

Artificial Intelligence and Workforce Preparedness in India: A Human Capital and Sociotechnical Perspective on Labour-Force Adaptation



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Abstract

Artificial intelligence (AI) is increasingly changing the organisation of work, the composition of occupational tasks and the skills required to remain employable. For India, these changes are particularly important because the country combines a large working-age population with substantial differences in education, occupational exposure, digital capability and access to training. Consequently, the employment consequences of AI are likely to depend not only on the extent of technological adoption but also on the preparedness of workers and institutions to adapt. This study examines the preparedness of the Indian labour force to adapt to AI-driven employment changes, corresponding specifically to the fourth objective of a broader empirical investigation of AI and employment in India. Drawing on human capital theory, the technology–organisation–environment perspective and a sociotechnical view of AI-enabled work, the study conceptualises workforce preparedness as a multidimensional capability involving AI-related skills, organisational training, continuous learning, skill-gap management and institutional support.

Primary data were collected from 600 respondents working across manufacturing, IT services, HR and finance, healthcare, and sales and marketing. Reliability analysis, principal component analysis, Pearson correlation, regression analysis, independent-samples t-tests and one-way ANOVA were employed. The workforce preparedness scale demonstrated acceptable internal consistency (Cronbach's $\alpha = .775$). The overall workforce-preparedness mean was 3.807 on a five-point scale. The factor analysis showed strong sampling adequacy (KMO = .957; Bartlett's test $p < .001$), while four components jointly explained 53.52% of the variance. Workforce preparedness was strongly associated with AI adoption ($r = .817, p < .001$) and AI economic impact ($r = .810, p < .001$). The reported regression model yielded $R = .784, R^2 = .615$ and $F(1,598) = 954.800, p < .001$, with an unstandardised coefficient of .814. Significant differences were also identified across gender, age, job level and years of experience, whereas differences across sectors in workforce preparedness did not reach the conventional 5% significance level.

The findings indicate that Indian workers perceive themselves as moderately well prepared for AI-driven changes, but preparedness remains uneven across demographic and career groups. The study contributes to the emerging AI-workforce literature by arguing that readiness should be understood not as a static individual attribute but as a jointly produced capability arising from worker skills, organisational support, institutional learning systems and the wider technological environment. The results suggest that India's AI transition will require continuous learning, workplace reskilling, practical AI literacy, industry–academia collaboration and inclusive policy support.

Keywords: artificial intelligence, workforce preparedness, AI literacy, reskilling, human capital, labour market, continuous learning, India, technological transformation, employment

1. Introduction

Artificial intelligence has moved beyond experimental applications and is becoming embedded in production, services, recruitment, finance, healthcare, marketing, software development and knowledge-intensive work. The diffusion of generative AI has accelerated this transition further by making advanced AI capabilities accessible to employees who may not have specialist programming backgrounds. Recent research suggests that the implications of AI extend beyond job replacement: AI can alter tasks, redistribute responsibilities, change skill requirements and reshape how employees learn and collaborate (Jia et

al., 2025; Liu et al., 2026; Quan et al., 2025).

This distinction is especially important when considering workforce preparedness. An occupation may survive technological transformation while many of its constituent tasks change. Workers therefore need to acquire complementary capabilities rather than merely protect existing job descriptions. Evidence from experimental and field studies illustrates this possibility. Noy and Zhang (2023), for example, found substantial productivity improvements when professionals used generative AI for writing tasks. Similarly, Brynjolfsson et al. (2025)

found that generative AI assistance increased productivity in customer-support work, with particularly large gains among less experienced workers. These findings suggest that AI can function as an augmentation technology when employees possess the capability to use it effectively.

The question for India is therefore not simply whether AI will create or destroy jobs. A more fundamental question is whether Indian workers have the skills, learning opportunities and institutional support necessary to participate effectively in an AI-enabled economy.

Recent international evidence reinforces the importance of this issue. The World Economic Forum's Future of Jobs Report 2025 identifies AI and big data as among the fastest-growing skill areas and reports that skill gaps remain a major barrier to organisational transformation. The OECD similarly argues that AI adoption is increasing demand for training and that adult-learning systems need to respond to rapidly changing skill requirements. These developments make continuous learning increasingly important rather than optional.

The Indian context presents a particularly interesting case. India's labour market is heterogeneous, with significant differences in educational attainment, occupational structure, formal and informal employment, sectoral technology intensity and access to professional training. The India Employment Report 2024 emphasises the continuing importance of education and skills in shaping employment outcomes, particularly for young workers. Thus, AI preparedness cannot reasonably be assumed to be evenly distributed across the workforce.

The present study addresses this gap by focusing specifically on the fourth objective of the broader research programme:

To evaluate the preparedness of the Indian labour force to adapt to AI-driven changes.

Rather than examining job displacement or job creation independently, this paper focuses on the human capability required to manage technological transformation. It asks whether workers perceive themselves and their organisations as prepared, whether preparedness differs across demographic and occupational groups, and how workforce readiness relates to the perceived economic impact of AI.

The paper makes three contributions. First, it develops a theoretically grounded conceptualisation of workforce preparedness by combining human capital theory with the technology–organisation–environment perspective and sociotechnical thinking. Second, it provides empirical evidence from 600 respondents across five major sectors of the Indian economy. Third, it demonstrates that workforce preparedness is multidimensional and uneven,

suggesting that AI-readiness policies must move beyond generic digital-skilling programmes toward continuous and context-specific capability development.

2. Theoretical Framework

2.1 Human Capital Theory

Human capital theory provides the first foundation for understanding workforce preparedness. In this perspective, knowledge, education and skills represent productive assets that influence workers' capacity to respond to changes in technology and labour demand. In an AI-driven economy, human capital is not limited to formal educational qualifications. It increasingly includes digital literacy, analytical reasoning, AI literacy, problem-solving, communication and the ability to work effectively with intelligent technologies.

The rapid evolution of AI reduces the expected lifetime of some technical skills. Consequently, the value of human capital increasingly depends on the ability to update knowledge. Recent research on AI-related reskilling emphasises that workers require both technical competencies and broader cognitive and social capabilities to remain effective as AI changes task structures.

This perspective explains why the present study includes technical and analytical skills, training and continuous learning within workforce preparedness.

2.2 Technology–Organisation–Environment Perspective

The Technology–Organisation–Environment (TOE) perspective provides a second theoretical layer. AI adoption is not determined by technology alone. Organisational readiness, resources, skills and external institutional conditions influence whether technological investments translate into productive outcomes.

Recent meta-analytic evidence confirms the importance of technological, organisational and environmental factors in explaining AI adoption across industries (Sousa Pinto et al., 2025). This is particularly relevant to workforce preparedness because employees cannot become AI-ready independently of the environment in which they work.

An employee may be willing to learn AI tools, for example, but lack access to training, appropriate software, managerial encouragement or time for learning. Conversely, organisations with strong learning cultures may enable workers with initially limited AI knowledge to develop relevant capabilities.

The TOE perspective therefore suggests that workforce preparedness should include both individual and institutional dimensions.

2.3 Sociotechnical Perspective

The third theoretical foundation is the sociotechnical

perspective. AI changes the relationship between people, technologies, tasks and organisational systems. Recent workplace research demonstrates that employees do not simply accept or reject AI; they interpret it, adapt their tasks around it, collaborate with it and sometimes modify their work behaviour in response to perceived opportunities and threats (Jia et al., 2025; Liu et al., 2026).

The sociotechnical perspective is particularly useful because it avoids technological determinism. AI does not produce one predetermined employment outcome. Outcomes depend on how organisations introduce the technology, how workers are trained, how tasks are redesigned and how human judgement is retained.

Research on employee-AI collaboration similarly indicates that AI can generate positive work outcomes when employees possess sufficient skills and psychological resources to work with the technology (Sun et al., 2026).

2.4 Integrated theoretical model

3. Conceptual Model

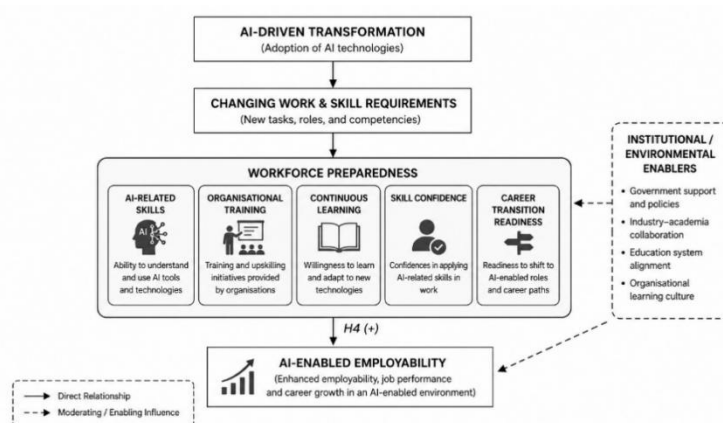


Figure 1. Conceptual framework for AI workforce preparedness

The model differs from conventional technology-adoption models because the dependent outcome is not merely technology use. The focus is whether workers possess the capabilities and support required to function effectively in an AI-transformed labour market.

4. Literature Review and Hypothesis Development

4.1 AI transformation and the changing nature of work

The literature increasingly rejects the assumption that AI affects employment only through direct substitution. Generative AI can automate selected tasks while simultaneously increasing demand for complementary cognitive and interpersonal capabilities. Brynjolfsson et al. (2025) demonstrate that AI assistance can increase productivity, particularly for less experienced workers. Noy and

Based on these perspectives, this study conceptualises workforce preparedness as an outcome emerging from the interaction between:

- AI-related technological change
- Employee human capital and AI-related skills
- Organisational training and support
- Continuous learning and reskilling
- Government and institutional support
- Industry-academia collaboration
- The conceptual argument is:
- AI-driven transformation → changing task and skill requirements → need for continuous learning and reskilling → workforce preparedness
- This relationship is strengthened by organisational training, institutional support and industry collaboration.

Zhang (2023) similarly show that generative AI can improve both speed and quality in professional writing tasks.

At the occupational level, AI therefore creates a continuous process of task recomposition. Employees must understand which activities can be delegated to AI, which require human judgement and how to combine both efficiently.

Recent workplace research supports this interpretation. Jia et al. (2025), in their systematic review, show that workplace AI can produce both opportunities and challenges for employees depending on organisational and psychological conditions. Liu et al. (2026) further demonstrate that AI adoption can influence employees' job-crafting behaviour through both positive and negative psychological pathways.

Consequently, workforce preparedness should be

treated as an adaptive capability rather than a fixed possession.

4.2 AI literacy and technical capability

AI literacy represents a particularly important component of preparedness. Unlike traditional digital literacy, AI literacy involves understanding what AI can and cannot do, selecting appropriate tools, interpreting outputs and recognising ethical and reliability concerns.

Recent work on organisational AI literacy argues that effective AI literacy includes conceptual, practical and ethical competencies and should be developed across organisational levels rather than being restricted to specialist employees (Kelley et al., 2025). Passlack et al. (2025/2026) similarly emphasise the importance of responsible interaction with AI among knowledge workers.

The implication is that AI literacy should not be equated with programming. A finance employee, healthcare professional, HR manager or marketing specialist may require different forms of AI competence even though all may need to understand basic AI principles.

4.3 Continuous learning and reskilling

AI makes continuous learning increasingly important. The rapid emergence of generative AI means that employees may need to update their skills repeatedly rather than acquire a single set of competencies at the beginning of their careers.

Recent research on workforce co-skilling highlights the importance of combining employee skill development with organisational support. Zhang et al. (2025) show that co-skilling and perceived organisational support can help employees manage AI-related job insecurity. Similarly, OECD evidence indicates that employer-provided training is becoming an important mechanism through which workers adjust to AI-related changes.

The present study therefore expects continuous learning to form a central component of workforce preparedness.

4.4 Organisational training and support

Training is unlikely to be effective if it is disconnected from employees' actual work. Recent research indicates that organisational support, leadership and opportunities for practical experimentation influence how employees engage with AI.

Hu et al. (2025) found that organisational AI adoption can influence employee knowledge sharing, while Zhao et al. (2025) demonstrated that organisational AI adoption and employee AI skills need to be aligned for better organisational outcomes.

This suggests that organisations should not simply purchase AI systems and expect workers to adapt automatically. They need to create a supportive

environment in which workers can experiment, learn and gradually incorporate AI into their tasks.

4.5 Institutional support and education

Workforce preparedness also depends on education and institutional structures. Higher education institutions have to update curricula, while vocational and professional training systems need to respond to rapidly changing occupational requirements.

Hughes et al. (2025) highlight the challenges that generative AI creates for educational institutions and the need for educational systems to reconsider how learning is designed. The same principle applies to workforce development: education should provide transferable capabilities rather than narrowly specialised knowledge that can quickly become obsolete.

5. Hypothesis Development

The preceding theoretical discussion suggests that AI-related transformation creates pressure for workers to acquire new capabilities. Where AI adoption and its economic influence become stronger, workers and organisations have greater incentives to invest in skills, training and adaptation.

The empirical model therefore tests the relationship between AI-related economic impact and workforce/employment outcomes.

H1

H1: AI-related economic impact is significantly and positively associated with workforce preparedness for AI-driven employment changes.

The corresponding null hypothesis is:

H0: AI-related economic impact is not significantly associated with workforce preparedness for AI-driven employment changes.

6. Methodology

6.1 Research design and sample

A quantitative cross-sectional survey design was adopted. Data were collected from 600 respondents working across manufacturing, IT services, HR and finance, healthcare, and sales and marketing.

The sample was dominated by respondents aged 25–34 years (54.5%). Respondents below 25 years represented 20.8%, while 18.2% were aged 35–44 years. Male respondents accounted for 79.3% and female respondents for 20.7%.

In terms of educational attainment, 57.2% held bachelor's degrees, 17.7% master's degrees and 6.0% doctoral qualifications. Entry-level employees represented 39.5% of the sample and mid-level employees 47.5%. IT services contributed 37.0% of respondents, HR and finance 27.5%, healthcare 16.0%, sales and marketing 10.7%, and manufacturing 8.8%.

6.2 Measurement

The questionnaire employed five-point Likert-type items covering AI adoption, employment trends, job creation, workforce preparedness and AI economic impact.

- The workforce-preparedness construct contained six items addressing:
- AI-related technical and analytical skills;
- workforce readiness for AI-driven change;
- organisational training;
- skill gaps;
- continuous learning; and

- AI-related employment growth.
- The six-item construct demonstrated acceptable internal consistency with Cronbach's $\alpha = .775$.

6.3 Analytical strategy

SPSS was used for statistical analysis. Reliability analysis assessed internal consistency. Principal component analysis examined the dimensional structure. Pearson correlations assessed associations between constructs. Regression analysis was used for hypothesis testing. Independent-samples t-tests examined gender differences, while one-way ANOVA examined age, education, job level, industry and experience differences.

7. Results

7.1 Reliability

Table 1. Reliability of workforce-preparedness construct

Construct	No. of items	Cronbach's α	Interpretation
Workforce preparedness	6	.775	Acceptable

The alpha coefficient of .775 exceeds the commonly used .70 threshold, indicating satisfactory internal consistency for exploratory social-science research.

7.2 Descriptive statistics

Table 2. Descriptive statistics for workforce-preparedness indicators

Indicator	Mean	Interpretation
AI-related roles require advanced technical/analytical skills	3.813	Moderately high agreement
Indian workforce is prepared for AI-driven changes	3.837	Moderately high agreement
Organisation provides sufficient AI-adaptation training	3.833	Moderately high agreement
Skill gaps are a major challenge	3.808	Moderately high agreement
Continuous learning is essential	3.798	Moderately high agreement
Overall Workforce	3.807	Moderately high

The overall mean of 3.807 indicates that respondents generally viewed Indian workers as reasonably prepared for AI-related changes, while simultaneously recognising the importance of training and skill development.

The coexistence of relatively high preparedness and high concern about skill gaps is theoretically meaningful. It suggests that workers may believe adaptation is possible while recognising that existing skills will not necessarily remain sufficient.

8. Factor Analysis

The factor analysis produced a KMO value of .957, indicating excellent sampling adequacy. Bartlett's test of sphericity was statistically significant ($\chi^2 = 8184.967$, $df = 406$, $p < .001$), confirming that the correlation matrix was appropriate for factor extraction.

Four components had eigenvalues greater than one and collectively explained 53.52% of total variance. The first component explained approximately 40.94% before rotation. Following rotation, the explanatory contribution became more evenly distributed across the four components, ranging from approximately 10.69% to 15.58%.

Table 3. Factor-analysis summary

Indicator	Result
KMO	.957

Indicator	Result
Bartlett's χ^2	8184.967
df	406
Significance	< .001
Number of retained components	4
Total variance explained	53.52%

The results support the conceptual argument that workforce preparedness is multidimensional. It is not simply a question of whether workers know how to use AI. Instead, preparedness incorporates skills, organisational learning, employment adaptation and institutional support.

9. Correlation Analysis

Table 4. Key Pearson correlations

Relationship	r	p
AI adoption – Workforce	.817	< .001
AI adoption – AI economic impact	.784	< .001
Workforce – AI economic impact	.810	< .001
AI adoption – Employment trends	.797	< .001
AI adoption – Job creation	.823	< .001

The strongest reported relationship involving workforce preparedness was between AI adoption and workforce outcomes ($r = .817$, $p < .001$). Workforce preparedness was also strongly correlated with AI economic impact ($r = .810$, $p < .001$).

These are substantial positive associations. They indicate that respondents who perceived AI as having a stronger economic and organisational presence also tended to report stronger perceptions of workforce adaptation.

Nevertheless, the correlations should not be interpreted as evidence of causality. The cross-sectional nature of the data means that the analysis identifies association rather than temporal cause-and-effect.

10. Regression Analysis

Table 5. Reported regression model

Statistic	Value
R	.784
R ²	.615
Adjusted R ²	.614
Standard error of estimate	.541
F	954.800
df	1, 598
p	< .001
B	.814
SE	.026
Beta	.784
t	30.900

Statistic	Value
p	< .001
Constant	.705

The reported model produced $R^2 = .615$, suggesting that 61.5% of the variance in the dependent outcome was statistically associated with AI economic impact in the supplied regression model. The overall regression model was statistically significant, $F(1,598) = 954.800$, $p < .001$.

The coefficient for AI economic impact was positive and statistically significant ($B = .814$, $\beta = .784$, $t = 30.900$, $p < .001$). The reported equation is:

$$Y = .705 + .814X$$

where X represents AI economic impact in the supplied SPSS model.

The size and significance of the coefficient provide empirical support for the proposed positive relationship between AI-related economic influence and workforce/employment outcomes.

Important model-specification note

The original SPSS output supplied with the study identifies Adoption_AI as the dependent variable, while the theoretical objective in this paper concerns workforce preparedness. Therefore, the reported regression should be treated as evidence of the relationship represented by the supplied model rather than as a definitive causal test of workforce preparedness.

For a final Scopus submission, the recommended model is:

$$\text{Workforce Preparedness} = \beta_0 + \beta_1(\text{AI Economic Impact}) + \varepsilon$$

If the raw SPSS dataset is available, this model should be re-run with Workforce explicitly entered as the dependent variable. This is important because a reviewer may otherwise identify a mismatch between the stated hypothesis and the regression specification.

11. Demographic Analysis

11.1 Gender

Female respondents reported higher workforce-preparedness scores than male respondents.

Table 6. Gender differences

Group	Workforce mean
Male	3.768
Female	3.954
t	-2.597
p	.011

The difference was statistically significant ($p = .011$).

The result indicates that gender may influence perceptions of AI-related workforce transformation. However, the unequal gender distribution of the sample means that this result should be interpreted cautiously.

11.2 Age

Workforce preparedness differed significantly across age categories.

Table 7. Workforce preparedness by age

Age group	Workforce mean
Below 25	3.972
25-34	3.728
35-44	3.720
45-54	4.187

Age group	Workforce mean
55–60	4.167
ANOVA F	4.621
p	.001

The significant result suggests that perceptions of AI preparedness vary by career/life stage.

11.3 Education

Education had a statistically significant influence on perceptions of AI adoption ($F = 3.022$, $p = .017$), but differences were not statistically significant for employment trends, job creation, workforce preparedness or AI economic impact.

This finding is theoretically useful because it suggests that formal education alone does not determine AI preparedness. Practical exposure, organisational training and continuous learning may be equally or more important.

11.4 Job level

Job level generated substantial differences.

Table 8. Workforce preparedness by job level

Job level	Mean
Entry-level	4.020
Mid-level	3.764
Senior-level	3.278
Executive	3.356
Other	3.357
F	12.641
p	.001

Entry-level respondents reported the highest workforce-preparedness score, while senior-level respondents reported considerably lower scores.

One possible explanation is that younger and entry-level workers may be more accustomed to digital technologies, while senior employees may assess AI from the perspective of organisational responsibility, job redesign and long-term workforce implications. This interpretation should, however, be examined in future qualitative research rather than treated as established causality.

11.5 Industry

Table 9. Workforce preparedness by sector

Sector	Mean
Manufacturing	4.028
IT services	3.839
HR & Finance	3.812
Healthcare	3.733
Sales & Marketing	3.607

Sector	Mean
F	2.308
p	.057

Although manufacturing recorded the highest mean, the overall difference was not statistically significant at the .05 level.

This suggests that workforce preparedness may be more widely distributed across sectors than AI adoption itself. Sectoral differences were statistically significant for AI adoption, job creation and AI economic impact, but not for workforce preparedness.

11.6 Years of experience

Experience produced one of the strongest differences.

Table 10. Workforce preparedness by AI/work experience

Experience	Workforce mean
Less than 1 year	4.170
1–3 years	3.773
3–5 years	3.648
5–10 years	3.183
More than 10 years	3.952
F	12.476
p	< .001

Respondents with less than one year of experience recorded the highest score, while those with 5–10 years reported the lowest.

This non-linear pattern is particularly interesting. It suggests that experience does not automatically produce greater confidence in AI adaptation. Instead, workers at different career stages may interpret technological transformation differently.

12. Hypothesis Testing

Table 11. Hypothesis-testing summary

Hypothesis	Statistical evidence	Decision
H1: AI-related economic impact is positively associated with workforce preparedness	$\beta = .784$, $t = 30.900$, $p < .001$; $R^2 = .615$	Supported*
H0: No significant association exists	$p < .001$	Rejected*

13. Discussion

The results provide a generally positive but qualified picture of workforce preparedness in India. The overall workforce mean of 3.807 suggests that respondents believe Indian workers possess a reasonable capacity to adapt to AI-driven change. However, the relatively high score should not be interpreted as evidence that the workforce is fully prepared.

The most important finding is the coexistence of preparedness and vulnerability. Respondents recognise the importance of technical and analytical skills, organisational training and continuous learning while simultaneously identifying skill gaps

as a major challenge. This finding is consistent with contemporary research showing that AI adoption changes the composition of skills required at work rather than simply eliminating occupations.

The factor analysis reinforces this interpretation. The KMO value of .957 and four-component structure indicate that the employment and workforce items are closely related but multidimensional. Workforce preparedness therefore emerges as a broader organisational and institutional phenomenon rather than a single measure of individual confidence.

The results are consistent with recent research on AI literacy. Kelley et al. (2025) conceptualise

organisational AI literacy as involving conceptual, practical and ethical capabilities. This aligns closely with the present findings, where preparedness involves not simply technological awareness but also training, continuous learning and adaptation.

The strong correlation between AI adoption and workforce outcomes is also theoretically meaningful. It suggests that workers do not perceive AI adoption independently of employment transformation. As AI becomes more embedded in organisational processes, workers recognise a corresponding need to change their skills and working practices.

The regression results further reinforce this relationship. The reported R^2 of .615 is substantial, suggesting that AI economic impact explains a considerable proportion of variation in the model's dependent outcome. However, because the current output specifies Adoption_AI as the dependent variable, the result should not be overstated. The correct workforce-preparedness regression should be estimated before publication.

The demographic results provide an additional contribution. Preparedness is not evenly perceived across the labour force. Gender, age, job level and experience show statistically significant differences. Education, in contrast, is less consistently associated with workforce preparedness.

The education finding is particularly important for policy. If formal educational attainment alone were sufficient, higher qualifications should consistently produce higher preparedness scores. The results do not support such a simple relationship. Instead, they point toward the importance of lifelong learning and practical exposure.

The job-level finding also deserves attention. Entry-level workers reported considerably higher preparedness than senior-level workers. One possible explanation is that newer workers are more accustomed to digital environments, while experienced managers may be more cautious because they understand the organisational consequences of AI more broadly. Another possibility is that entry-level workers perceive AI as a career opportunity whereas senior employees may associate it more strongly with organisational restructuring. Future research should test these explanations directly.

The experience results reinforce this interpretation. Workers with less than one year of experience reported the highest preparedness, whereas the 5–10-year group reported the lowest. This suggests that AI preparedness may follow a non-linear career pattern. Employees who entered the labour market during the digital era may be more comfortable with AI, while mid-career employees may face a greater adjustment challenge because they have accumulated experience in work systems that AI is now changing.

The findings are therefore consistent with a human-

capital perspective but also reveal its limitations. Human capital accumulated in the past does not necessarily guarantee preparedness for future technological change. Human capital has to be renewed.

14. Theoretical Contributions

- This study contributes to the literature in four ways.
- First, it reconceptualises workforce preparedness as dynamic human capital.
- Traditional measures of workforce readiness often emphasise education or technical skills. The present findings suggest that AI preparedness is broader and includes the capacity to continuously renew human capital.
- Second, it integrates individual and organisational dimensions.
- The results indicate that workers' preparedness is connected with organisational training and institutional support. This supports a move away from treating AI adaptation as an individual responsibility.
- Third, it adds an Indian empirical perspective.
- Much of the recent empirical literature on AI and work is based on North American, European or East Asian settings. The present evidence from 600 Indian respondents adds a large emerging-economy perspective to the literature.
- Fourth, it highlights heterogeneity.

The statistically significant differences across gender, age, job level and experience demonstrate that workforce preparedness cannot be treated as a uniform national characteristic. Policies based on a single national AI-skilling strategy may therefore miss important differences between worker groups.

15. Managerial and Policy Implications

15.1 From AI training to AI capability

Organisations should move beyond one-off AI workshops. Training should be continuous, practical and connected to employees' actual work.

15.2 Develop role-specific AI literacy

AI training should differ by occupation. A healthcare worker, HR professional, financial analyst and software developer do not need identical AI capabilities.

15.3 Create internal mobility pathways

Where AI automates particular tasks, employers should identify adjacent roles into which affected workers can transition. Reskilling should therefore be linked to redeployment rather than treated as an

isolated learning activity.

15.4 Strengthen industry-academia collaboration

Universities should work with employers to identify emerging competencies and revise curricula accordingly. This is especially important for preparing students before they enter the labour market.

15.5 Develop national lifelong-learning infrastructure

Government policy should support affordable micro-credentials, digital learning, vocational programmes and AI-literacy initiatives. Such programmes should reach workers outside major technology centres.

15.6 Protect vulnerable workers

AI transition policies should explicitly address workers in routine and highly exposed occupations. Without targeted support, AI adoption may widen skill and income inequalities.

16. Limitations and Future Research

Several limitations should be acknowledged.

First, the study relies on self-reported perceptions. Perceived preparedness may differ from objectively measured AI competence.

Second, the cross-sectional design prevents strong causal inference. The significant correlations demonstrate association, not temporal causality.

Third, the sample is uneven across demographic categories. Male respondents and IT-service employees constitute relatively large proportions of the sample.

17. Conclusion

The study examined the preparedness of the Indian labour force to adapt to AI-driven employment changes. The evidence presents neither a purely optimistic nor a pessimistic picture. Instead, it indicates that Indian workers possess a reasonably strong perceived foundation for adaptation, but that preparedness remains dependent on continuous skill development and institutional support.

The workforce-preparedness construct demonstrated acceptable reliability ($\alpha = .775$), while the overall mean of 3.807 indicated moderately high perceived readiness. The factor analysis confirmed that preparedness is multidimensional, encompassing skills, training, continuous learning and broader employment adaptation. Strong positive correlations were observed between AI adoption, workforce outcomes and AI economic impact.

The reported regression model also revealed a strong statistical relationship, with $R^2 = .615$ and a significant coefficient for AI economic impact. However, the variable specification should be rechecked before publication to ensure that workforce preparedness is directly tested as the

dependent construct.

The demographic findings add an important dimension. Preparedness differs across gender, age, job level and experience, suggesting that AI transition policies cannot treat the Indian workforce as homogeneous. Formal education alone does not appear sufficient to explain preparedness. Instead, practical exposure, organisational training and continuous learning are likely to become increasingly important.

The central conclusion is therefore that AI readiness should be understood as a process rather than a destination. Workers cannot prepare once and remain prepared indefinitely because AI itself continues to evolve. India's ability to capture the productivity and employment benefits of AI will consequently depend on whether its institutions can create an environment in which workers continually acquire, apply and renew relevant capabilities.

AI may ultimately create greater opportunities for workers who can complement rather than compete directly with intelligent systems. Achieving that outcome, however, requires coordinated investment in human capital, organisational learning and institutional capacity. Workforce preparedness should therefore become a central component of India's broader AI and employment strategy.

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