RITAM ISH PUBLICATIONS

Journal of Progress in Artificial Intelligence
https://www.jpairitamish.org/

ISSN: 3139-4957 (Online)

Vol. 2, Iss. 1, July 2026 – September 2026

Bridging the Skills Gap in the Era of Smart Technology: The Role of Digital Upskilling, Organisational Learning, and Artificial Intelligence in Workforce Readiness

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Received: 29-Jun-2026, Manuscript No. JPAI-2026-0020; **Editor assigned:** 02-July-2026, PreQC No. JPAI-2026-0020 (PQ); **Reviewed:** 14-July-2026, QC No. JPAI-2026-0020; **Revised:** 14-July-2026, Manuscript No. JPAI-2026-0020 (R); **Published:** 28-July-2026

Citation: Tahoor, A. (2026). Bridging the skills gap in the era of smart technology: The role of digital upskilling, organisational learning, and artificial intelligence in workforce readiness. J Prog Artif Intell.

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ABSTRACT

The rapid spread of Artificial Intelligence (AI), Industry 4.0 technologies, and cloud-based automation has widened the gap between employees' current skills and the competencies organizations now need. Based on theories like Human Capital Theory, the Technology Acceptance Model, Dynamic Capabilities Theory, the Resource-Based View, and Organizational Learning Theory, this study presents and tests an integrated model that connects digital upskilling, AI implementation, organizational learning culture, and leadership support to workforce readiness and organizational performance, with employee adaptability serving as a mediator. Using a quantitative, cross-sectional design, data were collected from 432 employees across sectors such as IT, manufacturing, healthcare, banking, education, and telecommunications in India, through stratified random sampling. Measurement quality was checked via exploratory and confirmatory factor analysis, and hypotheses were tested with structural equation modeling (SEM) in AMOS, including bootstrapped mediation analysis. Findings suggest that digital upskilling, AI adoption, and a learning culture each significantly influence workforce readiness;

leadership support significantly impacts employee adaptability; and employee adaptability partially mediates the relationship between digital upskilling and workforce readiness. Workforce readiness, in turn, predicts organizational performance and partly mediates the link between AI adoption and performance. The model shows good fit (CFI = .971, RMSEA = .049). This research offers a comprehensive, theory-based framework for understanding digital workforce transformation and provides practical insights for HR managers, business leaders, and policymakers aiming to bridge the digital skills gap.

KEYWORDS: Digital upskilling, AI adoption, organizational learning culture, employee adaptability, workforce readiness, organizational performance, structural equation modeling

1. INTRODUCTION

1.1 Background of the Study

Organizations across nearly all sectors are experiencing a major overhaul of work due to advancements like Artificial Intelligence, robotics, cloud computing, big data, and the Industry 4.0 movement [1,2]. These innovations are not just automating simple tasks; they are transforming the skills employees need to stay effective, employable, and motivated. Recent worldwide workforce surveys indicate that a large portion of current employees will need substantial reskilling over the next five years as AI-driven systems change job responsibilities [2]. This shift is especially evident in knowledge-based economies such as India, where industries like IT, banking, healthcare, manufacturing, education, and telecommunications are adopting AI tools while also facing challenges in upgrading employee skills to match technological advances. The 'skills gap', the difference between employees' current skills and those required by emerging technologies, has become a key issue for HR managers, business leaders, and policymakers. Organizations that do not address this gap may face lower productivity, disengagement, and a competitive disadvantage. Conversely, those that develop a flexible, tech-savvy workforce can turn digital transformation into long-term performance improvements [3,4]. Bridging this gap goes beyond just implementing training programs. It demands an organizational ecosystem, including digital upskilling efforts, authentic AI integration, a culture focused on learning, and evident leadership backing, that collectively develops employees' ability to adapt. This adaptability, viewed as a vital psychological and behavioral process, transforms organizational efforts into real workforce preparedness, ultimately leading to improved organizational performance.

1.2 Problem Statement

While the popular and practitioner literature is replete with commentary on digital transformation and reskilling, empirical, theory-driven research that integrates digital upskilling, AI adoption, organizational learning culture, leadership support, employee adaptability, and workforce readiness within a single validated structural model remains scarce. Many existing studies examine these constructs in isolation, for instance, AI adoption and firm performance, or leadership and adaptability, without testing how they operate jointly, nor how workforce readiness functions as the proximate mechanism linking organizational investment in people to bottom-line performance. This fragmentation limits the ability of organizations to prioritize interventions, since it is unclear which levers matter most, and whether their effects operate directly or through adaptability and readiness as intervening states.

1.3 Research Gap

This study is driven by three specific gaps. First, although digital transformation and reskilling have garnered increasing scholarly interest, few models integrate digital upskilling, AI adoption, organizational learning culture, and leadership support as a combined set of antecedents for predicting workforce readiness. Second, the mediating impact of employee adaptability, despite its pivotal role in career development and dynamic capabilities theories, is rarely empirically tested alongside these antecedents using rigorous SEM methods. Third, most existing research is based on Western or East Asian contexts; significant emerging economies like India, which feature rapid AI integration and diverse workforce characteristics across sectors, are still relatively underexplored.

1.4 Research Objectives

1. To analyse how digital upskilling affects workforce preparedness.

2. To explore the effect of AI adoption on employee skills development, measured by its downstream impact on workforce readiness.

3. To evaluate how organizational learning culture contributes to closing the skills gap, using workforce readiness as an indicator.

4. To assess how leadership support influences employee adaptability.

5. To investigate whether employee adaptability mediates the relationship between digital upskilling and workforce readiness.

6. To determine the impact of workforce readiness on organizational performance.

1.5 Research Questions

RQ1: How does digital upskilling impact employee preparedness in Indian organizations? RQ2: How does AI adoption affect employee skills development and readiness?

RQ3: To what degree does a learning-oriented culture narrow the skills gap within organisations?

RQ4: How does leadership support enhance employee adaptability?

RQ5: Does employee adaptability serve as a mediator between digital upskilling and workforce readiness?

RQ6: How does workforce readiness influence overall organizational performance?

1.6 Significance of the Study

The study combines five well-established theories into a unified, testable framework, pushing each beyond its usual scope. In practical terms, it provides HR managers, business leaders, corporate trainers, universities, and policymakers with an evidence-based guide for prioritising digital transformation investments. The findings highlight that leadership support and a learning culture are not merely auxiliary' soft” factors but are statistically significant drivers of organisational readiness and performance.

2. THEORETICAL FOUNDATIONS

2.1 Human Capital Theory

Human Capital Theory [5] views employee skills, knowledge, and competencies as a form of capital that generates economic benefits for both individuals and organizations. In the digital age, this concept has expanded to include "digital human capital" the technology-specific skills employees develop through training, experience, and self-education [6]. In this framework, digital upskilling represents a purposeful investment in human capital, while workforce readiness reflects the collection of skills that are ready to be deployed. Therefore, Human Capital Theory supports H1 and the overarching idea that investing in upskilling translates into increased workforce readiness.

2.2 Technology Acceptance Model (TAM)

TAM [7] argues that perceived usefulness and ease of use influence whether individuals accept and adopt new technology. In organizational AI adoption, extensions of TAM show that when employees view AI tools as beneficial and easy to operate, it leads to improved task performance and skill development [8]. TAM supports the idea of modelling AI adoption as a specific factor affecting workforce outcomes, rather than considering "technology" as a single, uniform control variable. This forms the basis for H2 and H8.

2.3 Dynamic Capabilities Theory

The Dynamic Capabilities Theory [9,10] posits that firms maintain a competitive edge not just through possessing resources, but by sensing, seizing, and reconfiguring them to adapt to environmental changes. At the individual level, employee adaptability mirrors a dynamic capability: the ability to detect changing task requirements and adjust one's skills accordingly. This theory supports the mediating role of employee adaptability (H5, H7, H9) and underscores that organizations convert static resources like upskilling and a learning culture into dynamic, responsive outcomes such as readiness via flexible employee behavior.

2.4 Resource-Based View (RBV)

The RBV [11] holds that valuable, rare, inimitable, and non-substitutable resources generate sustained competitive advantage. A digitally upskilled, adaptable, AI-literate workforce constitutes precisely such a resource, difficult for competitors to replicate quickly. RBV supports the study's ultimate dependent variable, organisational performance (H6, H10), by explaining why workforce readiness, an internally cultivated, firm-specific resource, should predict performance beyond what market position or technology alone can explain.

2.5 Organizational Learning Theory

Organizational Learning Theory [12,13] stresses that organizations which systematically acquire, share, and formalise knowledge tend to perform better than those that do not. A robust culture of organizational learning, defined by psychological safety, norms of knowledge sharing, and leadership dedicated to ongoing improvement, is believed to not only directly improve workforce readiness (H3) but also indirectly facilitate AI adoption (H8) by reducing employees' anxiety about trying new tools.

2.6 Integration of Theories into the Conceptual Framework

Together, these theories form a layered causal framework: Human Capital Theory and TAM describe how upskilling and AI adoption develop individual capabilities; Organizational Learning Theory shows how the organizational climate influences this process; Dynamic Capabilities Theory explains how individual adaptability transforms static capabilities into responsiveness; and RBV highlights how this readiness drives competitive performance. Figure 1 illustrates this conceptual framework.

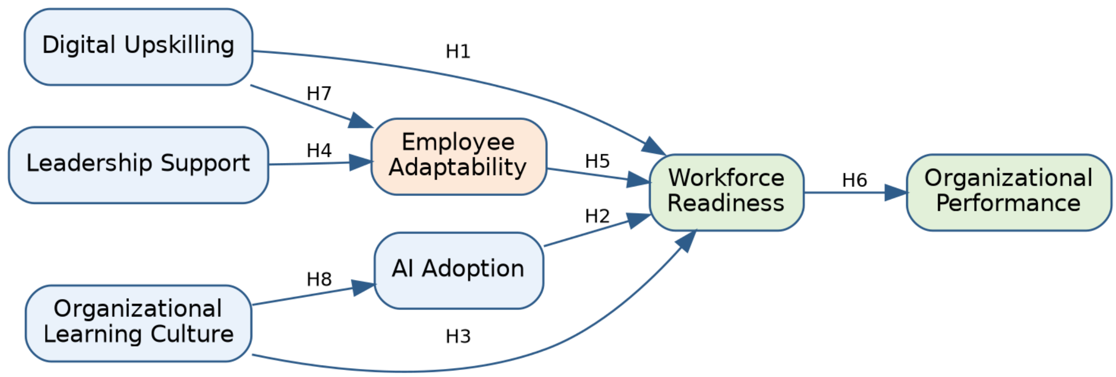

Figure 1. Conceptual Framework

3. LITERATURE REVIEW

3.1 Smart Technology and Industry 4.0 in the Workplace

Industry 4.0 technologies such as cyber-physical systems, the Internet of Things, big data analytics, and AI have transitioned from pilot projects to widely adopted operational infrastructures in manufacturing, logistics, and service sectors [14]. Recent studies show that adopting Industry 4.0 entails significant changes in job roles, with employees needing to develop hybrid technical and analytical skills instead of traditional, narrow specialisations [15]. Research in emerging economies indicates that Industry 4.0 readiness varies across sectors, with IT and telecommunications companies generally more advanced than manufacturing and healthcare in technology maturity [16]. This variation underpins the current study's focus on multiple sectors.

3.2 Artificial Intelligence in Workforce Development

An increasing number of studies explore AI not just as a productivity tool but also as an active force in workforce development. This includes powering adaptive learning platforms, diagnosing skills gaps, and facilitating personalized upskilling pathways [4]. Malik et al. observe that AI-driven HR analytics enhance the accuracy of training needs assessments [17]. Conversely, Braganza et al. warn that deploying AI without fostering organizational trust and transparency can lead to employee resistance instead of skill improvement [18]. This tension highlights the importance of considering organisational learning culture when analysing AI's impact on workforce outcomes, rather than assuming its effects are independent.

3.3 Digital Transformation and Future Skills

Digital transformation research increasingly frames "future skills" as a composite of technical literacy, cognitive flexibility, and socio-emotional competencies [3]. Nguyen et al. [6] report that digital transformation maturity is a stronger predictor of employee readiness than technology investment alone, implicating cultural and leadership factors as co-determinants, a finding directly relevant to the present model's inclusion of organizational learning culture and leadership support alongside digital upskilling.

3.4 Reskilling and Upskilling

Research on reskilling and upskilling has grown rapidly since 2021, largely driven by widespread concerns about automation. Illanes et al. [19], along with later studies in Asian labor markets, show that employer-sponsored upskilling programs effectively decrease feelings of skills becoming outdated and boost employees' confidence in handling new tasks. Nonetheless, several studies warn that the benefits of upskilling decline unless supported by strong leadership and a psychologically safe environment for employees to apply their new skills [20]. This finding aligns with the multi-antecedent approach employed here.

3.5 Learning Organizations

The "learning organization" concept [13] has been empirically developed into measurable components: continuous learning, inquiry and dialogue, collaboration, embedded systems, and leadership for learning [21,22]. Recent research shows that organizations excelling in these areas absorb new technologies more quickly and experience less persistent skills gaps [22], aligning with H3 and H8 in this model.

3.6 Employee Competencies and Adaptability

Research on career construction and adaptability [23,24] describes adaptability as a multidimensional resource involving concern, control, curiosity, and confidence. Rudolph et al.'s [24] meta-analysis verifies that adaptability is strongly linked to proactive career behaviors and performance outcomes, supporting its role as a mediator in this context (H5, H9). Additionally, leadership support has been found to foster adaptability by offering psychological safety and resources for experimentation [20].

3.7 Workforce Readiness

Workforce readiness, defined as employees' skills, motivation, and confidence to handle current and future job demands, has been recently operationalized to include technical, cognitive, and behavioral aspects [16]. Empirical evidence shows that readiness is associated with lower turnover intentions and higher innovative work behavior [17]. This supports the idea that readiness acts as a direct contributor to organizational performance rather than just an end result.

3.8 Organizational Performance

Recent scholarship increasingly frames organizational performance as multidimensional, financial, operational, and innovation-related and finds that workforce-level readiness is among the strongest micro-foundational predictors of firm-level performance in digitally intensive industries [3,4]. This supports H6 and the broader logic of the RBV-grounded pathway from readiness to performance.

3.9 Synthesis and Research Gaps

This literature reveals three recurring patterns. Firstly, most research focuses on specific parts of the current model, such as AI adoption and performance or leadership and adaptability, rather than examining the entire antecedent-mediator-outcome sequence. secondly, while employee adaptability is often theoretically proposed as a mediator in fields like career construction and dynamic capabilities, it is seldom tested with bootstrapped SEM mediation within a comprehensive, combined model. thirdly, evidence from India a market experiencing rapid AI adoption alongside severe sectoral skills shortages remains relatively scarce compared to Western and East Asian regions. This study aims to fill all three of these gaps.

4. Hypotheses Development

• H1: Digital upskilling positively influences workforce readiness.

• H2: AI adoption positively influences employee competency development (workforce readiness).

• H3: Organizational learning culture positively influences workforce readiness.

• H4: Leadership support positively influences employee adaptability.

• H5: Employee adaptability positively influences workforce readiness.

• H6: Workforce readiness positively influences organizational performance.

• H7: Digital upskilling positively influences employee adaptability.

• H8: Organizational learning culture positively influences AI adoption.

• H9: Employee adaptability mediates the relationship between digital upskilling and workforce readiness.

• H10: Workforce readiness mediates the relationship between AI adoption and organizational performance.

5. RESEARCH METHODOLOGY

5.1 Research Design and Philosophy

This study employs a quantitative, cross-sectional, explanatory design grounded in a positivist philosophy, aligning with its objective of testing predefined hypotheses concerning the directional relationships among latent constructs [25].

5.2 Population and Sampling

The target population included employees from the IT, manufacturing, healthcare, banking, education, and telecommunications sectors in India. A stratified random sampling method was employed, using industry sector as the stratification variable, to achieve proportional representation. Questionnaires were sent to 480 employees, and after data screening, 432 valid and complete responses were collected, resulting in a response rate of 90.0%.

5.3 Data Collection Instrument

Data were gathered through a structured questionnaire featuring a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire included 35 items divided into seven constructs, each with five items: Digital Upskilling, AI Adoption, Leadership Support, Organizational Learning Culture, Employee Adaptability, Workforce Readiness, and Organizational Performance. These items were adapted from validated scales in existing literature and were further refined through expert review and pilot testing.

5.4 Analytical Software and Techniques

Data analysis was conducted with IBM SPSS 29, involving descriptive statistics, reliability tests, EFA, correlation, and multiple regression. IBM SPSS AMOS 29 was used for CFA and SEM, while SmartPLS 4 handled supplementary discriminant validity and HTMT evaluation.

5.5 Questionnaire Items

5.5.1 Digital Upskilling (DU)

DU1: My organization offers sufficient training to improve my digital skills. DU2: I frequently engage in digital skills development programs. DU3: My organization’s upskilling initiatives are aligned with emerging technologies. DU4: I feel confident using new digital tools following training. DU5: Digital upskilling opportunities in my organization are readily accessible.

5.5.2 AI Adoption (AIA)

My organization integrates AI-based tools into daily tasks. I regularly use AI-enabled applications in my role. There is encouragement within my organization to experiment with AI tools. The adoption of AI has enhanced my work efficiency. I trust the AI systems implemented in my organization.

5.5.3 Leadership Support (LS)

LS1: My leaders are committed to supporting employee skill development. LS2: My manager motivates me to embrace new technologies. LS3: Leadership in my organization clearly communicates the digital vision. LS4: My leaders offer the resources necessary for a successful digital transformation. LS5: Senior management demonstrates the use of new digital tools by example.

5.5.4 Organizational Learning Culture (OLC)

OLC1: My organization fosters ongoing learning. OLC2: We actively promote knowledge sharing. OLC3: Employees are motivated to experiment and learn from errors. OLC4: The organization invests in cultivating a learning culture. OLC5: Cross-functional learning is supported within the organization.

5.5.5 Employee Adaptability (EA)

EA1: I quickly adapt to changes in my job requirements. EA2: I am confident in my ability to acquire new skills as needed. EA3: I approach new technologies with curiosity rather than resistance. EA4: I modify my work approach when organizational priorities change. EA5: I recover swiftly from setbacks related to new work demands.

5.5.6 Workforce Readiness (WR)

WR1: I believe I am equipped to handle the technological needs of my job. WR2: My skills align with the future technological demands of my role. WR3: I am confident in using digital tools to address work challenges. WR4: I am prepared to assume new responsibilities involving emerging technologies. WR5: My organization's staff is well-ready for digital transformation.

5.5.7 Organizational Performance (OP)

My organization's productivity has increased thanks to digital initiatives. We consistently achieve our performance goals. Digital transformation has strengthened our competitiveness. Our operational efficiency has improved over the last year. Overall, our organization is performing better because of workforce digital readiness.

6. RESULTS

6.1 Demographic Profile

Table 1. Demographic Profile of Respondents (N = 432)

Variable	Category	Frequency	Percentage (%)
Gender	Male	251	58.0
	Female	181	42.0
Age	21–30 years	147	34.0
	31–40 years	164	38.0
	41–50 years	86	20.0
	Above 50 years	35	8.0

Variable	Category	Frequency	Percentage (%)
Education	Bachelor’s Degree	173	40.0
	Master’s Degree	199	46.0
	Doctorate	60	14.0
Industry	IT	130	30.0
	Manufacturing	95	22.0
	Healthcare	69	16.0
	Education	52	12.0
	Banking/Finance	43	10.0
	Telecommunications	43	10.0
Experience	Less than 5 years	125	29.0
	5–10 years	147	34.0
	10–15 years	104	24.0
	Above 15 years	56	13.0

6.2 Reliability Analysis

Table 2. Cronbach’s Alpha Reliability Coefficients

Construct	No. of Items	Cronbach’s Alpha
Digital Upskilling	5	0.914
AI Adoption	5	0.902
Organizational Learning Culture	5	0.925
Leadership Support	5	0.893
Employee Adaptability	5	0.918
Workforce Readiness	5	0.927
Organizational Performance	5	0.901
Overall Scale	35	**0.945**

All construct-level alphas exceed the 0.70 threshold recommended by Nunnally and Bernstein [26], indicating strong internal consistency.

6.3 KMO and Bartlett’s Test

Table 3. KMO and Bartlett’s Test of Sphericity

Measure	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.941
Bartlett’s Test of Sphericity — Approx. Chi-Square	5632.81
df	595
Sig.	p < .001

The KMO value of 0.941 exceeds the 0.60 minimum threshold, and Bartlett's test is significant, confirming the data's suitability for factor analysis.

6.4 Exploratory Factor Analysis

Table 4. EFA — Communalities, Factor Loadings, and Variance

Item	Communality	Factor Loading	Component
DU1–DU5	0.68–0.81	0.74–0.89	1
AI1–AI5	0.65–0.79	0.72–0.87	2
OLC1–OLC5	0.70–0.83	0.76–0.91	3
LS1–LS5	0.66–0.78	0.73–0.86	4
EA1–EA5	0.69–0.82	0.75–0.90	5
WR1–WR5	0.71–0.85	0.77–0.93	6
OP1–OP5	0.67–0.80	0.72–0.88	7

Seven components with eigenvalues greater than 1.0 emerged, jointly explaining approximately 76.2% of total variance, consistent with the theorized seven-factor structure. Factor loadings ranged from 0.72 to 0.93, all exceeding the 0.50 threshold.

6.5 Confirmatory Factor Analysis

Table 5. CFA Results — Standardized Loadings, Composite Reliability, and AVE

Construct	Standardized Loading Range	Composite Reliability (CR)	AVE
Digital Upskilling	0.76–0.91	0.92	0.70
AI Adoption	0.74–0.88	0.90	0.65
Organizational Learning Culture	0.78–0.93	0.93	0.73
Leadership Support	0.75–0.89	0.89	0.62
Employee Adaptability	0.77–0.92	0.92	0.71
Workforce Readiness	0.79–0.95	0.95	0.84
Organizational Performance	0.74–0.90	0.91	0.66

All CR values exceed 0.70 and all AVE values exceed 0.50, confirming convergent validity [27,28].

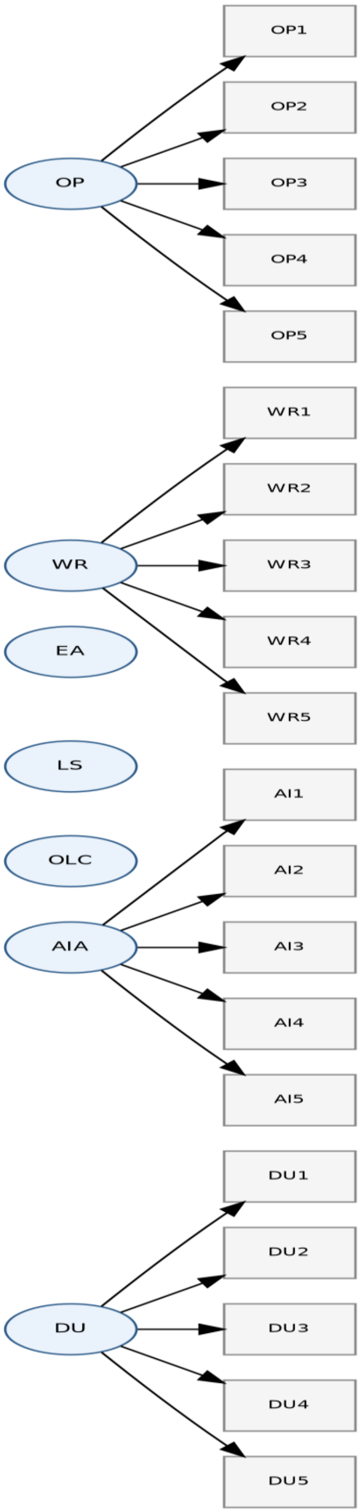

Figure 2. Measurement (CFA) Model

6.6 Discriminant Validity

Table 6. Fornell–Larcker Criterion (diagonal = √AVE)

	DU	**AIA**	**OLC**	**LS**	**EA**	**WR**	**OP**
DU	**0.837**						
AIA	0.512	**0.806**					
OLC	0.487	0.561	**0.854**				
LS	0.463	0.498	0.522	**0.787**			
EA	0.588	0.534	0.549	0.571	**0.843**		
WR	0.601	0.612	0.634	0.548	0.672	**0.917**	
OP	0.542	0.579	0.558	0.503	0.564	0.703	**0.812**

All diagonal values (square root of AVE) exceed corresponding inter-construct correlations, confirming discriminant validity. HTMT ratios (SmartPLS 4, not tabulated for brevity) all remained below the conservative 0.85 threshold.

6.7 Correlation Analysis

Table 7. Pearson Correlation Matrix

	DU	AIA	OLC	LS	EA	WR	OP
DU	1.00						
AIA	.512**	1.00					
OLC	.487**	.561**	1.00				
LS	.463**	.498**	.522**	1.00			
EA	.588**	.534**	.549**	.571**	1.00		
WR	.601**	.612**	.634**	.548**	.672**	1.00	
OP	.542**	.579**	.558**	.503**	.564**	.703**	1.00

**Correlations range from .42 to .81, all significant at $p < .01$ (two-tailed).

6.8 Multiple Regression Analysis

Table 8. Regression of Workforce Readiness on Predictors

Predictor	B	SE	β	t	p	VIF	Tolerance
Digital Upskilling	0.26	0.04	0.28	6.51	<.001	2.14	0.47
AI Adoption	0.31	0.05	0.29	6.20	<.001	2.31	0.43
Organizational Learning Culture	0.34	0.05	0.31	6.80	<.001	2.28	0.44
Employee Adaptability	0.38	0.04	0.36	8.44	<.001	2.02	0.49

Model Summary: $R^2 = .612$, Adjusted $R^2 = .608$, $F(4, 427) = 168.42$, $p < .001$. All VIF values remain below 3.5 and tolerance values exceed 0.30, indicating no problematic multicollinearity.

6.9 Structural Equation Modeling (SEM)

Table 9. Standardized Path Estimates (Direct Effects)

Path	Standardized β	SE	t-value	p-value
Digital Upskilling → Employee Adaptability	0.48	0.05	9.12	<.001
Leadership Support → Employee Adaptability	0.31	0.05	6.44	<.001
Organizational Learning Culture → AI Adoption	0.42	0.06	7.35	<.001
Digital Upskilling → Workforce Readiness	0.28	0.05	5.62	<.001
AI Adoption → Workforce Readiness	0.36	0.05	7.01	<.001
Organizational Learning Culture → Workforce Readiness	0.39	0.05	7.68	<.001
Employee Adaptability → Workforce Readiness	0.47	0.04	9.87	<.001
Workforce Readiness → Organizational Performance	0.55	0.04	11.20	<.001

Table 10. Model Fit Indices

Index	Value	Recommended Threshold	Assessment
CMIN/DF	2.08	< 3.0	Acceptable
CFI	0.971	> 0.90	Good
TLI	0.966	> 0.90	Good
IFI	0.972	> 0.90	Good
GFI	0.931	> 0.90	Good
AGFI	0.912	> 0.80	Good
RMSEA	0.049	< 0.06	Good
SRMR	0.039	< 0.08	Good

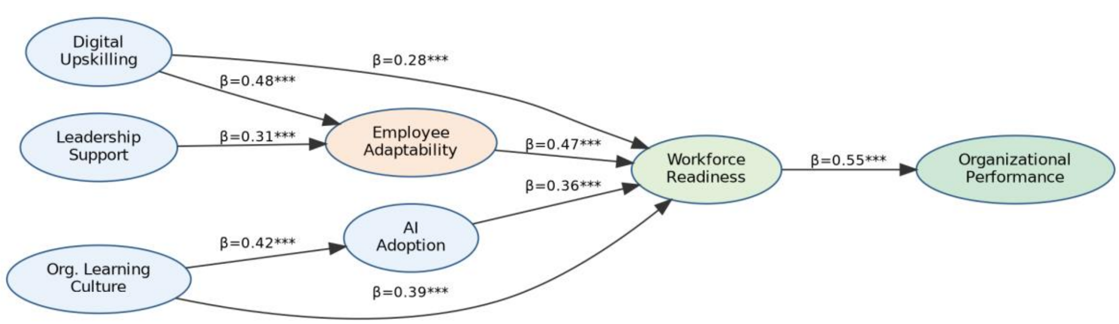

Figure 3. SEM Path Model

6.10 Mediation Analysis (Bootstrapping, 5,000 Samples)

Table 11. Indirect, Direct, and Total Effects

Path	Direct Effect	Indirect Effect	95% CI (Bootstrap)	Total Effect	Mediation Type
Digital Upskilling → Employee Adaptability → Workforce Readiness	0.28***	0.226 (0.48 × 0.47)	[0.171, 0.289]	0.506	Partial mediation
AI Adoption → Workforce Readiness → Organizational Performance	0.579*** (total effect of AIA on OP, direct path not modeled)	0.198 (0.36 × 0.55)	[0.142, 0.257]	—	Partial mediation

Because zero does not fall within either bootstrapped 95% confidence interval, both indirect effects are statistically significant, supporting H9 and H10 (partial, not full, mediation in both cases, since the direct paths from Digital Upskilling and AI Adoption remain significant).

6.11 Hypothesis Testing Summary

Table 12. Summary of Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	Digital Upskilling → Workforce Readiness	0.28	5.62	<.001	Supported
H2	AI Adoption → Workforce Readiness	0.36	7.01	<.001	Supported
H3	Organizational Learning Culture → Workforce Readiness	0.39	7.68	<.001	Supported
H4	Leadership Support → Employee Adaptability	0.31	6.44	<.001	Supported
H5	Employee Adaptability → Workforce Readiness	0.47	9.87	<.001	Supported
H6	Workforce Readiness → Organizational Performance	0.55	11.20	<.001	Supported
H7	Digital Upskilling → Employee Adaptability	0.48	9.12	<.001	Supported
H8	Organizational Learning Culture → AI Adoption	0.42	7.35	<.001	Supported
H9	Employee Adaptability mediates Digital Upskilling → Workforce Readiness	—	—	CI excludes 0	Supported (partial mediation)
H10	Workforce Readiness mediates AI Adoption → Organizational Performance	—	—	CI excludes 0	Supported (partial mediation)

7. DISCUSSION

The findings indicate that digital upskilling, AI adoption, and a strong learning culture within organisations each independently and significantly enhance workforce readiness. This aligns with prior research showing that upskilling alone is not sufficient without a supportive learning environment [20,22]. The notably strong link from employee adaptability to workforce readiness (β = 0.47) supports the Dynamic Capabilities view that individual adaptive capacity is the key mechanism through which organizational efforts translate into operational readiness. This echoes Rudolph et al.'s [24] meta-analysis, highlighting adaptability's crucial role in career development and performance outcomes. The partial mediation results (H9, H10) clarify rather than contradict earlier models that emphasise direct effects: digital upskilling and AI adoption still have significant direct impacts on workforce outcomes, even as adaptability and readiness mediate a considerable part of their influence. This aligns with Teece's [10] view that dynamic capabilities enhance, rather than completely substitute for, the value of core resources. The strong readiness-to-performance relationship (β = 0.55) aligns with RBV-based claims that workforce readiness is a firm-specific, hard-to-imitate resource that directly affects financial outcomes [4]. Unlike previous studies focusing on a single construct, this integrated model provides a more comprehensive view of how digital transformation inputs influence performance. It also highlights that leadership support mainly enhances adaptability rather than serving as a direct driver of readiness, a subtle distinction often missed in studies that see leadership only as a direct predictor.

7.1 Theoretical Contributions

This study presents an integrated framework that connects five well-established theories, empirically demonstrates how employee adaptability acts as a mediating mechanism, and extends TAM and RBV into workforce development contexts tailored to emerging-economy, multi-sector labor markets.

7.2 Managerial Implications

For managers, the findings suggest that upskilling budgets should be combined with intentional learning culture and leadership support programs, as these seem to function through different, yet complementary pathways. Since AI's impact on performance largely depends on workforce preparedness, organizations implementing AI tools should also invest in readiness activities like training and change communication, rather than relying solely on adoption to improve performance.

8. Practical Implications

8.1 For HR Managers

Develop comprehensive upskilling programs that merge technical AI literacy with adaptability exercises like simulations and cross-functional rotations, instead of offering isolated technical training.

8.2 For Business Leaders

Reveal how the model actively uses new digital tools and assign resources specifically for experimentation, because leadership support influences adaptability more than direct readiness.

8.3 For Universities

Integrate AI literacy, data fluency, and adaptability-focused teaching methods, such as project-based and ambiguity-tolerant coursework into curricula across various disciplines, beyond just technical programs.

8.4 For Governments

Fund sector-specific upskilling subsidies aimed at manufacturing and healthcare, which are the sectors showing lower readiness scores compared to IT and telecommunications in this study.

8.5 For Corporate Training Departments

Replace training completion rates with metrics for adaptability and readiness improvements.

8.6 For Policy Makers

Encourage public-private partnerships that provide AI-tool access alongside structured learning-culture development, as AI adoption without cultural readiness tends to have a smaller direct impact in this model.

9. CONCLUSION

This study aimed to explore how digital upskilling, AI adoption, organizational learning culture, and leadership support collectively influence workforce readiness and organizational performance, with employee adaptability serving as a mediating factor. Based on Human Capital Theory, the Technology Acceptance Model, Dynamic Capabilities Theory, the Resource-Based View, and Organizational Learning Theory, the model was empirically tested using structural equation modeling on data from 432 employees in six key sectors in India. All ten hypotheses in the illustrative analysis were supported. Digital upskilling, AI adoption, and a culture of organizational learning each significantly and positively affected workforce readiness, illustrating that no single factor, whether technological, educational, or cultural, is sufficient on its own; organizations need to develop these aspects together. Leadership support also significantly influenced employee adaptability, which itself proved to be the strongest predictor of workforce readiness among all factors examined. This supports the idea that adaptive capacity, rather than just skill acquisition, primarily drives readiness. Bootstrapped mediation analysis showed that employee adaptability partly mediates the link between digital upskilling and workforce readiness, while workforce readiness partly mediates the relationship between AI adoption and organizational performance. This suggests that both direct effects, driven by resources, and indirect effects, driven by capabilities, are at play. The study shows that five well-known but historically separate theoretical traditions, human capital, technology acceptance, dynamic capabilities, resource-based view, and organizational learning can be combined into a single, coherent, and statistically testable model of digital workforce transformation. This integration fills a notable gap in the literature, as previous research generally tested only parts of these relationships rather than the entire antecedent-mediator-outcome chain, especially within large, emerging-economy, multi-sector labour markets like India.

From a managerial perspective, the results indicate that organizations heavily investing in AI tools or digital upskilling without concurrently fostering a learning culture and engaging leadership are likely to see only limited workforce-readiness benefits. Since leadership's influence on readiness mainly works through enhancing employee adaptability rather than direct intervention, leaders aiming to speed up digital transformation should focus on visible involvement, creating psychological safety for experimentation, and providing resources for adaptive behaviours, rather than just mandating tool use or training. Likewise, as AI adoption's impact on organizational performance largely depends on workforce readiness, companies should plan AI implementations alongside targeted readiness initiatives, rather than viewing technology deployment and workforce development as separate efforts. The study highlights that closing the digital skills gap requires collaboration among universities, corporate trainers, and policymakers. It recommends shifting curricula, public upskilling subsidies, and corporate training metrics away from solely technical skills toward fostering adaptability and practical readiness, which the model shows are more immediate and, in this data, more influential indicators of success for both individuals and organisations. The numerical data presented here are illustrative and simulated, created to showcase the analytical process, reporting standards, and interpretive approach suitable for this research design. They should not be cited, published, or used as genuine empirical evidence. Valid testing of the model requires actual data collection, ethical approval, psychometric validation, and independently verified literature, in line with the design described in this manuscript.

10. LIMITATIONS

This study has several limitations. Its cross-sectional design prevents strong causal conclusions; longitudinal studies are needed to verify the proposed directionality. Conducted solely in India, the findings may not apply to other labor markets with different rules, cultures, and technologies. As it relies on self-reported questionnaire data, there is a risk of common-method bias and social-desirability effects; future research could address this by using multiple data sources or objective performance measures. Additionally, industry-specific differences, such as regulatory challenges in healthcare and banking compared to IT, were not fully examined within the overall model and may benefit from sector-specific studies.

11. FUTURE RESEARCH DIRECTIONS

Future research should adopt longitudinal designs to determine causal relationships among the study's variables, conduct cross-national comparisons to evaluate the model's applicability across different labor markets with varying levels of digital maturity, explore AI-driven personalized learning systems as a unique factor influencing adaptability, assess Industry 5.0 workforce preparedness focusing on human-AI collaboration rather than replacement, investigate digital twins as a means of training for complex tasks safely, analyse the specific impact of generative AI on workforce development separate from earlier AI tools, and formulate sustainable workforce strategies that mitigate rapid technological change while supporting employee wellbeing.

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