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From Talent Management to Organizational AI Capability: A Conceptual Framework for AI-Ready Organizations

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***Abstract:** Artificial intelligence (AI) technologies are still costing organizations a lot of money, but there remains a critical divide between those that deliver such investment into long-term benefit and those whose efforts fail at the pilot phase. This paper claims that the determining distinction is not the technological one but the organizational one and it finds the answer in how the firms transform their human and talent-related resources into a higher-order Organizational AI Capability (OAIC). Based on the resource-based view, the knowledge-based view, the dynamic capabilities theory, the human capital theory, and the organizational learning theory, we construct a conceptual framework that redefines talent management as an orchestrating organizational capability that creates the learning and knowledge base on which AI capability is based. The framework outlines a sequence of transformation where talent management influences the organizational learning processes and capability to share knowledge that in turn leads to OAIC, which ultimately leads to organizational AI readiness. We develop eight propositions outlining the processes, intermediate routes, and boundary conditions of this change and we discuss why investment in AI technology is neither necessary nor sufficient to achieve AI readiness when the underlying capability architecture is missing. The article is part of the growing body of literature on organizational AI capability by bringing together strategic human-resource and capability views, by defining OAIC as a second-order dynamic capability that has discernible microfoundations, and by explaining why otherwise similar organizations become drastically different in their capacity to become AI-ready. Theory implications, managerial implications and future empirical research implications are discussed.*

***Keywords:** Talent Management, Organizational AI Capability, AI Readiness, Dynamic Capabilities, Knowledge Sharing, Organizational Learning, Strategic Human Resource Management, Digital Transformation*

I. INTRODUCTION

Artificial intelligence (AI) has shifted its position as an organizational strategy to the core, redefining how companies compete, structure their work, and create value (Enholm et al., 2022). However, AI has a record of use in organizations that is remarkably uneven. To each company that integrates AI into its operating model and transforms it into a quantifiable benefit, dozens and dozens of tools, pilots, and proofs of concept never turn into long-term organizational capability. This disjuncture cannot be sufficiently attributed to the variation in access to technology. Compute, models and data infrastructure are becoming more commoditized and accessible to organizations with vastly different sizes and sophistication levels. The more interesting reason is the organizational conditions that define the absorption of technological potential, its recombination, and institutionalization into renewable routines (Mikalef and Gupta, 2021).

This observation reveals a gap in concepts. The two main streams of research that have emerged as the predominant in AI in organizations have taken two broadly different directions. A single track, which is based on information systems and strategy, explores AI as a technological and analytical asset and increcingly describes AI capability of a firm in terms of dynamic capabilities (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). The second track is based on strategic human-resource management (SHRM) and focuses on the role of the talent practices in the preparedness of an organization to technological change (Singh et al., 2023). These songs hardly address each other. The outcome is a literature which can tell us what an AI-capable organization would look like, and can tell us, separately, what good talent management would look like, but it cannot yet tell us how the organizational process of transforming the resources of talent into AI capability works. The issue of why certain organizations turn into AI-ready and others can fail even with similar technological investment has not been theoretically specified yet.

The current paper fills this gap by formulating a conceptual framework that connects talent management to the organizational AI capability via a particular chain of organizational processes. We do three movements. To start with, we re-conceptualize talent management as orchestrating organizational ability, as opposed to a set of discrete human-resource practices, re-placing it in resource-based and dynamic-capabilities traditions. Second, we conceptualize Organizational AI Capability (OAIC) as a higher-order dynamic capability, which can be defined as the ability of the organization to sense AI-relevant opportunities, take them by introducing AI into routines, and restructure its resource base because of the opportunity, and we differentiate it not only with the possession of AI technology but also with the more limited concept of AI adoption. Third, we hypothesize the pathway between the two where talent management influences organizational learning and knowledge-sharing ability, which together facilitate OAIC, which then is reflected in organizational AI preparedness.

By doing this, the paper is a consciously conceptual contribution. Instead of testing relationships, it combines theoretical views that have been kept apart and defines the logic of causation and conditions of the boundary of a transformation that previous empirical research has hinted at but not been able to fully articulate. According to recent empirical research, which includes evidence of emerging-economy technology startups, the relationships between talent management practices and AI adoption partially depend on knowledge sharing, but are not even across talent dimensions, nor fully mediated (Abuhaimed et al., 2024, 2025). These findings not only welcome but also do not dismiss a theoretical explanation of the organizational process at work. The model created below provides such an account.

Three particular moves make it novel in that there are three moves that, when combined, make it unique compared to the literature. First, unlike the AI-capability literature, which discusses AI capability as a result to be measured and correlated with performance, we describe the origin of AI capability in organizations, which is considered to be the talent system, serving as the antecedent capability. Second, the strategic human-resource literature ends at adoption but we apply the causal chain to a higher-order and AI-specific dynamic capability and to the emergent state of readiness. Third, unlike both literatures, which tend to consider their constructs as unidimensionally advantageous, we obtain a non-obvious and falsifiable conclusion, namely, that the dimensions of talent bifurcate, and that some dimensions of talent, and others, may be constraining AI potential. The paper will not, therefore, redesignate an existing chain at a higher altitude; it will designate a new construct, a new antecedent, and a new contingency. The rest of the paper discusses the pertinent literatures, conceptualizes talent management as a strategic resource, OAIC as a higher-order capability, combines the supporting theories, develops the framework and its propositions and talks about the contributions, boundary conditions and future research directions.

II. BACKGROUND AND LITERATURE REVIEW

2.1 Talent Management in the Digital Era

Talent management has come out of an administrative human-resource role as a strategic organizational adapting tool. Modern practices focus on a comprehensive framework of attraction and selection of talent, its development, empowerment, retention and career succession planning (Collings and Mellahi, 2009). This architecture is becoming more commonly perceived in digital contexts as the way in which organizations build and replenish human capital needed to change technology (Vrontis et al., 2022). The shift is consequential: it moves the management of talent as a supportive part of the execution to the constitutive part of the development of the organizational competencies that digital strategy relies on.

There are two constraints to the current treatment issue as regards the current argument. To begin with, talent management is often examined as a collection of independent practices the impact of which is believed to be additive and with a consistently positive outcome. New evidence complicates this assumption, pointing to the fact that the dimensions of talent may have different impacts on the technological outcomes, that some practices may facilitate and others may limit adoption based on their ability to channel knowledge and attention (Abuhaimed et al., 2025). Second, the literature has been inclined to believe that talent management is an input to technology adoption and not an ability that is itself reconfigured by, and co-evolves with, the technological path of the organization. The two restrictions lead towards a capability-based reconceptualization, which is built in Section 3.

2.2 Knowledge Sharing and Organizational Learning as Connective Mechanisms

When talent is the source of raw human capital of the organization, knowledge processes determine whether the latter will lead to collective capability. The flow, contextualization, and recombination of knowledge among people and units, or in other words, knowledge sharing, have been long recognized as one of the key processes that connect human-resource practices to the outcome of innovation (Wang et al., 2022). Knowledge sharing is important in the particular case of AI since AI integration is knowledge-intensive and cumulative: the value is not accrued based on the technical skills of individuals but on the capacity of the organization to share lessons of implementation, codify them into routines, and reuse them (Vrontis et al., 2022).

Knowledge sharing has a larger process through which organizational learning helps. The difference between exploratory learning (creating new knowledge) and exploitative learning (polishing and using previous knowledge) is especially relevant to AI, where companies have to both explore the new uses and simultaneously make the old ones a part of the organization (March, 1991). However, recent empirical research demonstrates that the connection between talent practices and technological outcomes is only partially mediated by knowledge sharing, which means that learning and knowledge processes are needed but not exhaustive channels that require a more comprehensive approach to place within a capability architecture (Abuhaimed et al., 2024). This encourages the view of organizational learning and knowledge-sharing capability as a means of transformation as opposed to an end explanation.

The fact that these two mechanisms (learning and subsequent knowledge sharing) are theoretically ordered should be explicitly justified, as the opposite sequence may be possible. We put learning at the forefront since the two processes have logically different roles; learning creates knowledge, and knowledge sharing spreads and institutionalizes knowledge. The new and refined knowledge that forms the raw material of the knowledge base of the organization, which is created due to the processes of exploratory learning and exploitative learning, is then shared by the knowledge-sharing capability that circulates this material throughout the individuals and units and encodes it into routines that can be reused. Knowledge sharing cannot institutionalize the knowledge that learning has not yet generated whereas learning can take place, initially at least, at the individual and team level before being shared across the organization. This does not refute feedback - common knowledge is the catalyst to further learning - but it sets the generative priority of learning in the forward direction which the framework defines.

2.3 From AI Adoption to Organizational AI Capability

A large body of literature takes the organizational interaction with AI as one of adoption-the choice to purchase and implement AI technologies. Adoption is, however, an event or a threshold and not an ability. An emerging literature claims that the AI capability of the organization is its strategically consequential construct: the ability to deploy tangible, human, and intangible resources in such a way that AI can create sustained value (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). This re-framing puts AI research at the same level as the capabilities tradition of strategy and re-focuses it on whether an organization has adopted AI or whether it can re-use it over time and adaptively.

The organizational origin of this capability is what is not well developed. The AI-capability literature lists its resource ingredients (data, infrastructure, technical expertise, coordination, and culture) but is relatively silent about the way that those ingredients are created and brought together over the years, and specifically about the contribution of the talent system to the creation of those ingredients. On the other hand, the SHRM literature theorizes the talent system but does not go further to capability but adoption. The framework below fills this gap by considering the talent management as the source capability in a chain that leads to OAIC.

III. TALENT MANAGEMENT AS A STRATEGIC RESOURCE

Resource-based view is the perspective that long term competitive advantage is based on resources, which are valuable, rare, inimitable and non-substitutable (Barney, 1991). The human capital and systems that constitute human capital are often given as examples, precisely due to their social complexity and path-dependence and hence imitable characteristics. However, the resource-based view in its unchanging form is a better explanation of the possession of advantage than its renewal. In a world where technology is changing fast, which is the hallmark of AI, it is not the amount of talent in the organization at any given time but the capacity to reorganize this amount of talent as needs change. This is where the dynamic capabilities lie (Teece, 2007).

We then promote a particular reconceptualization; talent management is best perceived not as a set of human-resource practices but as the orchestrating organizational capability that feels new competence needs, captures them through the acquisition and development of the relevant human capital and realigns the human resource base of the organization with changes in strategic conditions. In this perspective, the common dimensions of talents are projected on the microfoundations of dynamic capability. Attraction and selection serve as sensing and scan the environment to find and obtain competence that is scarce. Development and empowerment serve as the process of seizing, transforming gained potential into deployable, value creating competence. Retention and career succession are reconfiguring processes that control the stabilization, transfer and renewal of competence over time.

There is a significant implication of this mapping which is non-obvious. Since reconfiguring is a two-sided process: either stabilization will sustain competence of value or ossify old routines, the dimensions of talents related to continuity do not have to be equally advantageous to AI capability. In the areas where retention and succession fortify existing knowledge and shield it against challenge, they can hinder the exploratory learning the integration of AI demands, although attraction, development, and empowerment facilitate it. This hypothetical potential aligns with the empirical findings, according to which the dimensions of talent are not related to the results of AI in the same manner, and continuity-oriented practices are sometimes associated with the null or negative relations, whereas acquisition- and development-oriented practices are with the positive ones (Abuhaimed et al., 2025). Reframing talent management as a dynamic capability thereby not only relabels it, but creates a systematic expectation of what mechanisms of talent create AI capability and which could limit it, and in what circumstances. This will be revisited in the propositions and boundary conditions.

IV. CONCEPTUALIZING ORGANIZATIONAL AI CAPABILITY

We consider Organizational AI Capability (OAIC) to be a higher-order dynamic capability that consists of an organizational demonstrated capacity to sense AI-relevant opportunities and threats, to capture them by embedding AI into its products, processes, and decisions, and to restructure its resource base and routines in such a way that value afforded by AI is recreated as technology and competitive conditions evolve. There are three aspects of this definition that should be highlighted.

To begin with, OAIC is of higher order. It is not an individual ability or resource but an organizational ability that regulates the incorporation and revitalization of lower-order resources data, infrastructure, technical talent, and coordinating routines. This differentiates OAIC with the possession of AI technology, which is a lower-order resource that

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imparts little benefit when it is common in the market, and adoption of AI, which is the boundary of deployment, but not the ability to provide long-term value. An organization can implement AI without OAIC; it will not demonstrate OAIC without the potential to change.

Second, OAIC is dynamic. Its characteristic effort is rejuvenation in the face of change. Due to the fast development of AI technologies, models, and use cases, the ability characterized by a fixed configuration would lose value quite quickly. OAIC can thus be characterized more by its microfoundations, the sensing, seizing and reconfiguring routines enabling the organization to maintain pace, than by any fixed stock of resources (Teece, 2007). This specification also explains why OAIC is hard to copy: it has microfoundations that are entrenched in organization-specific learning and knowledge processes that can hardly be observed or replicated by competitors.

Third, OAIC is socio-technical. It is not within the technology or the individual experts but between the human competence and the technical systems, which are controlled by the organizational routines. This framing clarifies the reason why the talent system is constitutive of OAIC and not just supportive of it: the human component of the socio-technical configuration is created and reproduced through talent management and the routines that hold human and technical components together are perpetuated through learning and knowledge processes. In brief, OAIC is the organizational ability where the resources in terms of talent are finally converted.

And lastly, we differentiate between OAIC and organizational AI readiness. We consider readiness to be the emergent state of the organization that arises when OAIC is well developed-the state of being in a position to utilize and take advantage of AI throughout the organization. Preparation is therefore the expression of OAIC and not a distinct antecedent ability. This difference enables the framework to justify the key empirical puzzle: organizations that invest in AI technology and fail to build OAIC obtain the tools but not preparedness, but organizations that build OAIC obtain preparedness and are able to absorb the waves of AI with relative ease.

Since the literature in the surrounding employs various neighbouring constructs such as AI adoption, AI readiness, AI maturity and AI capability, which are frequently used interchangeably, it is necessary to place OAIC in opposition to them. Table 1 indicates the focal question, theoretical lens, and typical outcome of each construct and separates what is unique to OAIC. AI adoption refers to the implementation of technology and is measured in terms of use; AI preparedness refers to a state of being ready; AI maturity refers to a developmental stage achieved and AI capability as furthered by Mikalef and Gupta (2021) refers to the capacity to utilize AI to perform. OAIC contrasts with each in being clearly defined as a higher-order, socio-technical dynamic capability whose resultant outcome is the sustainable renewal of AI readiness in the face of change as opposed to individual performance episode or a fixed level.

Table 1. Differentiating Organizational AI Capability (OAIC) from adjacent constructs.

Construct	Focal question / focus	Theoretical lens	Characteristic outcome
AI adoption	Has the technology been deployed?	Technology diffusion	Use / deployment
AI readiness	Is the organization prepared to use AI?	Organizational preparedness	State of preparedness
AI maturity	How far along the development path is the organization?	Stage / maturity models	Level of development
AI capability	Can the organization leverage AI for value?	Resource-based / capability view	Firm performance

OAIC (this paper)	Can the organization repeatedly sense, integrate, and reconfigure around AI as conditions change?	Higher-order, socio-technical dynamic capability	Sustainable AI readiness

Another question that an astute reader would ask is whether OAIC is simply a generic dynamic capability by other names. It is not. Generic dynamic capabilities refer to the ability of firms to sense, grasp and rearrange resources in any area of change (Teece, 2007); OAIC is the domain specific embodiment of that ability to the unique requirements of artificial intelligence. The AI domain has three characteristics that render it non-generic and thus should have a specific construct. AI is data-dependent where common technologies are not, and thus OAIC integrates data and infrastructure orchestration as an element of it. AI is opaque, and probabilistic, and OAIC needs governance routines, such as oversight of fairness, accountability, and reliability, not defined by generic dynamic capabilities. And AI evolves at a speed and on paths that render reconfiguring a continuous process, as opposed to episodic. OAIC, therefore, is to dynamic capabilities what a digital sensing capability is to generic sensing in research on digital transformation (Warner and Wäger, 2019): a content-specified, domain-bound form that, however, has microfoundations that vary in content, but that share the generic logic.

These reflections enable the specification of OAIC to be four-dimensional, synthesized in Table 2, operationalising its socio-technical and dynamic nature. AI sensing deals with identifying and understanding AI-related opportunities and threats; AI integration deals with introducing AI into products, processes, and decisions; AI reconfiguration deals with renewing resources and routines as AI changes; and AI governance deals with responsible management that maintains a sense of legitimacy and reliability. The former three are analogous to the generic microfoundations in AI-specific terms, and the fourth is specific to the field.

The governance aspect goes beyond compliance and control to include the stewardship of AI-related organizational resources, such as data, models, intelligent agents, and organizational learning structures. Recent theoretical literature proposes that the successful management of such algorithmic resources is a key to the continued organizational flexibility, trustworthiness, and the creation of AI values in the long-term (Abuhaimed, 2026).

Table 2. Dimensions of Organizational AI Capability (OAIC).

Dimension	Description	Dynamic-capability analogue
AI sensing	Detecting and interpreting AI-relevant opportunities, threats, and use cases in the environment and the data the firm holds.	Sensing (AI-specific)
AI integration	Embedding AI into products, processes, and decision routines so that it generates value in everyday organizational life.	Seizing (AI-specific)
AI reconfiguration	Renewing the resource base, competencies, and routines as AI technologies and competitive conditions change.	Reconfiguring (AI-specific)
AI governance	Overseeing the responsible, fair, accountable, and reliable deployment of AI, sustaining legitimacy and trust.	Domain-distinctive (no generic analogue)

V. THEORETICAL INTEGRATION

The five theoretical perspectives incorporated in the framework bring unique and essential aspects of the explanation. We synthesize them and not list them: one theory answers a question that another leaves unanswered and the contribution of the framework is their combination.

The resource-based perspective lays the foundation of why talent is a possible source of advantage, its rarity, social complexity, and inimitability, and thus the argument that the human aspect of AI capabilities cannot be easily bought or imitated (Barney, 1991). It describes the worth of resource base but not renewal. The dynamic capabilities theory fills in that dynamism, re-conceptualizing both talent management and OAIC as the ability to sense, seize and re-configure in the face of change, and offers the microfoundational vocabulary which connects the two constructs with a shared logic (Teece, 2007). The knowledge based perspective defines the content that traverses this dynamic architecture and views knowledge as the key resource and knowledge combination as the core organizational activity; it is the ability to share knowledge, not talent or technology per se that is the proximate facilitator of OAIC (Grant, 1996).

Human capital theory elucidates the creating mechanism on the human side, how investment in humans increases the productive and adaptive capacity of the labor force and thereby fuels the resource base that the ability to orchestrate talent decides (Becker, 1964). The organizational learning theory provides the mechanism that transforms personal human capital into shared capacity, the difference between the element of exploration that creates new AI-relevant knowledge and the element of exploitation that institutionalizes it and hence the reason why knowledge is embedded in renewable routines instead of being stuck in individuals (March, 1991). Combined, these points of view lead to a consistent causal pathway: the human capital theory and the resource-based view explain how the talent base is created and its value; the dynamic capabilities theory explains how the talent base is coordinated and regenerated; organizational learning and the knowledge-based view explain how the talent base is converted to shared, institutionalized capability; the synthesis explains how OAIC emerges and, through it, AI preparedness.

VI. DEVELOPMENT OF THE CONCEPTUAL FRAMEWORK

The framework, presented in Figure 1, defines the organizational process, according to which organizational resources that are related to talent are converted into organizational AI capability and, eventually, AI readiness. It is structured in three theoretical phases; a resource base, a set of transformation mechanisms and a capability outcome, which are connected by propositional relationships and constrained by boundary conditions. We begin by stating the key theoretical proposition which the framework formalizes before articulating the stages.

Organizational AI Capability Theory (in brief). Organizational AI Capability arises when the organizational learning and knowledge-sharing processes that convert individual human capital into a higher-order, AI-specific dynamic capability are triggered by talent management, as an orchestrating capability, and becomes sustainable organizational AI readiness, which is mediated by environmental dynamism, data and digital infrastructure, and leadership and culture.

This assertion clarifies the construct (OAIC), antecedent (talent management as capability), mechanisms (learning and knowledge sharing), manifestation (readiness) and boundary conditions, as recommended in theoretical contributions, of specifying what, how, why, and when (Whetten, 1989). Each of the elements is elaborated in the following stages.

Talent management is the orchestrating capability at the resource base that comes together and reinvigorates human capital. It does not directly impact AI capability; talent is not transformed into AI capability without the process of learning and institutionalization of knowledge in between. This oblique is at the heart of the framework and why both

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talent investment and AI investment may exist without generating readiness.

The change processes include learning processes and sharing capability of knowledge within the organization. Talent management triggers the exploratory and exploitative learning, populating the organization with competence in an adaptable form and empowering its deployment; learning itself produces knowledge that needs to be shared and codified, in order to become collective. The capability of knowledge sharing, institutionalized capacity of the organization to disseminate and encode knowledge, transforms distributed learning into a joint asset that can be integrated by AI. The resource base is channeled through these mechanisms to the outcome of capabilities.

The outcome capability is OAIC that is reflected in AI preparedness of the organization. OAIC is a capability that arises when knowledge sharing ability and organizational learning are developed to an advanced level to facilitate the sensing, seizing and reconfiguring routines that constitute AI capacity. An observable condition of an organization that has gone beyond this threshold is called readiness. It is more of a recursive framework than a strictly linear one: the exercise of OAIC creates new learning and new competence demands that in turn feeds back into the talent system, thus the stages will co-evolve as time goes by. To be analytically clear, propositions below describe the forward path and also take into consideration this feedback.

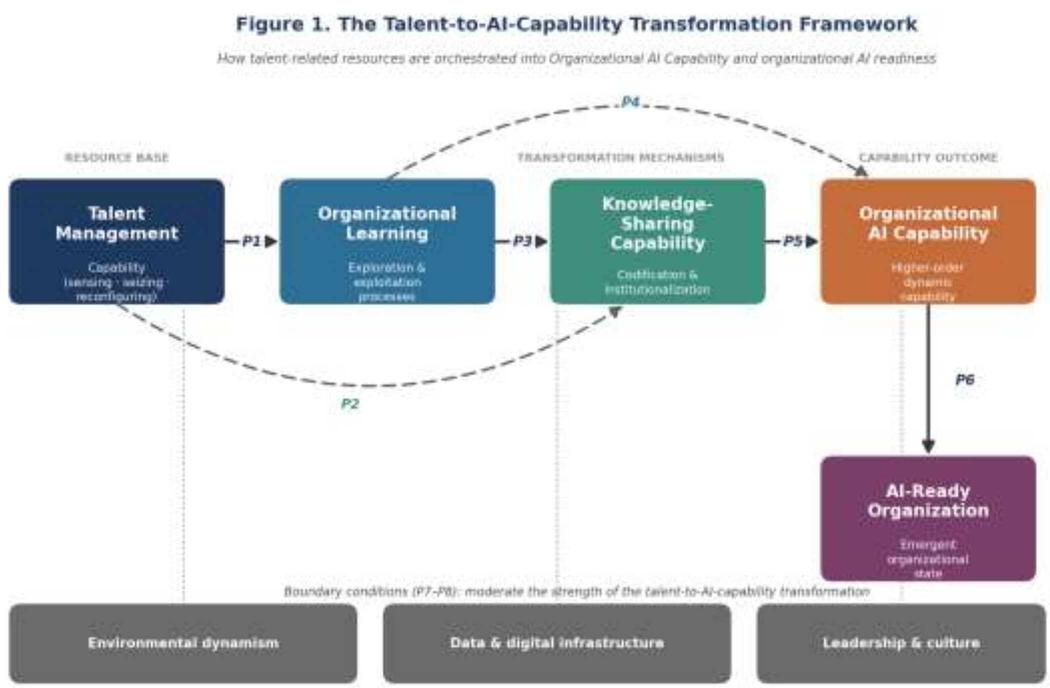

Figure 1. The Talent-to-AI-Capability Transformation Framework. The figure portrays talent management as an orchestrating ability that influences organizational learning and knowledge-sharing ability (transformation mechanisms), which together facilitate Organizational AI Capability and its manifestation as organizational AI readiness. Dashed paths represent the partial and direct effects; the lower band represents the boundary conditions which moderate the strength of transformation.

VII. PROPOSITIONS DEVELOPMENT

The following propositions are the formalizations of the relationships in Figure 1. They develop out of the starting capability by the transformation mechanisms to the capability outcome, and specify mediating structure and boundary conditions.

7.1 From Talent Management to Learning and Knowledge

The redefined concept of talent management as an orchestrating capability increases the organization stock of adaptable competence and enables its application, thus triggering the learning processes of new knowledge creation and application. The organization is filled with people who can explore by acquisition and development; given autonomy by empowerment; and by integrating the practices, both exploratory and exploitative learning is maintained.

- Proposition 1. As an orchestrating organizational capability, strategic talent management has a positive influence on the learning processes within the organization enhancing both the exploratory and exploitative learning. It is knowledge that is produced through learning that produces collective ability when shared and institutionalized. The capacity to circulate and encode knowledge is developed through talent practices that form and empower employees, structure collaboration and mobility. The impact of talent management on the capability of knowledge sharing is both direct, via the structure of collaborative functions and incentives, and indirect, via the learning that it triggers.
- Proposition 2. Strategic talent management has a positive impact on the capability of an organization to share knowledge both directly and indirectly via organizational learning processes.
- Proposition 3. The processes of organizational learning have positive effects on the capability to share knowledge, where exploratory learning increases the amount of knowledge to share and exploitative learning entraps the knowledge into routines that can be reused.

7.2 From Learning and Knowledge to AI Capability

Knowledge-sharing capability is the proximate enabler of OAIC. The integration of AI is dependent on how well the organization can disseminate implementation knowledge, encode lessons into routine and make them accessible across units; otherwise, technical expertise will be siloed and non-cumulative, and AI efforts will not scale. Organizational learning also helps in knowledge sharing, and, to some extent, directly, by maintaining the experimentation and refinement that the sensing and seizing of AI opportunities entail.

- Proposition 4. Organizational learning processes have a positive impact on the development of Organizational AI Capability, both directly and indirectly, and in part, it is due to the knowledge-sharing capability.
- Proposition 5. The ability to share knowledge contributes positively to the growth of Organizational AI Capability by institutionalizing AI-relevant knowledge to the sensing, seizing and reconfiguring routines that make up the capability.

7.3 From AI Capability to Readiness

OAIC is in the form of organizational AI preparedness. The ability to sense, seize, and reconfigure around AI, by definition, places an organization in a position to roll out AI into its operations and benefit from AI as new waves of technology roll through its operations, with fewer hitches. The emergent state of OAIC thus is not an antecedent but a by-product.

- Proposition 6. Organizational AI Capability has a positive impact on organizational AI readiness, in the sense that readiness is the emergent organizational state that is the result of a developed AI capability.

7.4 Mediating Structure and the Limits of Technology

The main explanatory assertion of the framework is related to mediation. The impact of talent management on the AI preparedness is not direct, but is mediated by the transformation processes; talent that is never transformed into shared, institutionalized knowledge does not translate to AI preparedness. This mediating form describes the lack of readiness as a result of investment in AI technology in the absence of this underlying capability architecture.

- Proposition 7. The linkage between strategic talent management and the organizational AI readiness is mediated by the organizational learning and knowledge-sharing ability and by the combination of these two factors to Organizational AI Capability; investment in AI technology is neither a requirement nor a sufficient condition of AI readiness without the capability pathway.

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7.5 Boundary Conditions

The power of the change is conditional. There are three boundary conditions which are of particular consequence. The dynamic-capability microfoundations become more valuable in an environment that is dynamically changing, such that the talent-to-AI-capability pathway is more robust in a setting where both technological and competitive change is fast. The lower-order resources orchestrated by OAIC are data and digital infrastructure; without them, even developed learning and knowledge capabilities cannot be completely captured in AI capability. Leadership and culture regulate the sharing and not hoarding of knowledge and psychologically safe exploratory learning, conditioning the transformation of talent into collective capability.

These circumstances also shed light on the two-sidedness of continuity-based talent practices which were found in Section 3. Incumbent knowledge entrenched in culture and leadership may stabilize obsolete practices and reduce the exploratory learning needed by AI integration where it entrenches them; or lead to retention and succession where it facilitates renewal, valuable competence is preserved and passed on through the same practices. Continuity-oriented talent dimensions and their impact on AI capability are therefore contingent and not uniform.

Proposition 8. The environmental dynamism, data and digital infrastructure and the leadership and culture moderate the strength of the talent-to-AI-capability transformation; specifically, the implication of continuity-oriented talent dimensions (retention and career succession) on AI capability is positive to negative depending on the context.

7.6 Linking Dimensions, Propositions, and Measurement

In order to render the internal structure of the framework explicit and to help guide its further operationalization, Table 3 matches the four dimensions of OAIC with the propositions they most directly contribute to, along with the transformation mechanism that contributes most to each dimension.

Table 3. Mapping OAIC dimensions to the framework's propositions.

OAIC dimension	Principal role in the transformation	Primary mechanism	Related propositions
AI sensing	Detection and interpretation of AI-related opportunities and threats; driven by exploratory learning which searches new applications.	Organizational learning (exploratory)	P1, P4, P5
AI integration	Integrating AI into products, processes and decision routines in such a way that value is achieved in daily operation.	Knowledge-sharing capability	P4, P5
AI reconfiguration	Refilling the resource base, skills, and practices with the development of AI; the site of the continuity-focused, dual-sided talent impact.	Learning + knowledge sharing	P5, P8
AI governance	Managing responsible, equitable, responsible, and trustworthy AI; maintaining the credibility of which further preparedness relies.	Knowledge-sharing + leadership/culture	P5, P6, P8
All four (as OAIC)	Combine to form the higher-order capability that shows itself as AI readiness and is moderated by the context.	Mediating capability pathway	P6, P7, P8

Table 4 provides exemplary, but not exhaustive indicators that should be used to operationalize the core constructs of the framework in the future. The indicators are suggested as a baseline of measure development, as opposed to a validated measure, and would have to be improved and undergo psychometric

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evaluation prior to their application in empirical testing.

Table 4. Illustrative operational indicators for the framework's constructs (guidance for future measurement).

Construct	Illustrative operational indicators	Candidate data sources
Talent management (as orchestrating capability)	Responsiveness to detecting and sealing developing gaps in AI-competence; acquisition/development/retention/succession investment balance; collaborative, knowledge-sharing succession designs.	HR analytics; competence-gap audits; policy review
Organizational learning	AI rate of experimentation; ratio of exploratory to exploitative projects; lessons learned through pilots recorded as being used in subsequent projects.	Project records; innovation logs; surveys
Knowledge-sharing capability	Cross-unit knowledge flows are dense; repositories and communities of practice exist and are used; the rate of reuse of codified implementation knowledge.	Network analysis; repository usage; surveys
Organizational AI Capability (OAIC)	AI detection: scan rhythms and horizon-scanning beat. AI integration: percentage of processes that have integrated AI. AI reconfig: frequency of regular renewal. AI governance: coverage of fairness/accountability oversight.	Capability audits; process inventories; governance records
Organizational AI readiness	Facilitation and acceleration of sequential AI waves; scale of AI application in generating value across units; decreased pilot to scale friction with time.	Longitudinal deployment metrics; managerial assessment

VIII. THEORETICAL CONTRIBUTIONS

The framework contributes five contributions each of which relates to a different aspect of theory in the form of genuine theoretical contributions which stipulate not only what and how but also why and under what conditions a relationship exists (Whetten, 1989). First, it combines two literatures which have evolved separately, strategic human-resource management and organizational AI capability, by defining the organizational process linking them. By doing so it would answer a question that neither of the two literature has answered: how resources based on talent are converted into AI capability. This integration re-locates the talent system as being part of, not an enabler of, the ability of an organization to take advantage of AI.

Second, the framework promotes conceptualizing OAIC by identifying it as a higher-order dynamic capability that has recognizable socio-technical microfoundations, and separating it clearly to the ownership of AI technology, AI adoption, and AI readiness. This theoretical elucidation offers a more rigorous framework to a new discipline where AI potential, uptake, and preparation are often mixed up. Third, the framework produces a predictable and testable expectation of the heterogeneous value of talent dimensions in AI capability by reimagining talent management as an orchestrating dynamic capability, having dimensions whose dimensions overlap sensing, seizing, and reconfiguring. The hypothesis that continuity-based dimensions can limit AI capacity when entrenching conditions are met, whereas acquisition-based and development-based dimensions can is a theoretical explanation of empirical heterogeneity that cannot be explained by an additive model of talent management (Abuhaimed et al., 2025).

Fourth, the framework provides a parsimonious account of the puzzle that characterizes the field of why similar technological investment has different organizational outcomes by taking the explanation to be in a mediating capability pathway, and not in the technology itself. This reverses the theoretical focus of AI research, which has been on the technology, to the organizational structure which consumes it.

Fifth, and cutting across the others, the framework adds to the growing AI-capability literature, by defining talent management as a capability antecedent instead of a human-resource practice or a fixed resource ingredient. In the context of the previous work listing skilled human capital as one of the inputs to AI capability, the current framework identifies the organizational capability that creates and constantly replenishes the skilled human capital and incorporates it, through learning and knowledge processes, into AI capability. This repositioning provides the literature on AI-capability with the antecedent originating it has been missing, and the literature on talent management with an outcome of higher order to which its practices are directed, which in turn forms a bridge in theory that can ground a cumulative research program on the AI-capability of organizations and AI-ready organizations.

IX. PRACTICAL IMPLICATIONS

To practice, the framework re-frames the managerial issue of becoming AI-ready. This means that AI preparedness is not reached through a purchase of technology but it is reached through the construction of the capability architecture that takes in the technology. Leaders who see AI as an issue of technology acquisition will be more likely to hoard tools without preparation; leaders who invest in talent, learning and knowledge processes that make up OAIC at the same time will transform investment into sustainable capability.

The framework also warns of the uniformity of all talent practices as supportive of AI capability. The exploratory competence AI integration needs is built through acquisition, development, and empowerment, and retention and succession should be developed to transfer and renew knowledge and not entrench it, or continuity-oriented practices may lead to stagnation of the very practices AI is supposed to change. In practice, this supports succession systems based on collaborative knowledge transfer and communities of practice as opposed to those based on protecting individual incumbency and supports knowledge infrastructures, such as shared repositories, cross-functional teaming and peer learning, that institutionalize implementation knowledge, turning it into a renewable organizational resource rather than the property of the departing expert.

X. FUTURE RESEARCH DIRECTIONS

The main contribution of the framework is that its relationships are specified and may be tested and refined by future research due to the conceptual nature of the framework. There are four directions that are particularly promising. Second, the hypothesis that talent dimensions do not have a homogenous impact on AI capability but that continuity-oriented dimensions are contingently and not homogenously advantageous should be measured disaggregately that recognizes the various talent practices instead of viewing talent management as a single composite (Abuhaimed et al., 2025).

Third, the operationalization of the construct of OAIC needs to be elaborated. It can be defined in terms of sensing, seizing and reconfiguring microfoundations but before the framework can be rigorously tested, valid and reliable measures that differentiate between OAIC and adoption and between technological resources are required. Fourth, the boundary conditions open comparative work across settings that vary in dynamism, infrastructure, and culture, such as those of emerging economies in which the fast digital transformation under national programs presents unique circumstances of the talent-to-AI-capability transformation (Abuhaimed et al., 2024). Comparative work of this kind would help to clear up how the framework can be generalized and what contingencies can determine it.

XI. CONCLUSION

This paper has contended that the reason why there is a continuing divide between organizations that are beneficiaries of AI and those that are not is not a technological divide but a gap in capability. Reconceptualizing talent management as an orchestrating dynamic capability, defining

Organizational AI Capability as the higher-order capability around which resources related to talent are converted, and outlining the learning and knowledge mechanisms which bind them together, the framework provides a consistent explanation of how organizations become AI-ready and why so many of them fail in spite of significant investment in technology. The account unites the views that have long been distinct, disaggregates constructs that are often confounded, and elucidates heterogeneity that cannot be explained using additive models. In this sense, AI readiness is not purchased but constructed, slotted together, of human, learning, and knowledge bases which form the basis of organizational capability to renew itself. The framework is provided as a basis of the new theory of organizational AI capability and a plan to the empirical work which should follow.

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