

Chapter

Developing People, Leading Change: Talent Development and Knowledge Leadership as Pillars of Human–AI Collaboration in UAE Government

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Abstract

The integration of artificial intelligence (AI) into government operations is reshaping what public sector employees are expected to know, do, and become. Yet technological capability alone does not determine the success of this transformation: the human dimensions of AI adoption, how organizations develop people for AI-era work, and how leaders navigate the cultural, cognitive, and institutional shifts that AI demands are the most consequential and least understood variables in the equation. This chapter advances a conceptual argument around two interconnected pillars of Human–AI collaboration (HAC) in the public sector: talent development and knowledge leadership for change. Drawing on organizational learning theory, human capital development frameworks, and the emerging literature on AI literacy, the chapter identifies three competency clusters for AI-era government work: AI literacy, data competence, and distinctly human skills. These themes theorize the conditions under which upskilling and reskilling initiatives translate into sustained individual and organizational performance improvement. On the change management and knowledge leadership front, the chapter examines why AI adoption so frequently fails to realize its potential, and what knowledge leaders must do to create the conditions for successful, sustained HAC. Drawing on Kotter’s transformational change model, psychological safety theory, and the KM leadership literature, the chapter identifies three core competency domains for AI-era knowledge leaders: strategic AI literacy, change facilitation capacity, and ethical stewardship. The chapter concludes with an integrative talent–leadership nexus framework and implications for government human resources (HR) leaders, knowledge management (KM) practitioners, and policymakers navigating the human side of AI-driven governance transformation.

Keywords: talent development, upskilling, reskilling, AI-enhanced learning, change management, knowledge leadership, human–AI collaboration, UAE government, public sector, organizational learning

1. Introduction

There is a paradox at the heart of artificial intelligence (AI)-driven government transformation. Governments around the world are investing extraordinary resources in AI: deploying intelligent automation, procuring machine learning systems, embedding predictive analytics into policy and service delivery, and building the data infrastructure that makes algorithmic governance possible. Yet the outcomes of these investments are profoundly uneven. Organizations with ostensibly similar AI systems achieve radically different results, and the differentiating variable, in case after case, is not the sophistication of the technology but the readiness, capacity, and leadership of the people deploying it [1].

This paradox reflects a structural imbalance in how AI adoption is typically conceived and resourced. The technical dimensions of AI, namely procurement, integration, data architecture, and algorithmic design, command the attention of policymakers, the budgets of transformation programs, and the headlines of government innovation announcements. The human dimensions, that is, how civil servants are prepared for AI-era work, how leaders navigate the cultural and psychological disruption that AI creates, how organizational knowledge is mobilized to sustain the transition from mandate to embedded practice, are treated as secondary concerns, addressed late, resourced inadequately, and evaluated rarely.

This chapter argues that this imbalance is not merely an oversight but a fundamental misdiagnosis of where the value of AI is actually created. AI systems do not collaborate; people do. The degree to which AI genuinely amplifies human judgment, knowledge creation, and service delivery rather than generating outputs that are ignored, misapplied, or actively resisted depends overwhelmingly on two human-centered conditions: the competency of people to work effectively with AI tools and the quality of leadership that creates the cultural and institutional environment in which that collaboration can occur and deepen over time.

The chapter focuses on two themes drawn from the broader HAC literature. The first is talent development: the organizational processes through which civil servants acquire AI literacy, data competence, and distinctly human skills that HAC requires. The second is change management and knowledge leadership: the leadership practices and organizational architectures through which governments create the conditions for AI adoption to move from strategic aspiration to sustainable, human-centered operational reality. These two themes are treated not as parallel independent topics but as mutually constitutive pillars of a single organizational challenge of making AI work, for people, in public service.

The United Arab Emirates provides the primary empirical anchor for the chapter's conceptual argument. The UAE is not merely a prominent adopter of government AI; it is one of the most institutionally ambitious and systematically documented cases of AI-driven governance transformation in the world [2, 3]. Having appointed the world's first Minister of State for Artificial Intelligence in 2017, launched the UAE National AI Strategy 2031, mandated generative AI retraining for all 75000 + federal civil servants, and deployed the Jahiz national upskilling platform at system scale, the UAE has created a uniquely rich laboratory for examining how governments approach the human dimensions of HAC. The chapter uses UAE government initiatives as illustrative cases that ground conceptual propositions in institutional reality, not as primary empirical data, but as the kind of

practice-grounded evidence that enriches conceptual theorizing in management and KM scholarship.

The chapter is organized around two research questions that reflect its dual focus:

What organizational conditions, learning architectures, and competency frameworks enable government employees to develop AI literacy, data competence, and distinctly human skills required for effective HAC in public sector contexts?

How do knowledge leaders in government organizations create the cultural, institutional, and psychological conditions that enable AI adoption to move from strategic mandate to embedded, human-centered practice, and what leadership competencies are most critical to this transformation?

The chapter proceeds as follows. Section 2 establishes theoretical foundations, positioning HAC as fundamentally a knowledge management (KM) challenge and introducing the key theoretical frameworks that animate the analysis. Section 3 addresses talent development in depth, responding to RQ1 through a three-cluster competency framework and the Jahiz case study. Section 4 addresses change management and knowledge leadership, responding to RQ2 through a three-domain leadership competency framework and UAE institutional architecture cases. Section 5 proposes an integrative talent-leadership nexus framework that synthesizes the two pillars into a coherent model. Section 6 develops implications for research, practice, and policy. Section 7 concludes.

2. Theoretical foundations: HAC as a KM challenge

2.1 Defining HAC in the public sector

Human-AI collaboration is defined here as an organizational arrangement in which humans and AI systems jointly perform knowledge work, with each contributing complementary capabilities toward shared performance objectives [4]. This definition emphasizes three elements. First, HAC is a joint arrangement, not a sequential one: It is not simply about humans using AI tools but about a genuinely collaborative division of cognitive labor in which the contributions of each party are designed to complement and amplify the other. Second, HAC involves knowledge work: the application, generation, and management of knowledge in service of organizational goals, rather than merely mechanical task execution. Third, HAC is oriented toward shared performance objectives: It is not technology deployment for its own sake but a purposeful organizational strategy for delivering better public services, more efficiently and more equitably.

Human-AI collaboration is best understood as a continuum rather than a binary state. At one end, AI assists human judgment by providing recommendations, flagging patterns, surfacing options, while humans retain full decision authority. At the other end, AI executes autonomous processes under human oversight, with humans intervening to handle exceptions, provide ethical judgment, or manage citizen relationships. In between, there is a rich spectrum of collaborative arrangements in which the boundary between human and AI contribution shifts dynamically depending on task type, risk level, citizen impact, and organizational readiness.

The public sector introduces particular considerations that shape where on this continuum, government HAC should primarily operate. Government workers

function under democratic accountability frameworks, public trust obligations, and legal duty-of-care requirements that constrain the degree to which AI can legitimately make decisions affecting citizens' lives without meaningful human judgment in the loop. The augmentation model, with its dimensions of AI informing, accelerating, and enhancing human judgment rather than replacing it, is thus not merely a pragmatic choice but a normative imperative in public administration contexts [5]. This normative framing has direct implications for talent development: If government HAC must be fundamentally augmentative, then the key question is not how to automate civil servant roles out of existence but how to develop civil servants whose judgment, empathy, and ethical reasoning become more valuable, not less, in partnership with AI systems.

2.2 HAC as a KM challenge

Framing HAC as a KM challenge reorients attention from technical AI deployment to the organizational knowledge conditions that determine whether AI genuinely adds value. Nonaka and Takeuchi's [6] model of Socialization, Externalization, Combination, Internalization (SECI) provides a useful diagnostic lens. AI systems accelerate and enhance two of the four knowledge creation modes in the SECI cycle: Combination, by systematically linking explicit knowledge across vast databases, identifying patterns, and generating insights that no individual could produce unaided; and Externalization, by converting tacit organizational knowledge into codified, searchable, shareable form at speeds and scales previously impossible. These are significant and genuine contributions to organizational knowledge creation.

However, the two modes most critical to the development of deep organizational capability and committed organizational identity remain irreducibly human. Socialization, which is the transfer of tacit knowledge through shared experience, mentorship, apprenticeship, and community of practice, requires the kind of interpersonal trust, empathetic attunement, and contextual judgment that current AI systems cannot provide. Internalization, the conversion of explicit knowledge into embodied professional judgment, ethical intuition, and practical wisdom, is a process of human development that cannot be delegated to an algorithm. The implication for HAC is clear: Artificial intelligence can augment the knowledge creation process, but the distinctly human modes of knowledge creation remain the organizational foundation on which AI's contributions must be built.

Organizational learning theory adds a complementary dimension to this analysis. Senge's [7] conception of the learning organization, an organization that continuously expands its capacity to create its desired future through disciplined personal mastery, shared mental models, a shared vision, team learning, and systems thinking, identifies the organizational conditions that enable learning to be sustained as an ongoing capacity rather than a one-off event. Argyris and Schön's [8] distinction between single-loop learning (adjusting actions within existing frameworks) and double-loop learning (questioning and revising the underlying frameworks themselves) is equally relevant. Effective HAC requires not merely that civil servants learn to use AI tools but that organizations develop the double-loop capacity to continually revise their understanding of what HAC means, what it requires, and how it should be governed as AI capabilities evolve.

Dynamic capabilities theory [9] provides the third theoretical anchor. Dynamic capabilities are an organization's ability to sense changes in its environment, seize new opportunities, and reconfigure resources and routines in response. In the HAC context, the critical dynamic capability is not AI adoption per se but the ongoing organizational capacity to reconfigure the boundary between human and AI contributions as technology, tasks, and strategic priorities evolve. This reconfiguration is not a one-and-done redesign; it is a continuous process that requires sustained investment in human capital, knowledge leadership, and organizational learning – the very themes that this chapter addresses [10].

3. Talent development in the AI-enabled government: Addressing RQ1

3.1 The skills disruption challenge in public sector AI contexts

AI adoption in government is generating a disruption in the competency landscape of civil service that is simultaneously profound and poorly understood. Tasks that have historically constituted core government functions such as processing applications, verifying documents, generating compliance reports, responding to standard citizen enquiries, and allocating routine benefits are increasingly performed by AI systems with greater speed, consistency, and scalability than their human counterparts. This is, in the narrowly technical sense, a success. But it creates a dual imperative for government human resource (HR) development that is far more challenging than the technical deployment it follows.

The first dimension of this imperative is shedding: Civil servants must shed dependence on routinized, rules-based task execution that AI now performs and which no longer constitutes their primary organizational contribution. This is not merely a matter of retraining; it involves a significant psychological and professional identity transition. For many civil servants – displaced by AI from competencies such as document processing, rule application, data entry, and form verification – these are not peripheral skills but the core of their professional identity, the basis on which they were recruited, evaluated, and promoted. The displacement of these competencies by AI can be experienced not as liberation from routine but as a fundamental challenge to professional self-worth.

The second dimension is acquiring: Civil servants must rapidly develop new competencies that enable them to operate alongside, supervise, critically evaluate, and extract value from AI systems. The World Economic Forum [11] projects that 44% of workers globally will see their core skills significantly disrupted by 2027, with 6 in 10 workers requiring substantive reskilling. In the public sector, where procurement cycles are long, workforce mobility is limited, and the political consequences of capability gaps are acute, this timeline represents a genuine organizational emergency.

Conventional government training approaches are poorly designed to meet this challenge. Episodic, classroom-based programs generate low transfer of learning because they sever skill acquisition from the work contexts in which those skills must be applied [8]. Generic technology exposure programs that teach civil servants what AI is rather than how to use it in their specific role context produce awareness without capability. Training programs that are not connected to performance management systems generate little sustained motivation, because employees

rationality discount competencies whose acquisition is invisible to career advancement processes. Meeting the talent development challenge of HAC in government requires a fundamentally different approach: systemic, contextually embedded, continuous, and consequential.

3.2 A three-cluster AI-era competency framework for government

Drawing on the human capital literature [12], the AI complementarity research [13], and KM frameworks [5, 14], the chapter proposes a three-cluster competency framework that identifies the priority human capital investments for AI-era government work. The framework is designed not as a comprehensive taxonomy of all relevant competencies but as a theoretically grounded prioritization guide that can inform upskilling architecture decisions.

3.2.1 Cluster 1: AI literacy

AI literacy encompasses the knowledge and judgment required to be an effective human participant in HAC arrangements. It is not about understanding the technical architecture of machine learning systems; it is about understanding what AI systems can and cannot do, how their outputs should be interpreted, and when human judgment should defer to or override AI recommendations. AI literacy has three sub-components. Conceptual AI literacy involves understanding the basic operating logic of AI systems (pattern recognition, probabilistic inference, and training data dependence) and their characteristic failure modes, including hallucination, bias amplification, and distributional shift. Critical AI literacy involves the capacity to evaluate AI outputs analytically: to assess confidence levels, identify anomalies, recognize when an AI recommendation conflicts with contextual knowledge that the AI system cannot access, and make informed decisions about relying on or departing from AI guidance. Practical AI literacy involves the hands-on capacity to use AI tools effectively in role-specific contexts to formulate productive queries, interpret outputs in context, and integrate AI-generated insights into decision-making workflows.

3.2.2 Cluster 2: Data competence

AI-enabled government is fundamentally data-enabled government, and the value of AI systems depends critically on the ability of human workers to work productively with the data those systems generate and require. Data competence for government HAC encompasses three elements. Data interpretation refers to the ability to read and understand data-driven outputs, including visualizations, statistical summaries, predictive scores, and performance dashboards, and to translate them into meaningful narratives that inform decision-making. Data quality judgment refers to the capacity to assess whether data inputs and outputs are reliable, complete, and appropriately representative, and to identify when data quality issues may compromise AI outputs. Bias awareness refers to the understanding that AI systems are trained on historical data that may reflect and amplify existing social inequities, and that this is a particular concern in public sector contexts where AI-assisted decisions affect the life chances of citizens [4]. Civil servants who lack data competence cannot be meaningful partners in HAC; they

become passive recipients of algorithmic outputs rather than active participants in the knowledge creation process that effective HAC requires.

3.2.3 Cluster 3: Distinctly human skills

Perhaps counterintuitively, the most urgent talent development priority for AI-era government work is not technical AI competence but the cultivation of capabilities that current AI systems cannot replicate and that become more, not less, valuable as AI assumes responsibility for routinized tasks. These distinctly human skills include empathy and interpersonal communication, the ability to understand citizens' emotional states, communicate with care and respect, and manage complex human situations with sensitivity; ethical reasoning and moral judgment, the capacity to identify the ethical dimensions of decisions, weigh competing values, and take principled positions in situations where algorithms cannot carry moral responsibility; adaptive and creative problem-solving, the ability to address novel, ambiguous problems that fall outside the pattern recognition capacity of AI systems; and cross-cultural and relational competence, the human skills of navigating diversity, building trust across difference, and sustaining the interpersonal relationships on which public service ultimately depends.

Autor's [13] research on the labor market effects of automation provides theoretical grounding for this cluster: The tasks most resistant to automation are those requiring nonroutine cognitive judgment, interpersonal interaction, and contextual adaptability, more specifically, the capabilities that constitute the irreplaceable human contribution to HAC in government. Developing these distinctly human skills is not a consolation prize for displaced workers; it is the strategic investment that determines whether government HAC realizes its augmentative potential or collapses into a hollow version of automation that produces outputs but not wisdom.

3.3 Organizational conditions for effective upskilling and reskilling

Identifying the right competency clusters is necessary but not sufficient for effective talent development. The organizational conditions in which upskilling and reskilling occur are equally determinative of whether skill acquisition translates into genuine HAC effectiveness. Four conditions emerge from the organizational learning literature as particularly critical.

Integration with performance management is the first and perhaps most consequential condition. Human capital theory [12] predicts that workers will invest in skill development proportional to the perceived returns of that investment and that organizations will fund training proportional to the organizational returns it generates. In practice, this means that upskilling programs that are disconnected from performance evaluation, career progression, and compensation systems will generate limited sustained engagement where employees rationally allocate effort toward activities whose value is recognized in the organizational reward structure. Effective talent development for HAC must therefore be architecturally connected to performance management: Competency acquisition must be visible, assessable, and consequential for career advancement.

Personalization of learning pathways is the second critical condition. One-size-fits-all training programs systematically misallocate learning resources: They invest

time in content already mastered by some participants, fail to address the specific role context in which others must apply new skills, and generate the disengagement and low transfer of learning that have made generic organizational training one of the least cost-effective human capital investments [7]. Effective upskilling for HAC must be differentiated by role, current competency level, and career trajectory, which creates pathways that connect AI skill development to the specific work contexts in which each employee must apply those skills.

Psychological safety is the third foundational condition. Upskilling in the context of AI adoption involves exposing and addressing current capability gaps, a process that carries significant psychological risk for employees whose professional identity is closely tied to competencies that AI is now rendering obsolete. Edmondson's [15] psychological safety theory holds that team members' willingness to engage in learning behaviors like asking questions, acknowledging uncertainty, experimenting with new approaches, and discussing errors, which generate genuine capability development, depends on their confidence that doing so will not result in embarrassment, punishment, or marginalization. Creating the psychological safety conditions for AI-era upskilling is therefore not a soft cultural preference but a hard prerequisite for learning effectiveness. This condition connects directly to the change leadership theme addressed in Section 4: Psychological safety in upskilling contexts is primarily a function of leadership behavior, not organizational program design.

Continuity of the learning infrastructure is the fourth condition. AI capabilities are evolving at a pace that makes episodic training interventions structurally inadequate. A training program designed to address today's AI capability landscape may be significantly outdated within 12 to 18 months. Effective talent development for HAC, therefore, requires not a series of discrete training events but a continuous learning infrastructure: an organizational architecture that anticipates future skill demands, tracks individual competency development over time, and enables ongoing learning as part of the normal rhythm of work rather than as an interruption to it.

3.4 Case study: The Jahiz platform – a national upskilling architecture

The Jahiz platform (**Table 1**) represents one of the most institutionally ambitious national upskilling architectures for AI-era government work in the world, and its design choices illuminate each of the four organizational conditions identified in the preceding section with particular clarity [16].

The integration of learning achievement with performance management is operationalized through the Future Skills Wallet, a portable, employee-owned digital credential that links competency acquisition to the formal performance management system used across all 83+ participating entities. Rather than treating training completion as a separate HR metric disconnected from performance evaluation, the Future Skills Wallet makes AI competency development visible, comparable across entities, and structurally consequential for career progression. The badge architecture creates a decentralized credentialing system that allows employees across diverse government entities, from defense to health to finance, to demonstrate AI-relevant competencies in standardized, verifiable form. This design choice directly addresses the motivation deficit that undermines most organizational training initiatives: When competency acquisition is visible in the system that determines career advancement, the incentive structure for sustained learning engagement is fundamentally transformed.

Dimension	Details
Initiative	Jahiz – UAE Federal Government Future Skills Platform
Oversight	Federal Authority for Government Human Resources (FAHR) and Government Development and Future Office
Coverage	75,000 + federal government employees across 83 + entities
Scope	20 future skills across 4 clusters: Digital Skills, Data and AI Skills, 10X Skills, and New Economy Skills
Scale	1.2 + million learning hours delivered; 800,000 + digital achievement badges issued
Architecture	AI-powered personalized learning journeys; Future Skills Wallet linked to performance management
Partners	Microsoft, Accenture, Udacity, Technology Innovation Institute, UAE Cybersecurity Council and 11 others
Edition	Second edition launched with enhanced AI personalization and specialized government sector content

Table 1.
The Jahiz platform – key parameters.

The AI-powered personalization of learning journeys addresses the one-size-fits-all failure mode that has historically limited government training effectiveness. By tailoring learning pathways to each employee’s existing competency profile, role requirements, and career trajectory, Jahiz embeds the augmentation logic into the learning experience itself: AI augments the human upskilling process, generating a learning pathway that is more contextually appropriate and more efficiently sequenced than any human training designer could produce for 75,000 individual learners. The second edition’s enhanced personalization capabilities, incorporating more sophisticated modeling of individual learning pace, preferred modalities, and role-specific application contexts, represent an iterative development of this augmentation logic that mirrors the dynamic capabilities framework’s emphasis on continuous reconfiguration.

Two critical dimensions of the Jahiz model merit particular theoretical attention for their implications beyond the UAE context. First, the explicit positioning of the platform as national infrastructure funded at the federal level, governed by a central authority (FAHR), but distributed in delivery across 83 + entities reflects a distinctive approach to the public goods character of AI upskilling. Rather than treating AI talent development as a cost to be absorbed by individual departments or an individual career investment to be funded by employees themselves, the UAE has framed it as a collective investment whose benefits accrue to the government as a whole. This framing has significant implications for equity of access: A national infrastructure approach reduces the risk that AI competency development becomes concentrated in well-resourced entities while smaller, less well-funded agencies fall behind. Second, the integration of Jahiz with the broader UAE AI governance architecture, including the UAE National AI Strategy 2031 and the 2026 mandate for 100% federal employee retraining in generative AI, reflects a systemic alignment between talent development strategy and national AI policy that most governments have yet to achieve.

3.5 Conceptual proposition 1

Proposition 1: Government organizations that institutionalize AI-augmented, personalized learning architectures that include integrating upskilling with performance management systems, treating talent development as a continuous national knowledge infrastructure rather than episodic training, and actively cultivating the psychological safety conditions for learning engagement will demonstrate superior levels of Human–AI collaboration effectiveness, employee adaptability, and sustained knowledge worker performance compared to those relying on non-integrated, generic, event-based training interventions.

4. Change management and knowledge leadership as enablers of AI adoption: Addressing RQ2

4.1 Why AI adoption fails: The change management problem

The history of large-scale technology adoption in organizations is marked by a persistent and costly paradox: Organizations that invest heavily in acquiring sophisticated technology systems frequently fail to realize anything approaching their potential value, because they invest comparatively little in the organizational and human conditions that determine whether technology investment translates into performance improvement. This paradox has been documented across waves of enterprise resource planning implementations, digital transformation initiatives, and e-government programs [17], [2], [18]. Artificial intelligence is not exempt from this dynamic; indeed, the evidence suggests that the gap between AI aspiration and AI outcome may be wider in government than in most other organizational contexts, precisely because the structural, cultural, and political conditions that impede change are more deeply entrenched in public administration than in private sector environments [19].

Change management theory provides the foundational analytical vocabulary for understanding why AI adoption fails and what is required for it to succeed. Kotter's [20] eight-step model of transformational change identifies the conditions under which large-scale organizational change achieves durable outcomes: establishing a credible sense of urgency that motivates action; building a guiding coalition of leaders with the authority, credibility, and commitment to sustain the change effort; developing a vision and strategy; communicating the change vision; empowering employees to act in accordance with the vision; generating short-term wins that demonstrate the credibility of the change narrative; consolidating gains to prevent regression; and anchoring new practices in the organizational culture so that they survive leadership transitions and resource pressures.

Each of these steps has specific and demanding implications for AI adoption in government. Establishing urgency requires leaders to communicate honestly about the pace and scale of skills disruption that AI is generating – a communication that risks provoking the very anxiety it must manage. Building a guiding coalition in government is complicated by the political complexity of public sector leadership, where ministerial priorities, bureaucratic hierarchies, and civil service tenure norms create institutional resistance to the kind of agile, risk-tolerant coalition that effective change leadership requires. Communicating a compelling vision is particularly challenging in the AI context. The most credible vision, one that honestly acknowledges both the genuine augmentation benefits of AI and the real

displacement risks it creates, is harder to sustain as a motivating narrative than either unqualified technological optimism or catastrophising about automation.

The specific form of resistance that AI adoption generates in government contexts is worth examining in some depth because it differs in important ways from the generic change resistance documented in the organizational behavior literature. The primary driver of AI resistance in the civil service is not technological skepticism or aesthetic preference for older ways of working; it is anxiety about professional displacement and institutional relevance. When civil servants perceive AI as a threat to their continued employment, their professional competence, or their organizational standing, their response is not passive disengagement but active resistance: withdrawal of knowledge-sharing cooperation that AI systems require to function effectively; strategic incompetence in engaging with AI tools; and the cultivation of narratives that emphasize AI's limitations and risks over its capabilities and opportunities. This form of resistance is particularly damaging in knowledge-intensive public sector contexts because it directly sabotages the knowledge creation and sharing processes that HAC depends on [21].

Managing this resistance requires change leaders who understand that the fundamental task is not technical training but identity reconstruction: Helping civil servants develop a new professional narrative in which their value is enhanced, not diminished, by AI. The AI literacy and the capacity for human-AI partnership become sources of professional pride and competitive advantage, rather than threats to established competence. This identity reconstruction is the deepest and most demanding task of change leadership in the AI adoption context, and it cannot be accomplished through communication campaigns or training programs alone; it requires sustained leadership presence, consistent modeling, and the creation of organizational conditions in which the new professional identity can be experienced, tested, and validated through actual practice.

4.2 A three-domain KM leadership competency framework for the AI era

Addressing RQ2 requires specifying not merely that leadership matters for AI adoption success but also what kinds of leadership, exercising what specific competencies, are required to create the conditions for effective and sustained HAC. Drawing on transformational leadership theory [22], the KM leadership literature [14], and psychological safety research [15], the chapter proposes a three-domain framework of KM leadership competencies for the AI era.

4.2.1 Domain 1: Strategic AI literacy

Strategic AI literacy refers to a leader's capacity to understand the capabilities and limitations of AI systems relevant to their domain of responsibility, to engage critically with AI-generated insights, and to make principled, informed decisions about where AI should and should not be deployed in their organizations. This competency is not technical in the conventional sense: It does not require leaders to understand the mathematics of machine learning or to write code. It requires leaders to understand AI at the level of strategic judgment: to know what kinds of questions AI systems are good at answering and what kinds they are not, to recognize when AI-generated recommendations should be trusted and when they should be questioned, and to model data-informed decision-making; the practice of treating AI

outputs as inputs to human judgment rather than as final verdicts in their own leadership behavior [23].

The modeling dimension of strategic AI literacy is critically important. Research on organizational learning consistently finds that leaders' own behavior is the most powerful signal available to organizational members about what is actually valued and expected [24] [7]. A leader who publicly expresses commitment to AI adoption while visibly ignoring AI-generated insights in their own decision-making sends an unambiguous organizational signal: The AI is for performance reporting, not for how we actually make decisions here. Conversely, a leader who demonstrably engages with AI recommendations, who asks in meetings where the data comes from, who draws attention to AI-generated insights, who publicly acknowledges when AI analysis has changed their thinking generates normative pressure across the organization that accelerates AI engagement far more effectively than any training program.

4.2.2 Domain 2: Change facilitation capacity

Change facilitation capacity is the cluster of leadership competencies most directly addressed by the Kotter framework: the ability to create and sustain the organizational conditions under which transformational change can occur and be embedded. In the AI adoption context, this domain encompasses four specific competency elements. First, creating psychological safety: Edmondson's [15] research establishes that the learning behaviors required for effective adaptation include acknowledging uncertainty, experimenting with unfamiliar tools, and discussing failures openly. These depend on employees' confidence that doing so will not result in negative consequences. Leaders create psychological safety around AI adoption through their response to early adopters' mistakes, through the questions they ask (which should emphasize learning rather than accountability), and through their own public acknowledgment of their own AI learning journey, including its difficulties.

Second, manage displacement anxiety through transparent, consistent, and credible communication of the augmentation narrative. This does not mean denying that AI will change roles. Dishonest reassurance is among the most corrosive forces in organizational change, because it destroys trust precisely when trust is most needed. It means honestly communicating both what AI will change and what it will not: that routinized tasks will be automated, that human judgment and relational competence will become more valuable, and that the organization's investment in talent development reflects a genuine commitment to employees' continued relevance and growth.

Third, build and sustain coalitions of change champions. Individuals at multiple levels of the organizational hierarchy who model AI engagement and provide peer support for colleagues navigating the learning curve serve as credible local advocates for the augmentation narrative. Change champions are particularly valuable in the AI adoption context because they bridge the gap between senior leadership's strategic vision and the practical, role-specific, day-to-day experience of employees working alongside new AI systems [1]. Fourth, generate and celebrate visible early wins. Concrete instances where AI adoption has made work demonstrably better, faster, or more impactful validate the change narrative and build the organizational confidence needed to sustain investment through the challenging middle stages of adoption.

4.2.3 Domain 3: Ethical stewardship

Ethical stewardship is the leadership competency domain most distinctive to the public sector context. Government leaders bear a responsibility for ensuring that AI systems embedded in their entities operate according to the principles of fairness, transparency, accountability, and non-discrimination that the public service demands. This responsibility is not merely reputational or legal; it is fundamental to the democratic legitimacy of government decision-making. When AI systems make or significantly influence decisions that affect citizens' access to services, rights, and opportunities – including decisions about benefit eligibility, permit approval, and regulatory enforcement – the citizens affected have a legitimate expectation that those decisions are made according to fair, transparent, and accountable processes. The AI leaders who fail to ensure this are not merely exposing their organizations to risk; they are compromising the public trust on which the legitimacy of government ultimately depends.

Ethical stewardship competence encompasses the capacity to establish governance frameworks for AI decision-making that specify where AI can operate autonomously, where human review is required, and where AI involvement is inappropriate regardless of technical capability. It includes creating audit mechanisms that allow AI outputs to be reviewed for accuracy, bias, and consistency; building organizational channels through which civil servants can surface concerns about AI behavior without fear of reprisal; and modeling a culture of responsible AI use in which the ethical dimensions of AI deployment are treated as strategic priorities, not compliance afterthoughts.

4.3 Multilevel change leadership: From national mandate to entity practice

One of the most important architectural questions in government AI adoption is the appropriate locus of change leadership. Top-down issuance of mandates for strategic directives, performance requirements, and resource allocations by the central government provides the authority, visibility, and institutional weight that large-scale transformation requires. Without a top-level mandate, AI adoption in complex, multientity government systems tends to remain fragmented: Some entities advance rapidly while others remain stationary, creating inequities in service quality and capability gaps that compound over time.

However, a top-down mandate alone is insufficient for the kind of deep, durable HAC that generates sustained performance improvement. Mandate without distributed leadership capacity produces compliance without commitment: Civil servants engage with AI tools to satisfy reporting requirements rather than because they have developed the intrinsic motivation and practical capability to derive genuine value from HAC. This shallow adoption that Argyris and Schön [8] would recognize as single-loop learning, at best, is fragile, reverting quickly when leadership attention or resource pressure shifts. Sustainable HAC requires change leadership that is distributed across organizational levels, present in the daily practice of entity-level leaders and team managers, and embedded in the organizational culture through the kind of double-loop learning that revises not just what employees do but how they understand their professional identity and organizational purpose.

The optimal architecture combines a top-level strategic mandate with entity-level KM leadership accountability and team-level psychological safety: three mutually

reinforcing levels of change leadership that together create the conditions for AI adoption to move from aspiration to embedded practice. National-level leadership establishes the strategic imperative, provides the resources for investment, and sets the accountability framework within which entity-level leaders operate. Entity-level AI leadership translates national strategic direction into operational reality, managing the specific organizational culture, workforce composition, and institutional dynamics of their entity. Team-level leadership creates the immediate relational environment in which the learning, experimentation, and identity reconstruction that effective HAC requires actually occur.

4.4 Case study: UAE institutional architecture for AI change leadership

The UAE’s institutional architecture for AI adoption (Table 2) represents a theoretically significant instantiation of the multilevel change leadership model, and its design choices illuminate each element of the three-domain competency framework with particular clarity.

The appointment of a dedicated Minister of State for AI in 2017, the world’s first such appointment, was an act of institutional signaling of the highest order. It established AI governance as a national strategic priority commanding ministerial authority, cross-government coordination, and sustained leadership attention. This is precisely the guiding coalition architecture that Kotter’s [20] model identifies as the foundational enabling condition for large-scale transformational change: a change leader with sufficient authority, visibility, and credibility to make AI adoption a non-negotiable national commitment rather than a departmental experiment. Critically, the appointment also established clear accountability: the Minister of State for AI bore responsibility for the UAE’s national AI trajectory, creating the performance pressure that keeps strategic mandates from dissolving into aspiration.

The creation of Chief AI Executive Officer (AI CEO) roles across all federal ministries and entities is the architectural move that translates the national strategic mandate into distributed entity-level change leadership. Rather than centralizing AI governance in a single ministry, an arrangement that would create

Dimension	Details
First mover	World’s first Minister of State for AI appointed in 2017; Ministry of AI, Digital Economy and Remote Work established in 2020
Strategy	UAE National AI Strategy 2031: targets 100% AI-enabled government services and AED 335 billion in additional economic value
AI CEO role	Chief AI Executive Officer position mandated across all federal ministries and entities
Council	UAE Council for Artificial Intelligence overseeing cross-entity integration and education sector AI adoption
Civil servants	100% of federal employees mandated for generative AI tools retraining under the 2026 AI Government Model
Philosophy	“People come first. Our goal is a government that is faster, more responsive and more impactful.” – Sheikh Mohammed bin Rashid Al Maktoum

Table 2.
UAE institutional architecture for AI governance and change leadership.

a bottleneck between national strategy and entity practice, and that would likely generate the compliance-without-commitment pattern described earlier, the UAE has built a distributed leadership architecture in which each entity owns its AI transformation within a nationally coordinated framework. The AI CEO role is designed precisely to exercise the three-domain competency framework: strategic AI literacy (understanding what AI can and should do in the entity’s specific context), change facilitation capacity (managing the organizational transition within the entity), and ethical stewardship (ensuring that AI deployment within the entity meets the standards of fairness and accountability that public service demands).

The guiding philosophy articulated by Sheikh Mohammed bin Rashid Al Maktoum – “People come first. Our goal is a government that is faster, more responsive, and more impactful” – is not merely a rhetorical statement; it functions as the master narrative of UAE AI adoption, framing AI transformation consistently in terms of augmentation (a government that is more responsive and impactful) rather than automation (a government that has replaced human workers with machines) [25]. Consistent, credible communication of this augmentation narrative at the highest levels of UAE leadership embodies the change facilitation competency most critical for managing displacement anxiety: not the denial of change, but the consistent, visible reframing of change as human-enhancing rather than human-replacing.

4.5 Case study: MoHRE AI as performance infrastructure and human development

The Ministry of Human Resources and Emiratisation (MoHRE) offers the most operationally detailed case of how the three-domain KM leadership competency framework manifests in entity-level AI adoption practice (**Table 3**). Its transformation is theoretically significant not merely for its scale – 13 million AI-processed transactions in 2025 and a 99% reduction in work permit processing time – but for its design logic, which reflects a sophisticated understanding of the augmentation model that the theoretical framework demands [26–28].

Dimension	Details
AI scale	13 million transactions processed via AI in 2025 with zero human intervention
Efficiency	Human effort reduced by 56%; work permit processing time reduced by 99% (from 10 days to 1 second)
Systems	Smart Work Permit Quota system; “Eye” AI system for document verification and fraud detection
Workforce model	Hybrid: routine transactions fully automated; complex, judgment-intensive cases escalated to human officers
Development	“Forecasting Future Jobs and Skills” tool; continuous upskilling of employees managing intelligent automation
Vision	AI embedded across all operations, services, and organizational structures; 100% AI-enabled services by 2031

Table 3.
MoHRE AI transformation – key parameters.

The most theoretically important feature of MoHRE's transformation is not the AI automation it has achieved but the human reallocation it has enabled. The Ministry did not simply automate existing processes and reduce headcount; it redesigned work architecture so that AI handles high-volume, rules-based transactions while human officers are systematically reallocated to the complex, relationship-intensive, judgment-requiring cases that are precisely beyond current AI capacity. This redistribution of human cognitive effort toward higher-order work is the augmentation model in operational form: It increases the value of human contribution by concentrating it where human judgment is irreplaceable, rather than competing human workers against AI systems in the task domains where AI has decisive advantages.

The integration of continuous workforce upskilling into MoHRE's operational transformation strategy, evidenced by the "Forecasting Future Jobs and Skills" tool and the Ministry's active approach to developing employees who manage intelligent automation, reflects the critical change management insight that talent development and operational transformation must be codesigned rather than sequenced. When organizations implement AI systems first and address workforce development afterward, they create a capability vacuum. Employees are expected to manage systems for which they have not been prepared, generating the resistance, error, and disengagement that give AI adoption a bad institutional reputation. MoHRE's approach, embedding human development within the logic of operational transformation, addresses this problem at its root, ensuring that capability development keeps pace with AI deployment rather than lagging behind it [29].

4.6 Conceptual proposition 2

Proposition 2: Government entities that establish multilevel AI change leadership that combines top-level strategic mandate with entity-level KM leadership accountability and team-level psychological safety and that integrate workforce development into operational AI transformation rather than treating it as a parallel HR initiative will demonstrate higher levels of AI adoption depth, employee engagement with AI tools, and sustainable Human-AI collaboration effectiveness than those relying on either mandate or organic adoption alone.

5. The talent-leadership nexus: An integrative conceptual framework

Sections 3 and 4 examined two pillars: talent development and knowledge leadership for change. Both have been presented as analytically distinct themes organized around separate research questions. But the deeper argument of this chapter is that they are not parallel independent variables; they are mutually constitutive conditions whose interaction produces the organizational environment in which effective, sustained HAC becomes possible. This section proposes an integrative framework, the talent-leadership nexus, that theorizes this mutual constitution and identifies four specific interaction effects that together explain how the two pillars reinforce each other.

5.1 Four interaction effects

The first interaction effect concerns the relationship between leadership modeling and upskilling effectiveness. Talent development research consistently finds that the transfer of learning from training contexts to work practice depends critically on the degree to which the immediate work environment reinforces, supports, and rewards the new behaviors being developed [8]. In the AI adoption context, this means that upskilling programs achieve their highest impact when leaders actively model the AI literacy and data-informed decision-making behaviors that the programs are developing. A leader who uses AI-generated insights in team meetings, who asks employees about what they are learning on the Jahiz platform, who publicly celebrates colleagues' AI competency development creates a work environment that amplifies the impact of formal learning investments. Conversely, a leader who is indifferent to or skeptical of AI tools creates a work environment that neutralizes upskilling investment: employees who develop AI competency in a learning platform but find no organizational reinforcement or application opportunity for that competency will not sustain their engagement.

The second interaction effect runs in the opposite direction: Robust upskilling programs generate a pool of AI-literate employees who extend the change leadership capacity of the organization. Change management research consistently identifies the coalition of change champions: credible, visible, enthusiastic advocates for the change at multiple organizational levels, as one of the most powerful accelerators of adoption. Upskilling programs that generate genuine AI competency development create exactly this pool: employees who have personally experienced the value of AI tools in their own work, who can speak credibly from practice about their benefits and limitations, and who can provide the peer-level support and encouragement that formal leadership communication cannot replicate. The Jahiz platform's 800,000 + digital achievement badges are not merely credentialing artifacts; they are the visible markers of an emerging community of AI-competent civil servants who constitute a distributed change leadership resource.

The third interaction effect concerns the role of integrated talent-performance systems in enabling adaptive change leadership. One of the most significant challenges for KM leaders navigating AI adoption is maintaining real-time visibility into the competency development of a large, distributed workforce: knowing where capability gaps are concentrated, where development is progressing faster than expected, and where resistance or disengagement signals are emerging. Talent development systems that are integrated with performance management, as in the case of Jahiz through the Future Skills Wallet, generate exactly the kind of organizational intelligence that enables adaptive, responsive change leadership. Rather than managing AI adoption through periodic surveys and lagging performance indicators, KM leaders with access to continuous competency development data can identify emerging capability gaps early, adjust learning pathways proactively, and direct change management interventions where they are most needed.

The fourth and perhaps most theoretically significant interaction effect concerns the role of operational integration in ensuring learning transfer. The most effective talent development is not what happens in a learning platform; it is what happens when learning is applied in practice, reflected upon, and refined through experience. Upskilling programs that are disconnected from operational transformation, that develop skills in a learning environment without creating the work contexts in which

those skills can be applied, practiced, and valued, generate awareness without genuine capability development. When talent development is embedded within operational transformation, as in MoHRE's approach of developing workforce capability alongside and within the deployment of AI systems, learning transfer is structurally guaranteed rather than left to chance. The work context itself becomes the learning context, and the boundary between talent development and operational change leadership dissolves.

5.2 Boundary conditions

The talent–leadership nexus framework is presented as a conceptual model with significant evidential grounding in the UAE case, not as a universal prescription. Several boundary conditions may moderate its effectiveness in different governance contexts. Organizational scale matters: the national infrastructure approach that characterizes the Jahiz platform requires the financial resources, administrative capacity, and political authority that characterize the UAE federal government context, and may not be replicable in smaller or more resource-constrained government systems. Political economy matters: The UAE's governance structure, which enables rapid deployment of strategic mandates with limited legislative friction, creates conditions for AI adoption at pace and scale that may differ substantially from more politically contested or procedurally constrained governance environments. Cultural context matters: The UAE's relatively high institutional trust, its workforce's relative familiarity with rapid technology adoption, and the specific character of Islamic organizational ethics create a cultural substrate for AI adoption that is distinctive and not universally transferable. Future empirical research should investigate the conditions under which the talent–leadership nexus model holds, where it requires modification, and what alternative configurations might achieve similar outcomes in different governance contexts.

6. Implications for research, practice, and policy

6.1 A research agenda

The conceptual framework and propositions developed in this chapter generate a focused agenda for future empirical inquiry. Five research directions emerge as particularly pressing.

First, the long-term human effects of AI-driven role redefinition in government deserve sustained empirical attention. The professional identity disruption associated with large-scale skills displacement is not merely a transitional challenge; it may generate enduring effects on civil servants' motivation, commitment, and well-being that affect both individual careers and organizational performance. Longitudinal research following civil servants through the AI transition, tracking not only competency development but also professional identity evolution, intrinsic motivation, and organizational commitment, would generate evidence that is currently almost entirely absent from the AI adoption literature.

Second, comparative research on change leadership approaches to AI adoption across different government contexts is urgently needed. The UAE case provides important evidence for a top-down mandate combined with distributed entity-level

leadership, but this is only one of several possible change leadership architectures. How do participatory codesign approaches to AI adoption in which civil servants are involved in designing the AI systems they will use compare in adoption depth, employee engagement, and performance outcomes to the mandate-and-deploy approach? How do peer-champion-led adoption programs compare to formal training initiatives? Systematic comparative evidence on these questions would provide policymakers with the evidence base needed to make informed choices among change management approaches.

Third, the specific KM leadership competencies that most strongly predict AI adoption outcomes merit empirical investigation. This chapter proposes a three-domain framework: strategic AI literacy, change facilitation capacity, and ethical stewardship. It is theoretically grounded but empirically untested. Survey-based and interview-based research investigating which leadership competencies employees identify as most consequential for their own AI adoption experience, and which organizational-level leadership practices most strongly predict HAC effectiveness at the entity level, would provide important empirical foundations for government leadership development investment.

Fourth, the transferability of the UAE's institutional innovations deserves systematic investigation. The Jahiz architecture, the Chief AI Executive Officer model, and the integration of AI governance within a dedicated Ministry represent institutional designs that may or may not be replicable in governance contexts with different political economies, administrative cultures, and resource endowments. Comparative case study research examining how these institutional designs translate or fail to translate across different Gulf Cooperation Council (GCC), Middle East and North Africa (MENA), and broader international governance contexts would provide policymakers with an evidence base for institutional learning and adaptation.

Fifth, the relationship between upskilling program design and HAC effectiveness outcomes at the organizational level requires rigorous empirical measurement. Existing research provides conceptual frameworks for effective upskilling design and case-based evidence for specific program implementations, but quantitative evidence linking specific design features, such as personalization, performance management integration, and continuity of infrastructure, to measurable HAC effectiveness outcomes is largely absent. Quasiexperimental research leveraging the variation in upskilling program designs across UAE government entities, or comparative research across national AI upskilling programs, would provide the causal evidence base that conceptual theorizing alone cannot provide.

6.2 Practical recommendations for government HR leaders

The HR leaders in government organizations navigating the AI transition should orient their talent development strategies around three principles derived from the chapter's framework. First, design for integration rather than addition: The AI upskilling programs that are layered onto existing HR structures without a structural connection to performance management, career development, and operational work design will generate low engagement and poor learning transfer. The most consequential HR investment is not the content of the upskilling program but the organizational systems that make competency acquisition visible, consequential, and connected to the work context in which it must be applied.

Second, invest in the human skills that AI cannot replicate. The instinct to focus AI-era talent development on technical AI competencies is understandable but strategically incomplete. The civil servants who will be most valuable in AI-enabled government are not those who know the most about AI; they are those who are most effective at doing the things that AI cannot do: building citizen trust, navigating ethical complexity, exercising contextual judgment in ambiguous situations, and communicating with empathy and clarity. The HR leaders who invest in developing these distinctly human capabilities are not resisting AI; they are making the human contribution to HAC more valuable.

Third, treat psychological safety as a design constraint, not a cultural aspiration. The organizational conditions under which civil servants engage authentically in AI upskilling – acknowledging gaps, experimenting with unfamiliar tools, discussing failures openly – are not natural states that emerge from good intentions; they are specific organizational conditions that must be deliberately created through leadership behavior, team culture, and organizational process design. HR leaders should work with line leaders to diagnose the current psychological safety climate around AI adoption and to design specific interventions – modeling by senior leaders, explicit learning contracts, and safe experimentation spaces – that create the conditions for authentic learning engagement.

6.3 Practical recommendations for KM practitioners

The KM practitioners in government organizations should position themselves as architects of human conditions for AI value realization, rather than as custodians of organizational knowledge repositories. The most consequential KM contribution to HAC is not the design of KM systems but the creation of organizational conditions of trust, a learning culture, knowledge-sharing norms, and feedback mechanisms in which human and AI knowledge can interact productively.

Mapping organizational knowledge flows to identify where AI augmentation generates the highest value, typically in the combination and externalization modes of the SECI cycle, and where human judgment remains irreplaceable, provides the analytical foundation for principled augmentation design. KM practitioners who undertake this mapping provide organizational decision-makers with the evidence base for informed HAC architecture decisions, rather than leaving augmentation design to technology procurement choices.

Building structured feedback mechanisms that enable civil servants to surface AI errors, limitations, and ethical concerns is a KM function that is consistently underinvested in government AI adoption programs. Without these mechanisms, organizations lose the critical quality assurance function that human oversight of AI is supposed to provide: errors compound, biases persist, and the responsible AI governance that public accountability demands becomes impossible to sustain. KM practitioners who design and maintain these mechanisms are not adding bureaucratic friction to AI deployment; they are making AI deployment sustainable.

6.4 Policy recommendations

Policymakers at the national and subnational levels should treat AI upskilling as a public good and invest in it accordingly. The UAE's Jahiz model demonstrates that

national-scale learning infrastructure – government-funded, FAHR-governed, and entity-delivered – can achieve coverage, equity of access, and continuous content relevance that departmental training programs cannot approach. Governments that fund AI upskilling as a departmental expense will generate uneven capability development that compounds existing inequalities across government entities and perpetuates the capability gaps that compromise HAC effectiveness at the system level.

Establishing dedicated AI leadership roles at both national and entity levels – the model of the UAE’s Ministry of AI and the AI CEO role – creates the distributed accountability architecture that enables AI adoption to proceed at scale without creating central governance bottlenecks. The AI CEO model is particularly significant: It embeds change leadership responsibility within line entities rather than locating it in a central support function, creating the ownership and contextual knowledge that effective entity-level change leadership requires.

Finally, policymakers should embed talent development imperatives within AI strategy documents and governance frameworks as coequal pillars of the transformation agenda, not as supplementary workforce programs. When AI strategy treats human capability development as a technical enabler of technology deployment rather than as a strategic investment in its own right, the funding, attention, and organizational priority that talent development requires will consistently lose out to the more visible and immediate demands of technology procurement. Making talent development structurally coequal in AI strategy, as the UAE has done by mandating 100% federal employee retraining within its national AI strategy, is the policy design choice that ensures the human dimensions of HAC receive the sustained investment they require.

7. Conclusion

This chapter has argued that the most consequential variables in AI-driven government transformation are not technical but human: the competency of civil servants to work effectively with AI tools, and the quality of leadership that creates the organizational conditions in which that work can occur, deepen, and generate sustained performance improvement. These two human dimensions, talent development and knowledge leadership, are not supplementary concerns to be addressed after technology deployment; they are the foundational pillars on which the value of any AI investment ultimately rests.

The talent–leadership nexus framework synthesizes these two pillars into an integrative model that specifies four mutual reinforcement effects: leadership modeling amplifying upskilling effectiveness; upskilling generating change champion capacity; integrated performance-competency systems enabling adaptive change leadership; and operational integration ensuring learning transfer. Together, these interaction effects explain why talent development and knowledge leadership must be codesigned rather than sequenced, coinvested rather than traded off, and coevaluated rather than assessed independently.

The broader invitation of this chapter is to KM and HRM scholars: The transformation of government in the age of AI is one of the defining KM challenges of our era, demanding inquiry that is simultaneously theoretically rigorous and practically grounded, attentive to institutional context, and sensitive to the human

experience of organizational change. The talent development and knowledge leadership themes explored here represent two of the most consequential and least understood dimensions of this challenge. They deserve the sustained scholarly attention that their importance demands.

Conflict of Interest

The authors declare no conflict of interest.

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