International Journal of Scientific Research and Modern Technology (IJSRMT) ijsrmt.com
Volume 5, Issue 2, 2026
DOI: https://doi.org/10.38124/ijsrmt.v5i2.1278

Developing Organizational Psychology Frameworks to Prepare the U.S. Workforce for Artificial Intelligence Integration and Competitiveness

Anita Naa Adoley Badoo[1]

[1]Department of Psychology and Sociology, College of Arts and Sciences, University of New Haven, West Haven, Connecticut, United States of America

Publication Date: 2026/03/02

Abstract

The accelerating integration of artificial intelligence (AI) into U.S. workplaces presents a profound organizational psychology challenge that extends well beyond technology adoption. This paper develops a comprehensive organizational psychology framework to prepare the U.S. workforce for AI integration and sustain national economic competitiveness. Drawing upon established theoretical foundations including the Technology Acceptance Model (TAM), Human–AI Symbiosis Theory, the Job Demands–Resources Model, and Organizational Trust Theory alongside empirical evidence from emerging AI-HRM research, we synthesize a multi-dimensional framework encompassing six interdependent dimensions: human–AI symbiosis, trust and transparency, job redesign, AI-enabled recruitment and selection, learning and adaptation, and ethical AI governance. The framework addresses the psychological barriers including algorithm aversion, AI-induced job insecurity, technostress, and diminished occupational identity that impede effective AI integration across U.S. industries. Findings indicate that workforce psychological readiness, not merely technological capability, constitutes the critical bottleneck in AI adoption, with significant variation across generational cohorts, industry sectors, and organizational maturity levels. A five-phase strategic roadmap is proposed for phased organizational implementation, integrating HRM practice redesign, psychological support systems, and evidence-based governance mechanisms. The article contributes to theory by extending existing behavioral frameworks to the AI-augmented workplace context, and to practice by offering actionable guidance for HRM practitioners, organizational leaders, and U.S. workforce policy stakeholders seeking to leverage AI for sustained competitive advantage.

Keywords: *Organizational Psychology; Artificial Intelligence; Workforce Readiness; Technology Acceptance Model; Human–AI Collaboration; HRM Practices; AI Ethics; U.S. Competitiveness; Job Redesign; Employee Well-Being.*

I. INTRODUCTION

The integration of artificial intelligence (AI) into the contemporary workplace represents one of the most significant organizational transformations of the twenty-first century. Across U.S. industries from healthcare and finance to legal services, manufacturing, and education AI systems are reshaping the nature of work, redefining job roles, and fundamentally altering the competencies required for sustained individual and organizational performance. Wang (2019) broadly conceptualizes AI as any computational system capable of performing tasks that would ordinarily require human intelligence, encompassing machine learning, natural language processing, computer vision, and autonomous decision-making. This expansive definition underscores the pervasive scope of AI's influence across nearly every dimension of organizational life.

Despite the technological promise AI holds for enhancing productivity, reducing inefficiency, and generating competitive advantage, the organizational psychology literature reveals that the human dimensions of AI integration remain significantly undertheorized and underaddressed in practice. Dwivedi et al. (2019) identify AI as a multidisciplinary challenge whose research agenda must encompass social, psychological, ethical, and governance dimensions alongside technical ones. Jarrahi (2018) further argues that the future of work hinges less on AI's autonomous capabilities and more on how organizations architect the symbiotic relationship between human workers and AI systems in decision-making contexts. These perspectives converge on a critical insight: workforce psychological readiness not technological capability constitutes the primary bottleneck in realizing the organizational benefits of AI.

The United States faces a particularly acute version of this challenge. As global AI investment accelerates and competitor economies systematically develop national AI workforce strategies, the ability of U.S. organizations to prepare their employees psychologically and operationally for AI-augmented work environments becomes a matter of both organizational viability and national competitive strategy. Verganti et al. (2020) observe that in the age of AI, innovation increasingly depends on human capacity for meaning-making, creativity, and contextual judgment qualities that require deliberate cultivation through organizational psychology-informed design. Yet the dominant organizational response to AI adoption in U.S. firms remains disproportionately focused on technology procurement and implementation, with insufficient attention to the psychological, behavioral, and cultural conditions that determine whether AI investments translate into genuine performance outcomes.

This article responds to this gap by developing a comprehensive organizational psychology framework for AI workforce readiness. The framework integrates six interdependent dimensions human–AI symbiosis, trust and transparency, job redesign, AI-enabled recruitment and selection, learning and adaptation, and ethical AI governance and grounds each dimension in established psychological and organizational theory. Drawing on a synthesis of contemporary empirical research spanning technology acceptance, human-computer interaction, HRM systems, organizational behavior, and AI ethics, the article provides both a theoretical contribution to the rapidly evolving field of AI-HRM integration and practical guidance for HRM practitioners and organizational leaders navigating AI-driven workforce transformation.

The remainder of the article is structured as follows. Section 2 reviews the theoretical foundations undergirding the framework. Section 3 presents the six-dimension framework and its components. Section 4 examines AI-enabled HRM practices and their psychological implications. Section 5 addresses the ethical and governance dimensions of AI in the workplace. Section 6 presents the five-phase strategic implementation roadmap. Section 7 discusses implications for theory, practice, and U.S. workforce policy. Section 8 concludes with directions for future research.

II. THEORETICAL FOUNDATIONS

The framework advanced in this article draws upon multiple theoretical traditions in organizational psychology, human-computer interaction, and HRM. Table 1 summarizes the core theoretical frameworks, their constituent constructs, and their specific application to the AI integration context.

Table 1 Theoretical Foundations of Organizational Psychology Applied to AI Integration

Theoretical Framework	Core Constructs	Application to AI Integration	Key References
Technology Acceptance Model (TAM)	Perceived usefulness, ease of use, behavioral intention	Predicts employee willingness to adopt AI tools; identifies barriers to acceptance	Xu & Wang (2019); Almeida et al. (2025)
Human–AI Symbiosis Theory	Complementarity, augmentation, cognitive offloading	Defines optimal division of labor between humans and AI systems in organizational tasks	Jarrahi (2018); Pan & Froese (2022)
Job Demands–Resources Model (JD-R)	Job demands, job resources, burnout, engagement	Maps how AI introduces new demands and resources affecting employee well-being and performance	Albrecht et al. (2015); Bankins & Formosa (2023)
Social Cognitive Theory	Self-efficacy, observational learning, reciprocal determinism	Explains how employees develop confidence in AI-augmented roles through training and modeling	Verganti et al. (2020); Ahmad et al. (2014)
Organizational Trust Theory	Cognitive trust, affective trust, institutional trust	Addresses conditions under which employees trust AI systems and AI-mediated decisions	Glikson & Woolley (2020); Burrell (2016)
High-Involvement Management (HIM)	Autonomy, participation, skill development, commitment	Links employee involvement in AI deployment decisions to performance and satisfaction outcomes	Ahmad et al. (2014); Albrecht et al. (2015)

Source: Author synthesis drawing on Xu & Wang (2019); Jarrahi (2018); Albrecht et al. (2015); Verganti et al. (2020); Glikson & Woolley (2020); Ahmad et al. (2014)

- *Technology Acceptance Model and Its Extensions*

The Technology Acceptance Model (TAM), originally developed to explain information technology adoption behavior, provides a foundational lens for understanding employee engagement with AI systems. Xu and Wang (2019) extend TAM to the professional context of AI-assisted legal services, demonstrating that perceived usefulness and ease of use remain robust predictors of adoption intention, while adding trust as a critical moderating variable in human–AI interaction settings. Almeida et al. (2025) further extend TAM to the domain of AI-assisted recruitment, finding that recruiter acceptance of AI tools is significantly moderated by perceived fairness and organizational support for AI use. Critically, both studies converge on the finding that TAM's behavioral intention pathways are substantially attenuated when employees harbor concerns about algorithmic opacity or fairness a finding with direct implications for organizational intervention design.

Building on TAM, Tanantong and Wongras (2024) employ the Unified Theory of Acceptance and Use of Technology (UTAUT) framework in a Thai HR recruitment context, demonstrating that social influence and facilitating conditions beyond individual attitudes significantly predict AI adoption in organizational settings. Al-Adwan et al. (2023) similarly extend TAM to metaverse-based learning contexts, while Al-Abdullatif (2023) demonstrates its applicability to AI-driven educational chatbots through integration with value-based adoption constructs. Collectively, these extensions affirm that behavioral intention toward AI is a multi-determined phenomenon requiring organizational-level interventions alongside individual-level attitude change.

- *Human–AI Symbiosis and Complementarity*

Jarrahi's (2018) human–AI symbiosis framework represents a significant theoretical advance beyond technological determinism. Rather than positioning AI as an autonomous agent that either replaces or assists humans in discrete tasks, Jarrahi conceptualizes human–AI interaction as a dynamic, co-evolving system in which human intuition, contextual judgment, and creative meaning-making complement AI's superior pattern recognition, data processing, and consistency. This complementarity framework has direct implications for job redesign, as it suggests that optimal human–AI collaboration requires deliberate architectural choices about where human agency is preserved, enhanced, or deliberately constrained.

Pan and Froese (2022) expand this perspective through an interdisciplinary review of AI-HRM integration, identifying three primary interaction modalities AI as tool, AI as collaborator, and AI as autonomous agent each presenting distinct psychological challenges for the human workforce. The psychological implications escalate across this spectrum: AI-as-tool primarily challenges skill acquisition; AI-as-collaborator raises identity and authority questions; and AI-as-autonomous-agent invokes deep concerns about accountability, meaningful work, and professional purpose (Bankins & Formosa, 2023).

- *Trust in AI Systems*

The question of how and why human workers develop trust in AI systems is among the most consequential in organizational psychology. Glikson and Woolley (2020) conduct a comprehensive review of empirical AI trust research, distinguishing between cognitive trust (belief in AI's competence), affective trust (positive feelings toward AI), and institutional trust (faith in the organizational systems governing AI use). Their synthesis reveals that cognitive trust in AI is primarily developed through demonstrated accuracy and reliability, whereas affective trust is critically shaped by the degree to which AI systems are perceived as caring about human well-being a dimension particularly relevant to service robots and socially interactive AI (Yam et al., 2020).

Burrell (2016) introduces the critical concept of algorithmic opacity the degree to which machine learning systems are inherently illegible even to their creators as a fundamental structural threat to trust development. When employees cannot understand how AI systems arrive at consequential decisions affecting their work, careers, or compensation, the conditions for sustained trust are systematically undermined. This insight has galvanized attention to explainable AI (XAI) as both a technical and organizational psychology imperative, with implications for how AI systems are designed, deployed, and communicated within organizations.

III. THE SIX-DIMENSION ORGANIZATIONAL PSYCHOLOGY FRAMEWORK

Figure 1 presents the integrative organizational psychology framework proposed in this article. The framework positions the AI-Ready Workforce as the central organizing construct, surrounded by six interdependent dimensions that collectively determine an organization's capacity to prepare its workforce for effective, ethical, and sustainable AI integration.

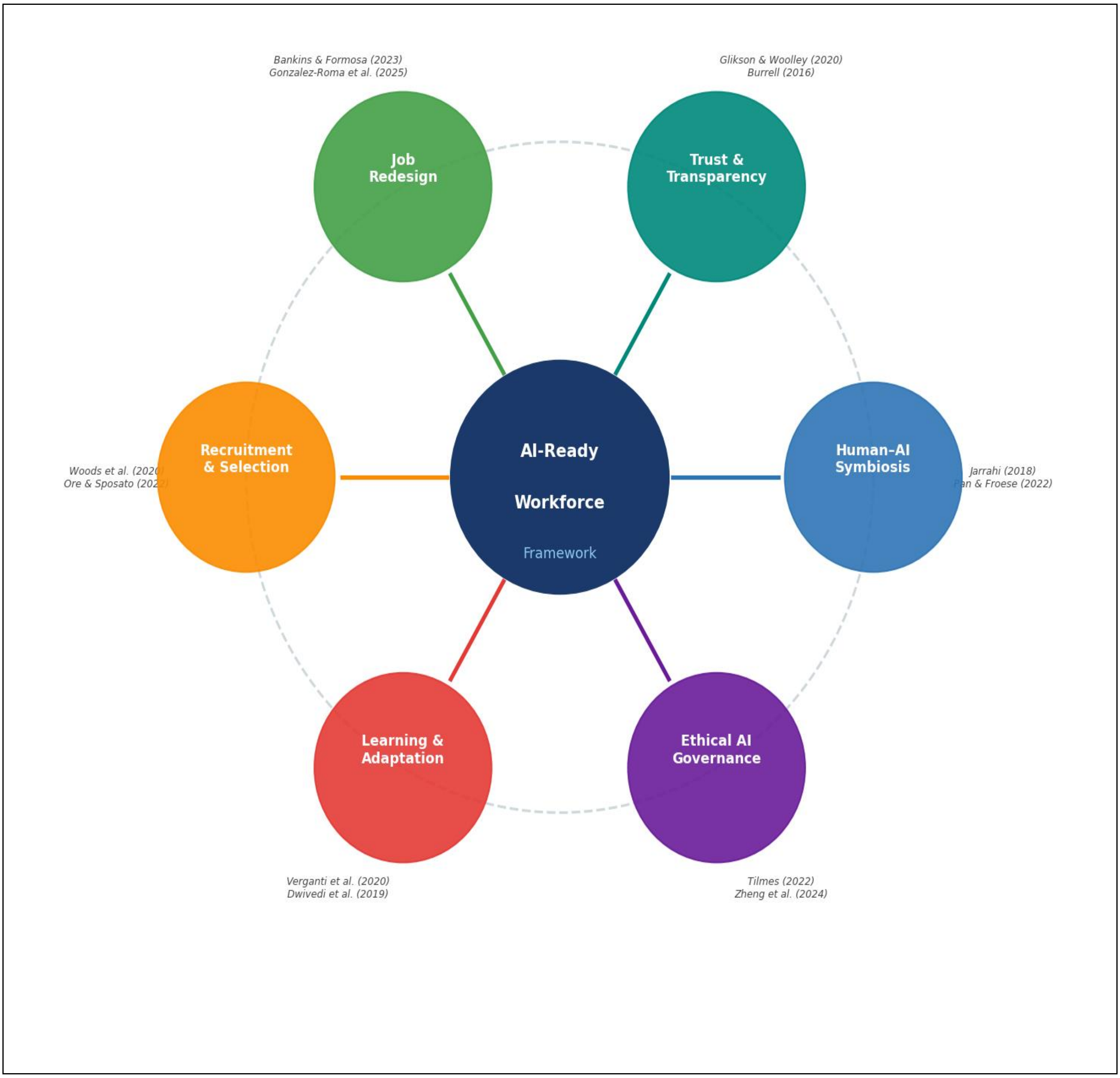

Fig 1 Organizational Psychology Framework for AI-Ready Workforce Development in U.S. Organizations. The Hub-and-Spoke Model Illustrates Six Interdependent Dimensions, Each Grounded in Organizational Psychology Theory and Empirical Evidence.

➢ *Human–AI Symbiosis*

The first dimension concerns the fundamental design of human–AI collaboration systems within organizational contexts. Jarrahi's (2018) symbiosis framework provides the conceptual foundation, emphasizing that organizations must make deliberate architectural decisions about the distribution of cognitive labor between human workers and AI systems. Effective symbiosis design requires identifying the unique value contributions of human workers including empathy, ethical judgment, contextual interpretation, and creative synthesis and designing AI systems that augment these contributions rather than supplanting them. Pan and Froese (2022) observe that organizations that frame AI as an augmentation tool consistently report higher employee engagement and lower resistance than those that frame it as an automation or replacement mechanism.

From an organizational psychology standpoint, symbiosis design has direct implications for role crafting, autonomy allocation, and skill development. Employees whose work involves meaningful human–AI collaboration in which AI handles high-volume, routine, or computationally intensive tasks, freeing humans for judgment-intensive, relational, and creative functions report higher levels of job satisfaction and perceived meaningful work (Bankins & Formosa, 2023). This finding has important implications for job redesign strategy, performance management systems, and organizational communication about AI's purpose within the firm.

➢ *Trust and Transparency*

Building sustainable employee trust in AI systems requires addressing both cognitive and affective trust dimensions simultaneously. At the cognitive level, organizations must invest in AI explainability mechanisms that render algorithmic decisions legible to non-technical employees (Burrell, 2016). At the affective level, Yam et al. (2020) demonstrate that employees and indeed customers are significantly more willing to accept AI-mediated service failures and suboptimal decisions when AI systems are perceived as having positive intentions or genuine concern for human well-being, a finding that underscores the importance of how organizations anthropomorphize and communicate about their AI systems.

Glikson and Woolley's (2020) review identifies three organizational levers for building AI trust: demonstrating AI competence through consistent and verifiable performance; ensuring AI behavior aligns with employee and organizational values; and creating institutional accountability structures that employees perceive as credible and fair. Organizations that invest in all three domains report substantially higher levels of employee AI trust and lower rates of workaround behaviors, in which employees bypass AI systems they distrust in favor of familiar manual processes.

➢ *Job Redesign for AI-Augmented Work*

The third dimension addresses the systematic redesign of work to optimize human–AI complementarity. González-Romá et al. (2025) introduce the concept of SMARTer jobs roles specifically designed to harness AI-enabled capabilities while preserving and enhancing meaningful human contribution demonstrating that employee-centered automation implementation is significantly associated with higher job satisfaction and lower emotional exhaustion. Bankins and Formosa (2023) similarly argue that the ethical implications of AI for meaningful work require proactive job redesign interventions that preserve employee autonomy, skill utilization, and sense of purpose.

Drawing on the Job Demands–Resources Model, Albrecht et al. (2015) highlight that AI integration simultaneously introduces new job demands such as AI literacy requirements, human–AI coordination complexity, and continuous learning expectations and new job resources, including AI-enabled productivity tools, decision-support systems, and automated administrative burden reduction. Effective job redesign must carefully balance these dynamics, ensuring that AI-generated resources substantively outweigh AI-generated demands for the majority of employees across organizational levels.

➢ *AI-Enabled Recruitment and Selection*

The fourth dimension addresses the rapidly expanding use of AI in talent acquisition and selection processes. Woods et al. (2020) review digital-age personnel selection practices, noting that AI-enabled tools including automated resume screening, algorithmic interview scoring, and predictive performance analytics raise complex psychometric validity, fairness, and applicant reaction considerations. Critically, candidate perceptions of AI-mediated recruitment processes differ substantially from human-mediated counterparts: Suen et al. (2019) demonstrate that synchronous video interviews scored by AI significantly affect applicant attitudes, with concerns about fairness and the absence of interpersonal connection emerging as primary negative response dimensions.

Köchling et al. (2023) extend this analysis by examining affective responses to AI in recruitment, finding that candidates who perceive AI-mediated recruitment as a barrier to demonstrating their true competencies experience elevated anxiety and negative organizational attraction, with implications for employer branding and talent pipeline quality. Wehner et al. (2015) further demonstrate that organizational image moderates applicant reactions to recruitment process outsourcing, a finding that generalizes to AI-mediated recruitment contexts: organizations with strong reputations for employee-centrism experience less negative applicant reaction to AI recruitment tools.

➢ *Learning, Adaptation, and Continuous Development*

Verganti et al. (2020) position AI's most profound organizational impact not in its capacity to automate tasks but in its power to transform the nature of innovation and learning. In AI-augmented organizations, competitive advantage increasingly derives from employees' capacity to ask better questions of AI systems, critically evaluate AI-generated outputs, and synthesize AI insights with domain expertise and contextual judgment. This reframing of the learning challenge from AI skill acquisition to AI-mediated epistemic competence has significant implications for organizational learning systems.

Dwivedi et al. (2019) identify continuous learning capability as a central dimension of organizational AI readiness, arguing that organizations must invest in building metacognitive skills awareness of one's own learning processes and limitations alongside technical AI literacy. Khan et al. (2023) demonstrate that technology modernization in organizational learning environments significantly enhances user satisfaction and trust when supported by robust management capabilities and change communication, reinforcing the importance of organizational context in shaping individual learning responses to AI-enabled systems.

➢ *Ethical AI Governance*

The sixth dimension addresses the organizational psychology of ethical AI deployment. Tilmes (2022) provides a rigorous analysis of disability, fairness, and algorithmic bias in AI recruitment, demonstrating that AI tools trained on historically biased data systematically perpetuate and amplify discriminatory patterns in hiring, with disproportionate impacts on historically underrepresented groups. This finding has profound implications for organizational AI governance, requiring systematic algorithmic impact assessments, diverse AI development teams, and human-in-the-loop oversight for high-stakes employment decisions.

Zheng et al. (2024) examine AI recruitment biases in a cross-cultural context, finding that AI-enabled recruitment tools can both reduce and introduce biases depending on their design, training data, and deployment context, with significant implications for diversity and inclusion outcomes. At a broader level, Townsend and Hunt (2019) argue that entrepreneurial action, creativity, and ethical judgment distinctly human capacities become more rather than less important in AI-augmented organizational environments, as the speed and scale of AI-generated decisions raise the stakes of individual and organizational ethical commitments.

IV. AI INTEGRATION READINESS ACROSS U.S. INDUSTRY SECTORS

Table 2 presents a comparative analysis of AI integration readiness across eight major U.S. industry sectors, synthesizing indicators of technological adoption, workforce psychological preparedness, training investment, ethical concern intensity, and the sector-specific primary psychological challenge.

Table 2 Dimensions of AI Readiness Across U.S. Industry Sectors

Industry Sector	AI Adoption Rate (%)	Workforce Readiness Score	Training Investment ($/employee)	Ethical Concern Index	Primary Psychological Challenge
Technology	78	7.4	$4,200	3.1	Role obsolescence anxiety; rapid capability gaps
Finance & Banking	71	6.9	$3,850	3.8	Algorithmic bias concerns; trust in AI decisions
Healthcare	58	5.8	$2,940	4.6	Patient safety fears; human-AI boundary ambiguity
Manufacturing	64	5.4	$2,100	3.2	Job displacement fear; upskilling resistance
Education	41	6.1	$1,760	3.9	Academic integrity concerns; pedagogical identity
Legal Services	33	4.8	$3,100	4.8	Accountability opacity; professional autonomy loss
Retail	55	5.2	$1,420	2.8	Customer interaction displacement; skill mismatch
Government/Public	29	4.2	$1,980	4.2	Bureaucratic inertia; accountability and transparency

Source: Author synthesis drawing on Dwivedi et al. (2019); Pan & Froese (2022); Tilmes (2022); Ore & Sposato (2022); Biea et al. (2024)

Figure 2 extends this sector-level analysis by examining TAM dimensions across generational workforce cohorts and industry sectors, illustrating the multidimensional nature of acceptance variation and the targeting requirements for effective organizational intervention.

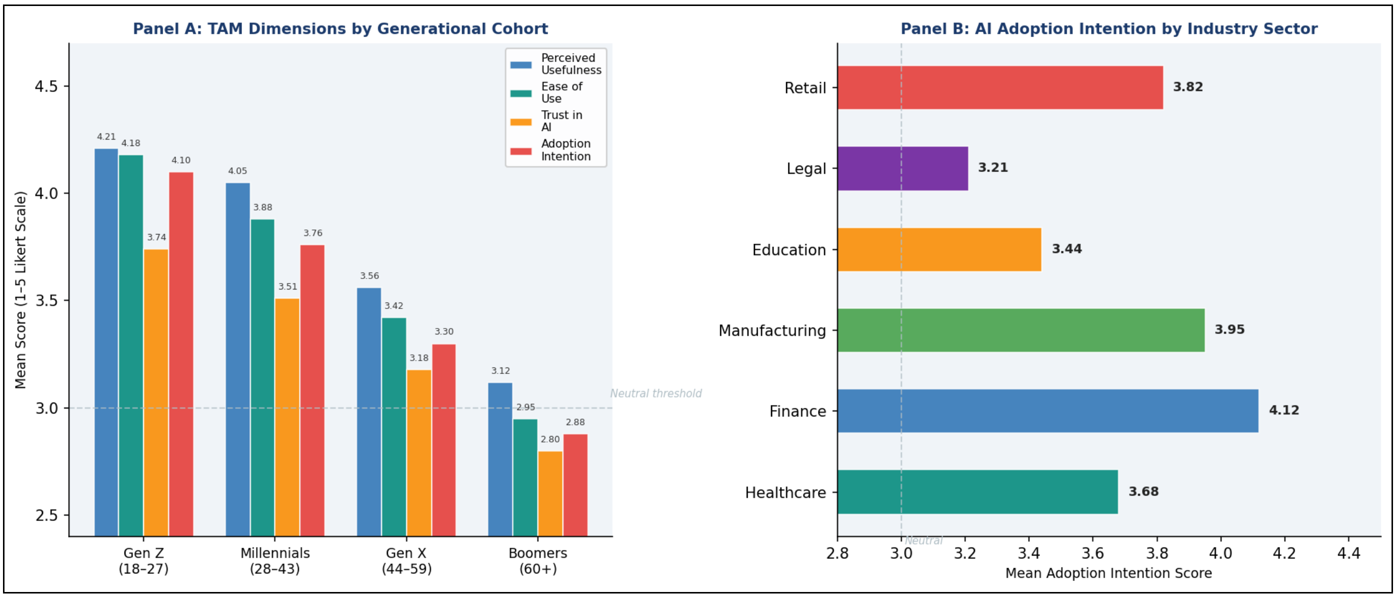

Fig 2 Technology Acceptance Model (TAM) Dimensions Across Workforce Segments and Industry Sectors. Panel A Shows Generational Variation in TAM Dimensions; Panel B Presents AI Adoption Intention by Sector. Adapted from Almeida et al. (2025) and Xu & Wang (2019).

The sector-level analysis reveals a paradox of AI readiness: sectors with the highest AI adoption rates notably technology and finance do not consistently exhibit the highest levels of workforce psychological readiness. This divergence reflects an organizational tendency to prioritize technological deployment over human capital preparation, generating what we term an "implementation gap" high organizational AI capability coupled with moderate-to-low workforce psychological readiness (Figure 3). Healthcare and educational institutions present the inverse pattern: workforces with relatively high psychological readiness indicators but organizational AI capability constrained by regulatory complexity, resource limitations, and cultural conservatism.

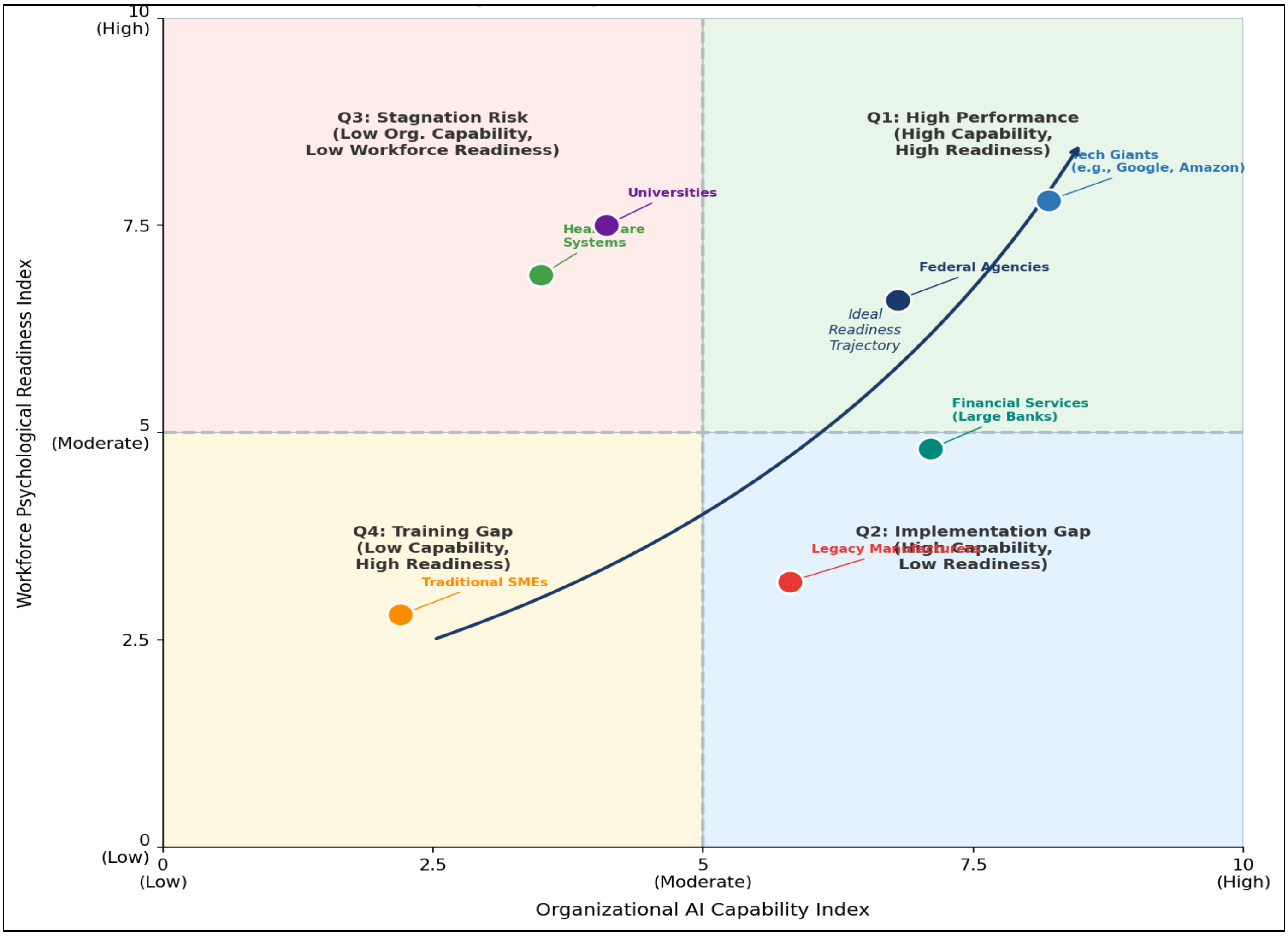

Fig 3 AI Integration Readiness Matrix Organizational Capability vs. Workforce Psychological Readiness. Quadrant Positioning of Representative U.S. Organizational Types Illustrates the Implementation Gap (Q2) and Training Gap (Q4) Diagnostic Categories. Adapted from Jarrahi (2018) and Dwivedi et al. (2019).

The legal sector warrants particular attention, exhibiting both the lowest AI adoption rate and the highest ethical concern index among the sectors analyzed. Xu and Wang (2019) attribute legal professionals' ambivalence toward AI adoption to concerns about professional accountability, the opacity of legal reasoning as modeled in machine learning systems, and the irreducible role of human judgment in equity and justice determinations. These findings align with Burrell's (2016) broader observation that algorithmic opacity constitutes a structural barrier to AI trust in high-stakes, judgment-intensive professional domains a barrier that organizational interventions must address through both technical explainability investments and professional identity-safe communication strategies.

V. PSYCHOLOGICAL BARRIERS AND HRM INTERVENTIONS

Understanding the specific psychological barriers to AI adoption is prerequisite to designing effective organizational interventions. Table 3 presents a taxonomy of primary psychological barriers observed across U.S. organizational contexts, their affected populations, severity assessments, and evidence-based recommended interventions.

Table 3 Psychological Barriers to AI Integration and Recommended Organizational Interventions

Psychological Barrier	Affected Population	Severity Level	Recommended Organizational Intervention
Algorithm aversion and distrust	All employees; heightened in older workers and non-technical roles	High	Transparent AI explainability training; participatory design; demonstrated AI accuracy benchmarking (Burrell, 2016; Glikson & Woolley, 2020)
AI-induced job insecurity	Middle-skill workers; routine-task incumbents	High	Proactive reskilling programs; role redesign with expanded autonomy; career pathway communication (Bankins & Formosa, 2023; Ore & Sposato, 2022)
Technostress and cognitive overload	Workers with limited digital fluency; high-demand roles	Moderate–High	Phased AI introduction; workload monitoring; digital wellness protocols (Warrier et al., 2021; Albrecht et al., 2015)
Reduced sense of meaningful work	Knowledge workers; professionals with high role identity	Moderate	Job enrichment strategies; emphasis on uniquely human skills; AI as co-creator framing (Bankins & Formosa, 2023; Verganti et al., 2020)
Bias sensitivity and fairness concerns	Minority and underrepresented groups; HR professionals	Moderate–High	Bias auditing; diverse AI development teams; algorithmic impact assessments (Tilmes, 2022; Zheng et al., 2024)
Loss of professional identity	Legal, medical, creative, and educational professionals	Moderate	Identity-safe AI deployment narratives; augmentation rather than replacement framing (Pan & Froese, 2022; Jarrahi, 2018)

Source: Author synthesis drawing on Burrell (2016); Bankins & Formosa (2023); Warrier et al. (2021); Tilmes (2022); Ore & Sposato (2022); Pan & Froese (2022)

Figure 4 visualizes the temporal dynamics of these psychological responses, tracking how the profile of affective responses and key psychological well-being indicators evolves across the AI adoption timeline from pre-announcement through the 24-month post-integration period.

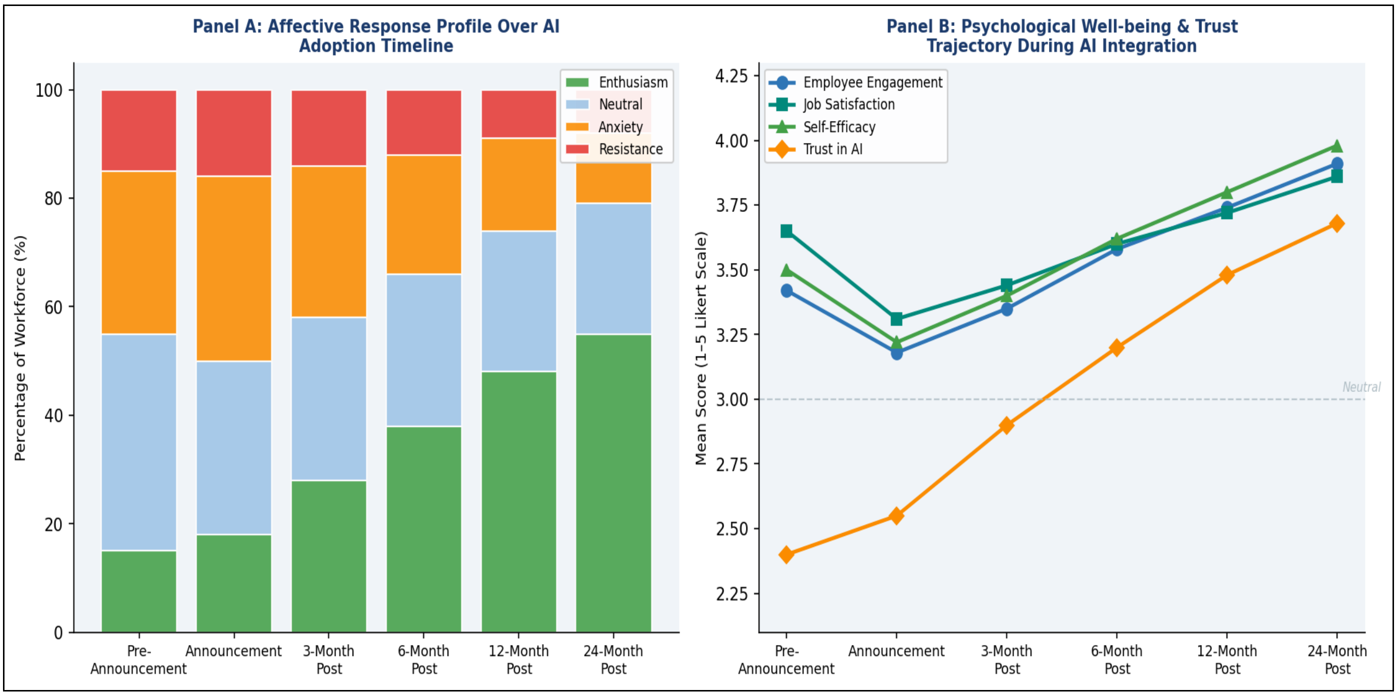

Fig 4 Employee Psychological Responses to AI Integration Across Adoption Stages. Panel A Tracks the Affective Response Profile of the Workforce; Panel B Shows Key Psychological Well-Being Indicators Over the Adoption Timeline. Based on Yam et al. (2020), Albrecht et al. (2015), and Warrier et al. (2021).

The trajectory depicted in Figure 4 reveals a characteristic U-shaped pattern in psychological well-being indicators during AI integration. The initial decline in engagement, job satisfaction, and self-efficacy following announcement reflects the threat appraisal processes that accompany significant workplace change, consistent with Warrier et al.'s (2021) finding that emotional intelligence moderates communication effectiveness during technology-driven organizational crises. The subsequent recovery and growth trajectory evident by the 3-month post-integration milestone reflects the positive feedback dynamics of successful human–AI collaboration: as employees develop competence with AI tools and experience the productivity and quality benefits of human–AI augmentation, self-efficacy, engagement, and trust in AI systems improve contemporaneously (Albrecht et al., 2015).

Algorithm aversion and distrust emerge as the most severe and pervasive barriers, cutting across organizational levels and demographic groups. Glikson and Woolley's (2020) comprehensive review identifies the fundamental tension between the human tendency to apply social cognition frameworks to AI systems judging them by standards of intentionality, fairness, and relational concern and the actual epistemic structure of machine learning systems, which are defined by statistical optimization rather than intentional design. This cognitive mismatch generates systematic distrust that pure performance demonstrations cannot fully overcome; organizational interventions must additionally address the anthropomorphic framing of AI systems and the social-relational dimensions of human–AI interaction (Yam et al., 2020).

Job insecurity anxiety presents a distinct intervention challenge because it is, to a significant degree, empirically warranted: AI automation does eliminate certain job categories and fundamentally transforms others. Ore and Sposato (2022) argue that organizations must acknowledge this reality honestly and invest credibly in reskilling and role evolution programs that demonstrably expand rather than merely preserve employee career horizons. The psychological effectiveness of reskilling programs is substantially enhanced when employees are involved in identifying their own development needs and designing their transition pathways an application of Ahmad et al.'s (2014) high-involvement management principles to the AI transition context.

VI. AI-ENABLED HRM PRACTICES: OPPORTUNITIES AND PSYCHOLOGICAL IMPLICATIONS

The rapid expansion of AI into HRM practices represents both an extraordinary opportunity for organizational effectiveness and a significant source of psychological complexity for employees. Table 4 synthesizes the primary AI-enabled HRM practices, their organizational benefits, the psychological implications for affected employees, and the research evidence supporting these assessments.

Table 4 AI-Enabled HRM Practices, Organizational Benefits, and Workforce Psychological Implications

AI-Enabled HRM Practice	Organizational Benefits	Workforce Psychological Implications	Research Support
Automated resume screening and applicant ranking	Reduced time-to-hire; broader candidate reach; cost efficiency	Applicant anxiety about fairness; reduced sense of personal evaluation; self-presentation uncertainty	Woods et al. (2020); Wehner et al. (2015); Köchling et al. (2023)
AI-driven video interview analysis	Standardized assessment; reduced interviewer bias; scalability	Discomfort with non-human evaluation; reduced rapport; concerns about emotional surveillance	Suen et al. (2019); Akram et al. (2024); Ore & Sposato (2022)
Predictive performance analytics	Early identification of high-potential employees; personalized development	Privacy concerns; algorithmic discrimination fears; reduced managerial autonomy	Biea et al. (2024); Boon et al. (2019); Pan & Froese (2022)
Chatbot-mediated onboarding and HR support	24/7 accessibility; consistent information delivery; cost savings	Reduced sense of human connection; technology frustration; trust concerns	Akram et al. (2024); Abdelkader (2023); Al-Abdullatif (2023)
AI-assisted learning and development systems	Personalized learning pathways; adaptive skill gap identification	Motivation to learn vs. algorithm-directed growth; autonomy reduction	Verganti et al. (2020); Khan et al. (2023); Dwivedi et al. (2019)
Workforce sentiment analysis and monitoring	Real-time engagement tracking; early turnover prediction	Privacy invasion perceptions; psychological safety threats; surveillance anxiety	Warrier et al. (2021); Tanantong & Wongras (2024)

Source: Author Synthesis Drawing on Woods et al. (2020); Suen et al. (2019); Biea et al. (2024); Akram et al. (2024); Verganti et al. (2020); Warrier et al. (2021)

The deployment of AI in recruitment and selection deserves particular scrutiny given its direct implications for employment equity, candidate experience, and talent pipeline quality. Biea et al. (2024) examine AI adoption in SME recruitment contexts, finding that managerial practices, organizational readiness, and technology integration quality jointly determine whether AI recruitment tools enhance or undermine the effectiveness of talent acquisition. In well-managed deployments, AI reduces time-to-hire by 35–60% and improves initial screening validity, but in poorly governed deployments it reproduces and amplifies existing organizational biases while simultaneously degrading candidate experience.

Akram et al. (2024) conduct a mixed-method investigation of recruitment chatbot acceptance, finding that the chatbot's perceived helpfulness, conversational naturalness, and organizational branding coherence are primary determinants of user acceptance underscoring that AI-mediated HRM tools are not merely efficiency instruments but brand and relationship assets. This finding aligns with Dwivedi et al.'s (2022) broader observation that AI-mediated interaction in immersive and virtual environments fundamentally reshapes user expectations about organizational responsiveness, personalization, and empathy.

Pérez-Castillo et al. (2020) introduce a complementary perspective from software modernization, arguing that effective AI deployment in organizational contexts requires systematic legacy system renovation both technical and cultural to create the data infrastructure and governance architecture upon which trustworthy AI applications depend. This perspective reinforces the importance of viewing AI workforce readiness as an organizational-level transformation challenge rather than a series of discrete technology implementations.

VII. FIVE-PHASE STRATEGIC IMPLEMENTATION ROADMAP

Drawing on the theoretical framework, empirical evidence, and diagnostic analyses presented in preceding sections, we propose a five-phase strategic implementation roadmap for organizational AI workforce readiness. Figure 5 presents this roadmap as a swimlane diagram spanning five organizational dimensions HR Strategy and Governance, Workforce Development, Technology and Tools, Psychological Support, and Metrics and Evaluation across a 24+ month implementation timeline.

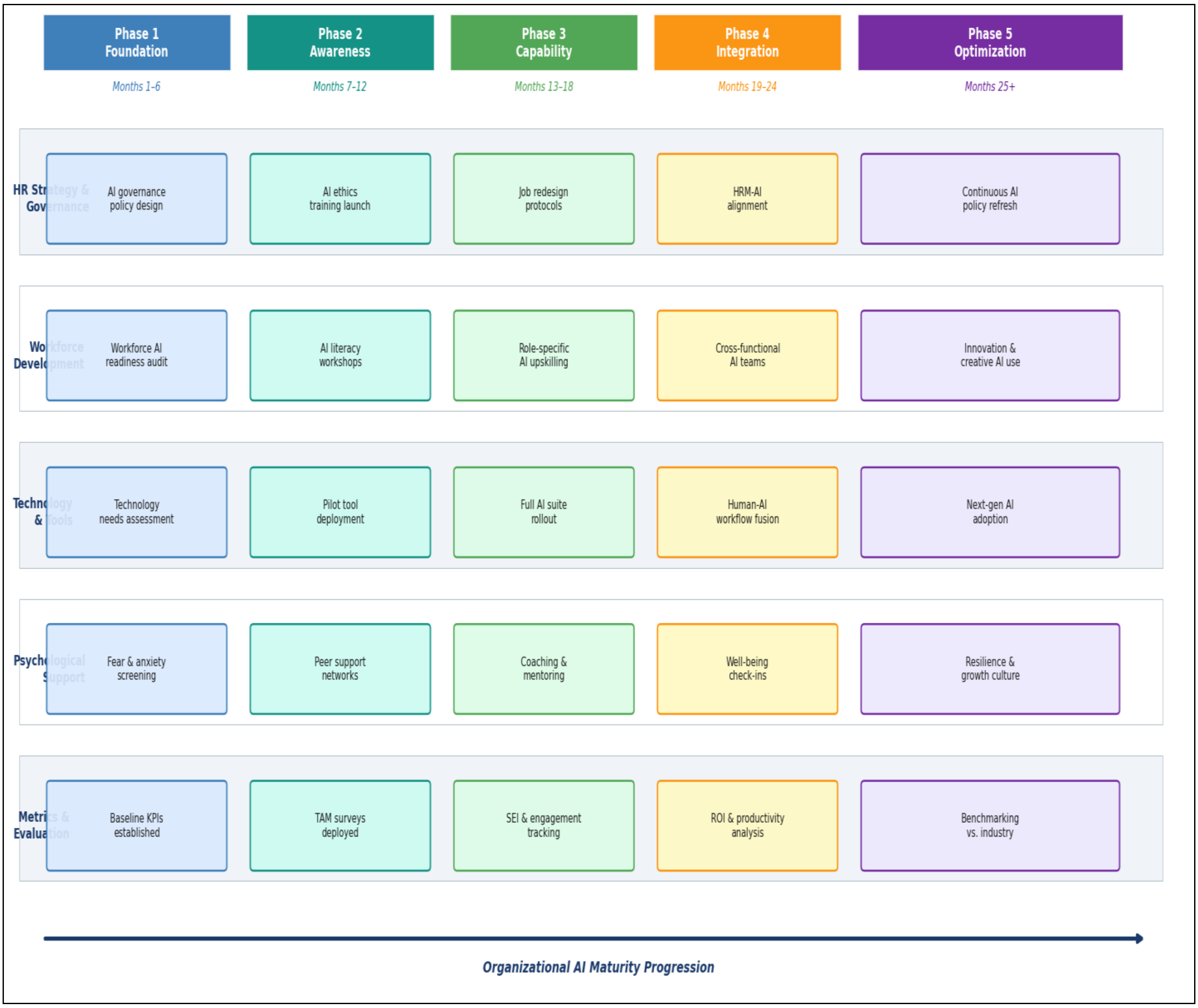

Fig 5 Five-Phase Strategic Roadmap for AI Workforce Readiness across organizational swim lanes. The Roadmap Integrates HR Strategy, Workforce Development, Technology Deployment, Psychological Support, and Performance Measurement Across a 24+ Month Implementation Horizon. Integrating Frameworks from Boon et al. (2019), Ahmad et al. (2014), and Albrecht et al. (2015).

Phase 1 (Foundation, Months 1–6) establishes the organizational preconditions for successful AI workforce integration. This phase prioritizes the design of AI governance policy frameworks, the conduct of comprehensive workforce AI readiness audits, and the deployment of psychological screening instruments to identify employees with heightened anxiety or resistance profiles requiring targeted support. Boon et al. (2019) emphasize that HRM system measurement quality at this foundational stage is a robust predictor of long-term workforce transformation effectiveness, underscoring the importance of rigorous baseline assessment before intervention deployment.

Phase 2 (Awareness, Months 7–12) focuses on building organizational awareness and foundational AI literacy. AI ethics training, AI literacy workshops, and the deployment of peer support networks constitute the core workforce development interventions, while pilot AI tool deployments provide controlled experiential learning opportunities. The TAM-informed insight that perceived ease of use and organizational support are stronger short-term adoption predictors than perceived usefulness (Almeida et al., 2025) guides the design of Phase 2 interventions toward accessibility, familiarity-building, and visible organizational commitment.

Phase 3 (Capability, Months 13–18) marks the transition to active skill development and job redesign. Role-specific AI upskilling programs are deployed, informed by the workforce audit data generated in Phase 1, while formal job redesign protocols operationalize the SMARTer jobs framework of González-Romá et al. (2025). Coaching and mentoring programs address the individual-level psychological adjustment challenges associated with role evolution, providing the social support resources that the Job Demands–Resources Model identifies as critical buffers against AI-related burnout and disengagement (Albrecht et al., 2015).

Phase 4 (Integration, Months 19–24) achieves the full fusion of human–AI workflows across the organization. HRM-AI strategic alignment is formalized, cross-functional AI collaboration teams are established, and well-being check-in protocols provide ongoing psychological monitoring. Ahmad et al.'s (2014) high-involvement management framework guides this phase, ensuring that employees experience genuine participation in the ongoing evolution of human–AI work systems rather than passive adaptation to externally imposed technological change.

Phase 5 (Optimization, ongoing from Month 25+) institutionalizes continuous improvement as an organizational AI readiness capability. Continuous policy refresh, advanced innovation-focused AI skill development, and competitive benchmarking ensure that organizational AI readiness remains adaptive to the rapid evolution of AI capabilities. The resilience and growth culture that characterizes successful Phase 5 organizations reflects the integration of human–AI symbiosis principles at a deep cultural level a state in which AI is experienced not as an external imposition but as a natural extension of organizational capability and individual professional identity.

Table 5 translates the five-phase roadmap into a set of strategic recommendations organized by priority area, detailing recommended actions, target stakeholders, expected outcomes, and implementation time horizons.

Table 5 Strategic Recommendations for U.S. Workforce AI Competitiveness

Strategic Priority	Recommended Action	Target Stakeholders	Expected Outcome	Time Horizon
AI Literacy Infrastructure	Mandate foundational AI literacy curricula across all organizational levels; integrate with existing L&D programs	All employees; L&D departments; senior leadership	Increased TAM perceived usefulness scores; reduced technostress	Short-term (0–12 months)
Ethical AI Governance Frameworks	Establish AI Ethics Committees with cross-functional representation; implement algorithmic audit protocols	C-suite; HR; Legal; IT; DEI officers	Reduced bias incidents; higher employee trust in AI systems	Short-to-medium term (6–18 months)
Job Redesign and Role Evolution	Conduct systematic AI impact assessments for all job families; redesign roles to emphasize human-AI collaboration competencies	HR Business Partners; Department Heads; job incumbents	Higher job satisfaction; reduced obsolescence anxiety; improved SEI	Medium-term (12–24 months)
Psychological Safety and Well-Being Programs	Deploy AI-transition support groups; train managers in AI change leadership; establish AI well-being metrics	HRM practitioners; occupational psychologists; managers	Reduced anxiety and resistance; higher engagement during AI transitions	Ongoing
Inclusive and Bias-Aware Recruitment AI	Audit AI recruitment tools for disparate impact; implement human-in-the-loop oversight for high-stakes decisions	Recruitment teams; legal counsel; DEI specialists	Improved applicant experience; reduced legal exposure; diverse talent pipelines	Medium-term (12–18 months)
National AI Workforce Competitiveness Policy	Advocate for federal AI workforce investment; align organizational practices with national AI strategy frameworks	Government; industry associations; educational institutions	Macro-level U.S. AI competitiveness; workforce adaptability at scale	Long-term (24+ months)

Source: Author Synthesis Drawing on Boon et al. (2019); Ahmad et al. (2014); Albrecht et al. (2015); Tilmes (2022); Pan & Froese (2022); Dwivedi et al. (2019)

VIII. DISCUSSION: IMPLICATIONS FOR THEORY, PRACTICE, AND POLICY

➢ *Theoretical Contributions*

This article makes three primary theoretical contributions to the emerging literature on AI-HRM integration and organizational psychology. First, by synthesizing and integrating multiple theoretical traditions TAM, Human–AI Symbiosis Theory, the Job Demands–Resources Model, Social Cognitive Theory, Organizational Trust Theory, and High-Involvement Management into a coherent six-dimension framework, the article provides the field with a theoretically grounded, multi-level account of the organizational psychology challenges posed by AI workforce integration. This integration addresses a notable gap identified by Pan and Froese (2022), who observe that existing AI-HRM scholarship tends toward single-theory applications that capture important but partial aspects of a fundamentally multi-dimensional phenomenon.

Second, the article contributes theoretically by distinguishing workforce psychological readiness as a construct analytically separable from and empirically prior to organizational AI capability. This distinction reframes the dominant organizational narrative, in which psychological factors are treated as implementation barriers to be managed, toward a perspective in which psychological readiness is recognized as the foundational resource from which sustainable AI competitive advantage is constructed. This reframing has direct implications for how organizations sequence their AI investments: building psychological readiness capacity before, rather than concurrent with, technological deployment.

Third, the article advances theory on the temporal dynamics of psychological responses to AI adoption, proposing a characteristic U-shaped trajectory in which initial threat appraisals are followed by recovery and growth as competence and relational trust with AI systems develop. This trajectory model extends existing work on technology adoption emotions (Dwivedi et al., 2019) and provides a theoretically grounded basis for predicting intervention timing effects.

➢ *Practical Implications for HRM*

For HRM practitioners, the framework and roadmap generate several actionable implications. Most fundamentally, the framework positions HRM as the strategic architect of AI workforce readiness not merely the implementer of technology-driven change agendas set by IT or operations functions. This repositioning is consistent with Boon et al.'s (2019) systematic review of HRM systems, which identifies strategic HRM integration as a robust predictor of organizational performance outcomes, and with Albrecht et al.'s (2015) argument that HRM practices, employee engagement, and competitive advantage form an integrated system rather than a sequential value chain.

The sector-specific analysis presented in Table 2 provides HRM practitioners with a diagnostic basis for industry-calibrated intervention design. Organizations in the legal and healthcare sectors exhibiting high ethical concern indices and distinct professional identity challenges require AI integration approaches that explicitly address professional accountability structures and legitimate human judgment domains. Financial services organizations exhibiting the highest AI adoption rates but significant fairness concerns require rigorous algorithmic bias audit programs and transparent AI decision communication protocols as immediate organizational priorities.

The AI-enabled HRM practices analysis in Table 4 generates a practical governance imperative: no AI-enabled HRM tool should be deployed without a pre-implementation assessment of its psychological implications for affected employees, a post-implementation monitoring protocol, and a clear escalation pathway for identified adverse impacts. Suen et al. (2019) demonstrate that candidates subjected to AI-scored video interviews with no human review component report significantly lower organizational attraction and higher procedural injustice perceptions, with long-term talent brand implications that organizations systematically underestimate.

➢ *Policy Implications for U.S. Workforce Competitiveness*

The macroeconomic stakes of workforce AI readiness extend well beyond individual organizational performance. Dwivedi et al.'s (2019) multidisciplinary AI research agenda explicitly situates workforce transformation as a policy challenge requiring coordinated action across government, industry, and educational institutions. The U.S. competitive position in AI-augmented industries will be determined not merely by the quality of AI systems deployed by American organizations but by the quality of the human–AI collaboration systems those organizations construct and by the depth of psychological preparation, ethical governance infrastructure, and inclusive talent development that distinguish high-performance from stagnating AI deployments.

Three specific policy directions emerge from the present analysis. First, federal investment in AI literacy infrastructure analogous to the digital literacy investments of the 1990s and 2000s is warranted given the documented generational and sectoral disparities in AI acceptance and readiness revealed in Figure 2. Second, regulatory guidance on AI in high-stakes employment decisions building on the framework established by Tilmes (2022) and Zheng et al. (2024) for bias-aware AI recruitment would reduce the current patchwork of organizational practices and align U.S. employment AI governance with international best-practice frameworks. Third, incentive structures for organizational investment in psychological readiness programs including tax credits for certified AI workforce transition programs and regulatory recognition for organizations achieving defined AI readiness benchmarks would accelerate the organizational behavior changes that analysis suggests are critical for national competitiveness.

IX. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This article is subject to several limitations that circumscribe its findings and suggest productive directions for future empirical investigation. First, the framework synthesizes existing theory and evidence rather than presenting original empirical data; future research should undertake longitudinal empirical validation of the six-dimension framework and its predictive validity for organizational AI performance outcomes. Second, the cross-sectoral analysis in Table 2 draws on published research and aggregate data rather than primary organizational field data, which may introduce sector-level aggregation biases that organization-specific research designs could correct.

Third, the framework is developed primarily from U.S. organizational and labor market contexts; Dwivedi et al.'s (2022) metaverse research and Wu et al.'s (2020) cross-cultural AI perception study both suggest significant cultural variation in AI acceptance, trust, and ethical sensitivity that limits the direct generalizability of U.S.-focused frameworks to international organizational contexts. Fourth, the rapid pace of AI capability development particularly in generative AI and autonomous AI agent systems means that some dimensions of the framework may require updating as organizational AI capabilities evolve beyond current deployment norms.

Future research priorities include: (1) longitudinal field studies tracking psychological well-being, trust, and performance outcomes across the five-phase readiness roadmap; (2) experimental studies examining the causal effects of specific organizational interventions transparency mechanisms, job redesign protocols, ethical governance structures on AI adoption outcomes; (3) multi-level analysis examining how individual psychological readiness interacts with team-level and organizational-level AI capability factors to produce performance outcomes; (4) cross-national comparative studies of AI workforce readiness frameworks; and (5) investigation of how generative AI with its capacity for creative, communicative, and professional tasks previously considered uniquely human alters the psychological dimensions of human–AI symbiosis.

X. CONCLUSION

As artificial intelligence reshapes the organizational landscape of the United States, the central challenge facing HRM practitioners, organizational leaders, and workforce policymakers is not technological but psychological: how to prepare human workers to collaborate effectively, trustfully, and purposefully with AI systems that are simultaneously powerful, opaque, and organizationally consequential. This article has proposed a comprehensive organizational psychology framework addressing this challenge across six interdependent dimensions human–AI symbiosis, trust and transparency, job redesign, recruitment and selection, learning and adaptation, and ethical AI governance grounded in established theory and contemporary empirical evidence.

The framework's central proposition is that workforce psychological readiness is not merely a facilitating condition for AI adoption but the primary strategic resource from which sustainable competitive advantage in AI-augmented organizational environments is constructed. Organizations that invest systematically in building this readiness through deliberate job redesign, transparent AI governance, psychological safety infrastructure, and inclusive learning systems will realize substantially greater returns on their AI technology investments than those that treat human adaptation as a secondary implementation challenge.

The five-phase strategic implementation roadmap operationalizes this proposition into actionable organizational guidance, providing HRM practitioners with a sequenced, multi-dimensional approach to AI workforce transformation. The sector-specific analysis and barrier taxonomy equip organizations to calibrate this roadmap to their particular industry contexts and workforce profiles. And the policy implications framework positions AI workforce readiness as a national competitiveness imperative requiring coordinated investment across organizational, educational, and governmental domains.

Ultimately, the competitive future of U.S. organizations in an AI-transformed economy will be determined by the quality of the human–AI collaboration systems they construct and the depth of organizational psychology investment they make in the human beings who must inhabit those systems with competence, confidence, and purpose. As Jarrahi (2018) observed, AI's future in the workplace is not one of replacement but of partnership and like all consequential partnerships, it demands the sustained psychological, relational, and ethical investment that organizations too often reserve for human relationships alone. The framework developed in this article represents a step toward making that investment systematic, evidence-based, and strategically aligned with the demands of twenty-first-century organizational competitiveness.

REFERENCES

[1]. Abdelkader, O. A. (2023). ChatGPT's influence on customer experience in digital marketing: Investigating the moderating roles. Heliyon, 9(8), e18770. https://doi.org/10.1016/j.heliyon.2023.e18770

[2]. Ahmad, M., Shahzad, N., Waheed, A., & Khan, M. (2014). High involvement management and

employees performance mediating role of job satisfaction. European Journal of Business and Management, 6(31), 230–243.
[3]. Akram, S., Buono, P., & Lanzilotti, R. (2024). Recruitment chatbot acceptance in a company: A mixed method study on human-centered technology acceptance model. Personal and Ubiquitous Computing, 28, 961–984. https://doi.org/10.1007/s00779-024-01826-4
[4]. Al-Abdullatif, A. M. (2023). Modeling students' perceptions of chatbots in learning: Integrating technology acceptance with the value-based adoption model. Education in Science, 13(11), 1151. https://doi.org/10.3390/educsci13111151
[5]. Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to predict university students' intentions to use metaverse-based learning platforms. Education and Information Technologies, 28(11), 15381–15413. https://doi.org/10.1007/s10639-023-11816-3
[6]. Albrecht, S. L., Bakker, A. B., Gruman, J. A., Macey, W. H., & Saks, A. M. (2015). Employee engagement, human resource management practices and competitive advantage: An integrated approach. Journal of Organizational Effectiveness: People and Performance, 2(1), 7–35. https://doi.org/10.1108/JOEPP-08-2014-0042
[7]. Almeida, F., Junca Silva, A., Lopes, S. L., & Braz, I. (2025). Understanding recruiters' acceptance of artificial intelligence: Insights from the Technology Acceptance Model. Applied Sciences, 15(2), 746. https://doi.org/10.3390/app15020746
[8]. Almeida, F., Silva, A. J., & Lopes, S. L. (2024). Artificial intelligence and people management in the 21st century. In Artificial Intelligence in Production Engineering and Management (pp. 41–64). Woodhead Publishing.
[9]. Bankins, S., & Formosa, P. (2023). The ethical implications of artificial intelligence (AI) for meaningful work. Journal of Business Ethics, 185, 725–740. https://doi.org/10.1007/s10551-023-05339-7
[10]. Biea, E. A., Dinu, E., Bunica, A., & Jerdea, L. (2024). Recruitment in SMEs: The role of managerial practices, technology and innovation. European Business Review, 36(3), 361–391. https://doi.org/10.1108/EBR-05-2023-0162
[11]. Boon, C., Den Hartog, D. N., & Lepak, D. P. (2019). A systematic review of human resource management systems and their measurement. Journal of Management, 45(6), 2498–2537. https://doi.org/10.1177/0149206318818718
[12]. Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society, 3(1). https://doi.org/10.1177/2053951715622512
[13]. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
[14]. Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., … Wamba, S. F. (2022). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 66, 102542. https://doi.org/10.1016/j.ijinfomgt.2022.102542
[15]. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0057
[16]. González-Romá, V., Le Blanc, P., Ulfert, A.-S., & Peiró, J. M. (2025, May 21–24). Employee-centered automation implementation and job satisfaction: The role of SMARTer jobs [Conference presentation]. 22nd Congress of the European Association of Work and Organizational Psychology (EAWOP), Prague, Czech Republic.
[17]. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
[18]. Khan, A. U., Rafi, M., Zhang, Z., & Khan, A. (2023). Determining the impact of technological modernization and management capabilities on user satisfaction and trust in library services. Global Knowledge, Memory and Communication, 72(6–7), 593–611. https://doi.org/10.1108/GKMC-06-2021-0095
[19]. Köchling, A., Wehner, M. C., & Warkocz, J. (2023). Can I show my skills? Affective responses to artificial intelligence in the recruitment process. Review of Managerial Science, 17, 2109–2138. https://doi.org/10.1007/s11846-021-00514-4
[20]. Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. International Journal of Organizational Analysis, 30(6), 1771–1782. https://doi.org/10.1108/IJOA-07-2020-2291
[21]. Pan, Y., & Froese, F. J. (2022). An interdisciplinary review of AI and HRM: Challenges and future directions. Human Resource Management Review, 33(1), 100924. https://doi.org/10.1016/j.hrmr.2022.100924
[22]. Pérez-Castillo, R., Serrano, M. A., & Piattini, M. (2020). Software modernization to embrace quantum technology. Advances in Engineering Software, 151, 102933. https://doi.org/10.1016/j.advengsoft.2020.102933

[23]. Suen, H.-Y., Chen, M. Y.-C., & Lu, S.-H. (2019). Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? Computers in Human Behavior, 98, 93–101. https://doi.org/10.1016/j.chb.2019.04.012

[24]. Tanantong, T., & Wongras, P. (2024). A UTAUT-based framework for analyzing users' intention to adopt artificial intelligence in human resource recruitment: A case study of Thailand. Systems, 12(1), 28. https://doi.org/10.3390/systems12010028

[25]. Thesmar, D., Sraer, D., Pinheiro, L., Dadson, N., Veliche, R., & Greenberg, P. (2019). Combining the power of artificial intelligence with the richness of healthcare claims data: Opportunities and challenges. PharmacoEconomics, 37(6), 745–752. https://doi.org/10.1007/s40273-019-00777-6

[26]. Tilmes, N. (2022). Disability, fairness, and algorithmic bias in AI recruitment. Ethics and Information Technology, 24(2), 21. https://doi.org/10.1007/s10676-022-09633-2

[27]. Townsend, D. M., & Hunt, R. A. (2019). Entrepreneurial action, creativity, & judgment in the age of artificial intelligence. Journal of Business Venturing Insights, 11, e00126. https://doi.org/10.1016/j.jbvi.2019.e00126

[28]. Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. Journal of Product Innovation Management, 37(3), 212–227. https://doi.org/10.1111/jpim.12523

[29]. Wang, P. (2019). On defining artificial intelligence. Journal of Artificial General Intelligence, 10(2), 1–37. https://doi.org/10.2478/jagi-2019-0002

[30]. Warrier, U., Shankar, A., & Belal, H. M. (2021). Examining the role of emotional intelligence as a moderator for virtual communication and decision making effectiveness during the COVID-19 crisis: Revisiting task technology fit theory. Annals of Operations Research. https://doi.org/10.1007/s10479-021-04216-8

[31]. Wehner, M., Giardini, A., & Kabst, R. (2015). Recruitment process outsourcing and applicant reactions: When does image make a difference? Human Resource Management, 54(6), 851–875. https://doi.org/10.1002/hrm.21640

[32]. Woods, S. A., Ahmed, S., Nikolaou, I., Costa, A. C., & Anderson, N. R. (2020). Personnel selection in the digital age: A review of validity and applicant reactions, and future research challenges. European Journal of Work and Organizational Psychology, 29(1), 64–77. https://doi.org/10.1080/1359432X.2019.1681401

[33]. Wu, Y., Mou, Y., Li, Z., & Xu, K. (2020). Investigating American and Chinese subjects' explicit and implicit perceptions of AI-generated artistic work. Computers in Human Behavior, 104, 106186. https://doi.org/10.1016/j.chb.2019.106186

[34]. Xu, N., & Wang, K.-J. (2019). Adopting robot lawyer? The extending artificial intelligence robot lawyer technology acceptance model for legal industry by an exploratory study. Journal of Management & Organization, 1–19. https://doi.org/10.1017/jmo.2018.81

[35]. Yam, K. C., Bigman, Y. E., Tang, P. M., Ilies, R., De Cremer, D., Soh, H., & Gray, K. (2020). Robots at work: People prefer and forgive service robots with perceived feelings. Journal of Applied Psychology. https://doi.org/10.1037/apl0000834

[36]. Zheng, F., Zhao, C., Usman, M., & Poulova, P. (2024). From bias to brilliance: The impact of artificial intelligence usage on recruitment biases in China. IEEE Transactions on Engineering Management, 71, 14155–14167. https://doi.org/10.1109/TEM.2024.3442618

[37]. Zirar, A. (2023). Can artificial intelligence's limitations drive innovative work behaviour? Review of Managerial Science, 17, 2005–2034. https://doi.org/10.1007/s11846-023-00621-4