger, 2019). Because dynamic capabilities theory underspecifies the internal, people-centered conditions of implementation, it is complemented, not replaced, by organizational readiness for change theory (Armenakis et al., 1993; Weiner, 2009), which was itself selected over general resistance-to-change or diffusion-of-innovation framing (Rogers, 2003) because readiness theory offers a multidimensional, organization-level construct (valence, efficacy, commitment) with an established measurement tradition (Holt et al., 2007) that can be operationalized in future empirical work.

2.5 Proposition-Development logic

Each proposition advanced in Section 3.4 is constructed using a three-layer rationale, consistent with the theory-mechanism-evidence logic used for hypothesis development in empirical dynamic-capabilities and readiness research: (a) the theoretical prediction, (b) the causal or associative mechanism specific to the AI-driven industrial management context, and (c) supporting evidence from prior conceptual or empirical work. Because no primary data are collected, propositions are stated as directional relationships to be tested in future empirical research rather than as findings, and causal language is deliberately avoided in favor of association and influence language, consistent with the non-empirical status of the paper.

3. RESULTS

3.1 Theoretical foundations

Dynamic capabilities theory. Teece et al. (1997) define dynamic capabilities as a firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Teece (2007) decomposes this ability into three microfoundations: sensing (identifying and assessing opportunities and threats), seizing (mobilizing resources to capture value from an opportunity, including designing business models and decision structures), and transforming (continuously renewing organizational structures, routines, and culture as conditions change). This decomposition provides a natural process backbone for a framework of AI-driven industrial management, because AI opportunity recognition, resource commitment, and structural renewal correspond closely to the three microfoundations.

Organizational readiness for change. Armenakis et al. (1993) define readiness as the cognitive precursor to change-related behaviors, encompassing organizational members' beliefs, attitudes, and intentions regarding the extent to which changes are needed and the organization's capacity to execute them successfully. Weiner (2009) extends this to a multilevel, multidimensional construct comprising change commitment (members' shared resolve to implement the change) and change efficacy (members' shared belief in their collective capability to implement the change), both of which are shaped by perceived discrepancy (the gap between current and desired states), appropriateness, and valence (personal benefit). Holt et al. (2007) operationalize readiness along appropriateness, management support, change efficacy, and personal valence, providing an established measurement tradition for future empirical testing of the present framework.

AI-driven industrial management capability. Building on Mikalef and Gupta's (2021) conceptualization of AI capability as a firm's ability to acquire, integrate, and deploy AI-based resources, this paper defines AI-driven industrial management capability as an organization's demonstrated ability to embed AI-based analysis into recurring industrial management decisions, including production planning, maintenance, quality control, and supply chain coordination, in a manner that measurably changes how those decisions are made rather than merely automating an isolated task.

3.2 Construct definitions

Table 2 defines each construct in the framework, its role, and an indicative measurement direction to guide future operationalization.

Table 2. Construct Definitions and Roles

Construct	Working definition	Role in model	Indicative measurement direction
Sensing capability	The organization's routines for scanning, interpreting, and evaluating potential AI applications relevant to its industrial operations	Antecedent (dynamic capability microfoundation)	Environmental scanning routines; technology-monitoring practices; pilot/experimentation frequency
Seizing capability	The organization's routines for mobilizing resources, redesigning decision structures, and committing investment to capture value from sensed AI opportunities	Antecedent (dynamic capability microfoundation)	Resource-allocation speed; cross-functional AI project governance; investment commitment
Transforming capability	The organization's routines for reconfiguring structures, roles, and culture to sustain AI-enabled ways of working	Antecedent (dynamic capability microfoundation)	Structural/role redesign frequency; retraining and reskilling programs; routine institutionalization
Organizational readiness for change	Collective change commitment and change efficacy regarding AI-enabled changes to industrial management routines	Mediating mechanism	Holt et al. (2007)-type readiness scale adapted to AI-related change
AI-driven industrial management capability	Demonstrated organizational ability to embed AI-based analysis into recurring industrial management decisions	Proximal outcome / mediator to performance	Extent and depth of AI use in planning, maintenance, quality, and supply chain decisions
Industrial management performance	Operational and managerial performance outcomes attributable to AI-enabled decision-making (e.g., production efficiency, downtime reduction, decision-cycle time, managerial responsiveness)	Distal outcome	Operational KPIs; managerial decision-cycle time; adaptive performance indicators
Technological and organizational context (boundary condition)	Firm size, industry type, data infrastructure maturity, and institutional environment	Moderator	TOE-derived contextual indicators (Tornatzky & Fleischer, 1990)

3.3 Conceptual Model

The framework proposes that sensing and seizing capabilities directly support the development of AI-driven industrial management capability, that transforming capability operates primarily through organizational readiness (Figure 1).

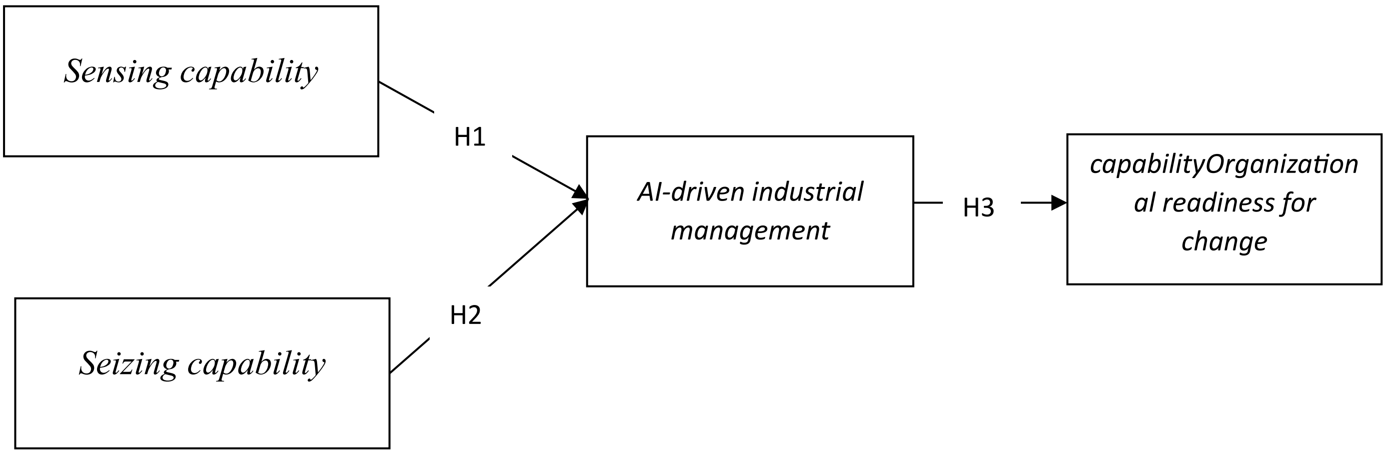

Figure 1. Conceptual Model 1

The proposed research model is grounded in Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997; Teece, 2007), which argues that organizations achieve sustainable competitive advantage by continuously sensing opportunities, seizing them through strategic actions, and transforming organizational resources to adapt to dynamic business environments. In the context of industrial digitalization and artificial intelligence (AI), dynamic capabilities enable firms to develop AI-driven management practices that enhance organizational performance (Figure 2).

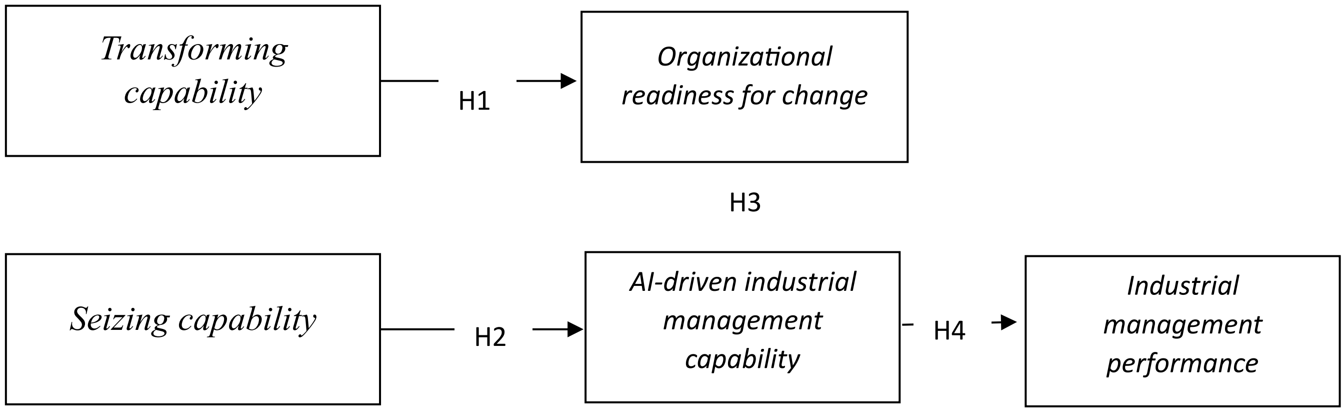

Figure 2. Conceptual Model 2

4. DISCUSSION

4.1 Theoretical Contributions

The framework makes three theoretical contributions relative to the gaps identified in Section 1.2. First, it integrates dynamic capabilities theory and organizational readiness for change into a single explanatory sequence, addressing calls to connect capability-based and change-management perspectives on digital transformation (Warner & Wäger, 2019). Second, by proposing readiness as a mediator of seizing and transforming effects (P5) rather than as an independent, static precondition, the framework reconceptualizes readiness as an output of capability-building routines as well as an input to further capability development, which is a testable departure from readiness research that treats readiness as a pre-implementation checklist (Weiner, 2009; Jöhnk et al., 2021). Third, the paper offers an explicit working definition and construct table for AI-driven industrial management capability, responding to the observation that AI-capability constructs in the information-systems literature often remain loosely specified relative to the level of analysis and industry context in which they are applied (Mikalef & Gupta, 2021).

4.2 Managerial Implications

For industrial managers, the framework implies that AI initiatives should be sequenced rather than treated as a single implementation decision. Because sensing and seizing routines are proposed to act directly on AI-driven industrial management capability while transforming routines act through readiness, managers who invest only in technology procurement (a seizing-type action) without parallel investment in role redesign and reskilling (transforming-type actions) are predicted to see AI-driven industrial management capability form more slowly and less durably, since organizational readiness is not being built in parallel. The framework also suggests a diagnostic use: rather than a one-time readiness assessment, industrial organizations can track readiness indicators (change efficacy and commitment) as a recurring signal of whether ongoing AI initiatives are being adequately supported by transformation activity, and can use gaps between seizing investment and readiness levels to anticipate implementation stalling before it occurs.

4.3 Boundary Conditions and Moderators

Three contextual factors are expected to condition the strength of the proposed relationships. First, data infrastructure maturity likely constrains how much sensed opportunity can realistically be seized, independent of readiness, because AI applications in industrial settings depend on data quality and system integration (Frank et al., 2019). Second, firm size is likely to affect the seizing-to-capability path, because larger industrial firms typically possess more slack resources to mobilize following sensing, while smaller firms may depend more heavily on readiness-driven workforce cooperation to compensate for resource constraints. Third, industry type, particularly the degree of safety-criticality and regulatory oversight, is expected to strengthen the readiness-to-capability path (P4), because safety-critical industrial contexts place a higher premium on workforce trust and change efficacy before AI-informed decisions are allowed to influence operational practice (Chatterjee et al., 2021).

4.4 Limitations

As a conceptual paper, this framework has not been empirically tested, and the propositions should be read as directional relationships to be examined rather than established findings. The theoretical lens comparison in Table 1 is not exhaustive; institutional theory and absorptive capacity theory, in particular, offer complementary but distinct explanations that were outside the paper's chosen scope and are noted as candidates for future integration rather than incorporated here. The construct definitions in Table 2 are proposed as a starting point for operationalization; item-level scale development and validation, including confirmatory factor analysis, remain necessary before the framework can be tested empirically. Finally, because the review underlying Section 2.3 followed an integrative rather than systematic search protocol, it does not claim the exhaustive coverage of a PRISMA-based systematic review, and readers seeking a comprehensive inventory of the AI-readiness or dynamic-capabilities literatures should consult it alongside dedicated systematic reviews.

4.5 Directions for Future Research

Four directions follow directly from the limitations above. First, the six propositions could be operationalized and tested using survey-based structural equation modeling among industrial firms undertaking AI initiatives, using established readiness (Holt et al., 2007) and AI-capability (Mikalef & Gupta, 2021) scales adapted to the industrial management context. Second, the mediation proposition (P5) is well suited to longitudinal or multi-wave designs, since readiness is theorized to change over the course of an AI initiative rather than remain fixed. Third, multi-case, comparative case-study research across industrial firms of different sizes and safety-criticality levels could examine the boundary conditions proposed in Section 4.3 in depth, including how transforming-capability routines are sequenced in practice. Fourth, future work could extend the framework by incorporating absorptive capacity or institutional-pressure constructs alongside dynamic capabilities and readiness, to test whether they explain additional variance in AI-driven industrial management capability beyond the present framework.

5. CONCLUSION

This paper developed an integrative conceptual framework explaining how industrial organizations convert AI investment into sustained AI-driven industrial management capability and performance, by combining dynamic capabilities theory with organizational readiness for change. The central theoretical move is to treat organizational readiness not as a static precondition assessed prior to AI adoption but as a renewable capacity generated by, and feeding back into, an organization's seizing and transforming routines. Six propositions operationalize this logic and are offered as a testable research agenda rather than as confirmed findings. For industrial management scholarship, the framework offers a way to connect capability-based and change-management explanations of AI-driven transformation that have largely developed in isolation from one another. For industrial managers, it reframes AI implementation as a sequential capability-and-readiness-building process rather than a single technology-adoption decision, with practical implications for how AI initiatives should be resourced, governed, and sequenced.

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Corresponding Author: Ho Thi Ha