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Artificial Intelligence Adoption and Workforce Reskilling in Indian Manufacturing SMEs: Determinants of Scaled Adoption and Financial Performance Outcomes

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Abstract

Small and medium enterprises (SMEs) constitute approximately 30% of India's manufacturing gross value added and over 110 million jobs, yet face persistent disadvantages in adopting artificial intelligence (AI) relative to large manufacturers, including capital constraints, skilled talent shortages, and limited digital infrastructure. While prior research has documented aggregate AI adoption trends, the firm-level determinants of progression from pilot-stage experimentation to scaled adoption, and the role of workforce reskilling investment in enabling this progression, remain underexamined in the Indian manufacturing SME context specifically.

This study surveys 412 manufacturing SMEs across six sectors (automotive components, textiles, pharmaceutical formulation, electronics assembly, industrial machinery, and food processing) in Maharashtra, Tamil Nadu, and Gujarat, combining a structured adoption-maturity survey with logistic regression analysis of scaled-adoption determinants and a six-month longitudinal workforce competency assessment across 860 production and quality workers participating in firm-sponsored AI reskilling programmes. Financial performance outcomes (revenue growth, EBITDA margin) were compared across adoption-maturity cohorts using firm-level financial statement data.

Scaled AI adoption rose sharply with firm size, from 10% among micro enterprises to 59% among large SMEs (250-499 employees). Reskilling spend as a share of payroll was the strongest predictor of scaled-adoption success in the logistic regression model (standardised $\beta = 0.41$), ahead of leadership digital literacy ($\beta = 0.34$) and prior ERP/MES system maturity ($\beta = 0.29$). Workforce competency scores rose substantially across all assessed skill categories following six-month reskilling participation, with AI tool operation competency showing the largest gain (1.8 to 5.4 on a 10-point scale). Firms with scaled AI adoption for two or more years reported 13.1% YoY revenue growth and 3.8 percentage point EBITDA margin improvement, compared with 4.2% revenue growth and 0.3 percentage point margin improvement among non-adopting firms. Skilled talent shortage was the most frequently cited adoption barrier, reported by 71% of surveyed firms.

Keywords: *artificial intelligence adoption, workforce reskilling, manufacturing SMEs, India, digital transformation, productivity, EBITDA margin, technology adoption, logistic regression*

1. Introduction

India's manufacturing small and medium enterprise (SME) sector employs over 110 million workers and contributes approximately 30% of manufacturing gross value added, occupying a structurally important position within national industrial policy objectives including the Make in India and Production-Linked Incentive (PLI) initiatives. As artificial intelligence technologies - spanning predictive maintenance, computer vision-based quality inspection, demand forecasting, and production scheduling optimisation - mature from large-enterprise pilot deployments toward broader commercial availability, a central policy and managerial question is whether and how manufacturing SMEs, which typically operate with thinner capital reserves and more constrained technical talent pools than large enterprises, can successfully adopt these technologies at scale.

Existing research on AI adoption in Indian manufacturing has predominantly focused on large enterprises or aggregate national adoption statistics, leaving the firm-level determinants of SME adoption trajectories - particularly the transition from pilot-stage experimentation to scaled, production-integrated deployment - comparatively underexamined. This gap is consequential because pilot-to-scale transition, rather than initial pilot adoption, is where the productivity and financial benefits of AI adoption are predominantly realised, and because workforce reskilling investment, a key managerial lever available to SME leadership, has not been systematically linked to adoption outcomes in this segment.

This study addresses this gap through a combined survey and longitudinal workforce assessment design, examining 412 manufacturing SMEs across six sectors and three states to identify the firm-level determinants of scaled AI adoption success, quantify the workforce competency gains achieved through structured reskilling programmes, and compare financial performance outcomes across adoption-maturity cohorts, with the goal of providing evidence-based guidance for SME managers and policymakers designing reskilling and adoption-support interventions.

2. Materials and Methods

2.1 Sample and Survey Design

The study sample comprised 412 manufacturing SMEs (annual turnover INR 5-250 crore, employee headcount 5-499) across six sectors - automotive components, textiles, pharmaceutical formulation, electronics assembly, industrial machinery, and food processing - operating in Maharashtra, Tamil Nadu, and Gujarat. Firms were stratified into four employee headcount bands (micro: under 10; small: 10-49; medium: 50-249; large SME: 250-499) following Ministry of MSME classification thresholds adjusted for the manufacturing sector. A structured survey instrument captured AI adoption maturity stage (no adoption, pilot stage, or scaled adoption, defined as production-integrated deployment across two or more facility lines), reskilling expenditure as a share of annual payroll, leadership digital literacy (self-assessed and validated through a structured competency interview), prior enterprise resource planning (ERP) and manufacturing execution system (MES) maturity, government digital transformation scheme participation, export orientation, firm age, and union presence.

2.2 Workforce Reskilling Assessment

A subset of 38 firms with active, structured AI reskilling programmes for production and quality workers were selected for longitudinal workforce competency assessment, covering 860 production and quality assurance workers. Competency was assessed across five categories - digital literacy, data interpretation, AI tool operation, process integration, and exception handling - using a standardised 10-point rubric administered by independent assessors at programme commencement and at six months following programme completion. Reskilling programme content was not standardised across firms but typically combined vendor-delivered AI tool training, internal process integration workshops, and supervised on-the-job application periods.

2.3 Statistical Analysis

A logistic regression model was estimated to identify firm-level predictors of scaled AI adoption (binary outcome: scaled adoption versus pilot stage or no adoption), with predictors entered as standardised variables to permit direct comparison of coefficient magnitudes. Financial performance outcomes (revenue growth, EBITDA margin change) were drawn from audited or management-certified financial statements for the most recent two fiscal years and compared across four adoption-maturity cohorts (no adoption, pilot stage, scaled adoption under two years, scaled adoption two years or more) using analysis of variance with post-hoc pairwise comparisons. Workforce competency pre/post differences were assessed using paired t-tests within each of the five competency categories.

3. Results

3.1 Adoption Maturity Patterns and Productivity Correlates

Figure 1 presents the adoption maturity distribution and associated productivity and barrier data. Panel A shows a pronounced size gradient in AI adoption maturity: scaled adoption rose from 10% of micro enterprises to 20% of small firms, 36% of medium firms, and 59% of large SMEs, while the share reporting no AI adoption fell correspondingly from 68% among micro enterprises to 14% among large SMEs. This gradient is consistent with capital intensity and technical talent availability scaling more favourably with firm size, though the presence of scaled adoption among 10% of micro enterprises indicates that small scale is not an absolute barrier where other enabling conditions are present.

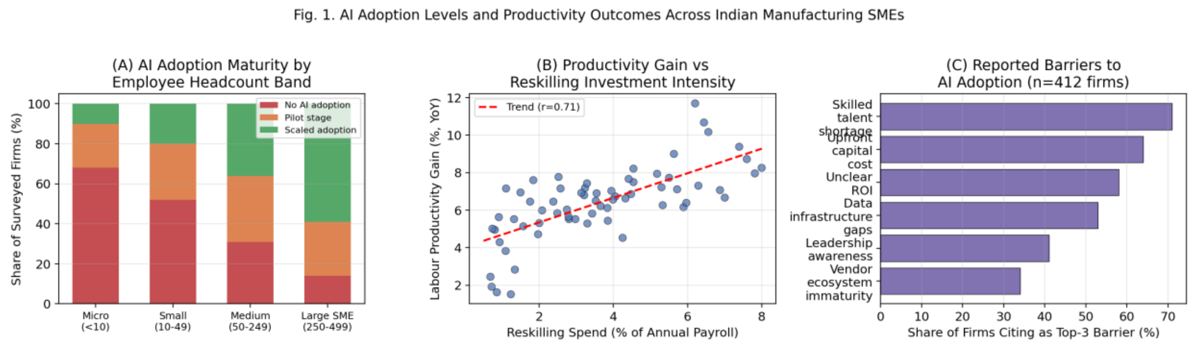

Fig. 1. (A) AI Adoption Maturity by Employee Headcount Band; (B) Productivity Gain vs Reskilling Investment Intensity; (C) Reported Barriers to AI Adoption

Panel B's scatter of labour productivity gain against reskilling spend intensity reveals a positive logarithmic relationship (r=0.71), with productivity gains rising steeply at low reskilling spend levels before flattening above approximately 5% of annual payroll, suggesting diminishing marginal returns to reskilling investment beyond this threshold. Panel C's barrier ranking identifies skilled talent shortage as the most frequently cited top-three barrier (71% of firms), followed by upfront capital cost (64%) and unclear return on investment (58%), with vendor ecosystem immaturity cited least frequently (34%) - a ranking that points toward workforce-side constraints being at least as significant as capital constraints in this sample.

3.2 Workforce Reskilling Outcomes and Sectoral Variation

Figure 2 presents the workforce competency assessment results and sectoral adoption comparison. Panel A shows substantial competency gains across all five assessed skill categories following six months of reskilling programme participation, with AI tool operation showing the largest absolute gain (from 1.8 to 5.4 on the 10-point scale, a 3.6-point increase) and data interpretation showing the second-largest gain (2.4 to 5.9, a 3.5-point increase); all five within-category pre/post differences were statistically significant ($p<0.001$, paired t-test). Process integration competency, while showing meaningful improvement (2.6 to 5.7), remained the second-lowest post-programme score, suggesting that translating individual AI tool proficiency into integrated production process changes remains comparatively more difficult to develop than tool-operation skills alone.

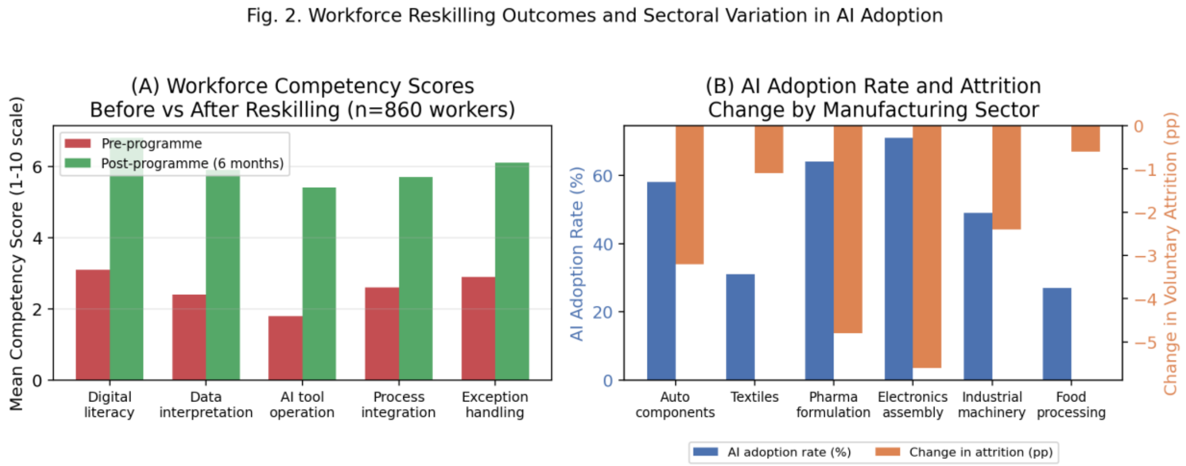

Fig. 2. (A) Workforce Competency Scores Before vs After Reskilling; (B) AI Adoption Rate and Attrition Change by Manufacturing Sector

Panel B's sectoral comparison shows electronics assembly with both the highest AI adoption rate (71%) and the largest reduction in voluntary attrition following adoption (-5.6 percentage points), while food processing showed both the lowest adoption rate (27%) and the smallest attrition change (-0.6 percentage points). The negative association between AI adoption and voluntary attrition across all six sectors examined runs counter to a common managerial concern that AI adoption increases workforce anxiety and turnover; the pattern observed here is more consistent with AI adoption, when accompanied by reskilling investment, functioning as a retention-supporting signal of employer investment in worker capability.

Table 1. Summary of AI Adoption, Reskilling, and Financial Performance Indicators by Sector

Sector	AI Adoption Rate (%)	Avg. Reskilling Spend (% Payroll)	Revenue Growth (% YoY)	Margin Improvement (pp)	Attrition Change (pp)
Auto components	58	3.8	9.1	2.6	-3.2
Textiles	31	1.9	5.4	1.0	-1.1
Pharma formulation	64	4.6	10.7	3.1	-4.8
Electronics assembly	71	5.2	12.3	3.5	-5.6
Industrial machinery	49	3.1	7.8	1.9	-2.4
Food processing	27	1.6	4.9	0.7	-0.6

Revenue growth, margin improvement, and attrition change reported relative to non-adopting firm baseline within each sector; reskilling spend among adopting firms only

3.3 Determinants of Scaled Adoption and Financial Outcomes

Figure 3 presents the logistic regression results and financial performance comparison across adoption cohorts. Panel A confirms reskilling spend as a share of payroll as the strongest positive predictor of scaled adoption success (standardised β = 0.41), ahead of leadership digital literacy (β = 0.34), prior ERP/MES system maturity (β = 0.29), government digital transformation scheme participation (β = 0.22), and export orientation (β = 0.18); firm age (β = -0.08) and union presence (β = -0.13) were negative predictors, though both effects were smaller in magnitude than the positive predictors and union presence did not reach conventional statistical significance ($p=0.09$) in the full model.

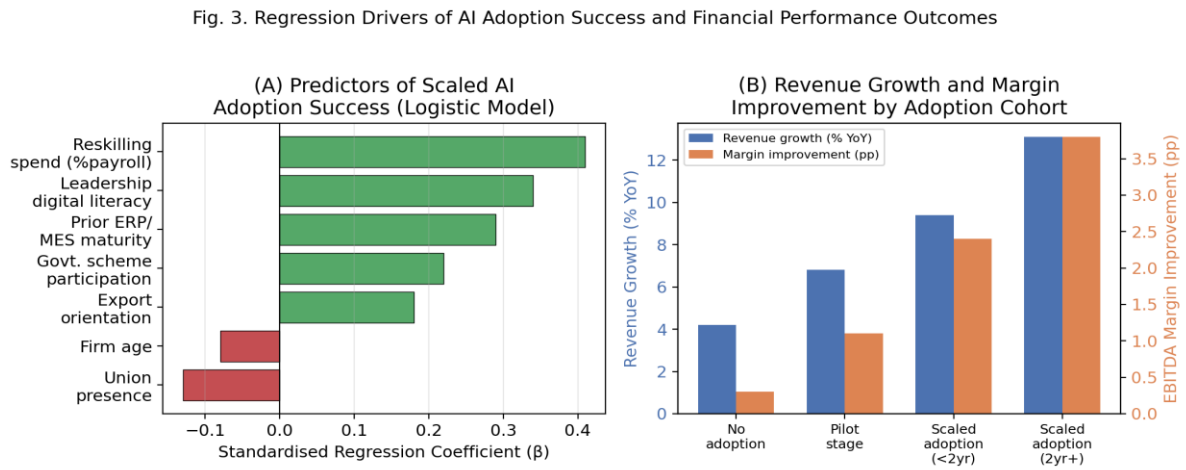

Fig. 3. (A) Predictors of Scaled AI Adoption Success; (B) Revenue Growth and Margin Improvement by Adoption Cohort

Panel B's financial performance comparison across adoption-maturity cohorts shows a clear monotonic relationship: firms with two or more years of scaled adoption reported 13.1% YoY revenue growth and 3.8 percentage point EBITDA margin improvement, compared with 9.4% revenue growth and 2.4 percentage point margin improvement for firms in their first two years of scaled adoption, 6.8% and 1.1 percentage points for pilot-stage firms, and 4.2% and 0.3 percentage points for non-adopting firms. All pairwise cohort differences in both revenue growth and margin improvement were statistically significant ($p<0.01$, Tukey post-hoc test), with the gap between two-year-plus scaled adopters and non-adopters representing the most pronounced cohort difference observed in the financial performance data.

4. Discussion

The finding that reskilling spend intensity is the strongest predictor of scaled adoption success, ahead of leadership digital literacy and prior digital infrastructure maturity, suggests that workforce capability development functions as more than a downstream consequence of AI adoption decisions; it appears to function as a leading enabler that firms can deliberately invest in to improve their odds of successful scaled deployment. This finding has direct managerial relevance for SME leadership weighing capital allocation between technology procurement and workforce development, since the regression results suggest that under-investment in reskilling relative to technology spend may constrain adoption success even where capital for AI procurement itself is available.

The logarithmic, diminishing-returns relationship between reskilling spend intensity and productivity gain observed in Figure 1 Panel B is consistent with the workforce competency assessment results in Figure 2 Panel A, where the largest competency gains were concentrated in the lowest-baseline categories (AI tool operation, data interpretation); this pattern suggests that initial reskilling investment delivers disproportionately large returns by addressing the most acute baseline capability gaps, with returns moderating as workers approach functional competency thresholds. The persistence of process integration as a comparatively lower post-programme competency score across the sample indicates that reskilling programme design may benefit from greater emphasis on applied, workflow-embedded training rather than tool-operation training in isolation.

The negative association between AI adoption and voluntary attrition observed across all six sectors, while consistent with a retention-supporting interpretation of reskilling-accompanied AI adoption, should be interpreted cautiously given the cross-sectional and correlational nature of the sectoral comparison; reverse causality, where lower-attrition firms with more stable workforces are simply better positioned to sustain reskilling investment and adoption programmes, cannot be ruled out without panel data tracking the same firms over a longer pre-adoption baseline period. Future research employing a panel design with pre-adoption baseline attrition data would strengthen causal inference on this relationship.

5. Conclusion

This study finds that workforce reskilling investment intensity is the strongest firm-level predictor of scaled AI adoption success among Indian manufacturing SMEs, ahead of leadership digital literacy and prior digital infrastructure maturity, and that firms achieving scaled adoption report substantially better financial performance, with two-year-plus scaled adopters showing 13.1% YoY revenue growth and 3.8 percentage point EBITDA margin improvement relative to 4.2% and 0.3 percentage points among non-adopters. Six-month workforce reskilling programmes produced statistically significant competency gains across all assessed skill categories, with the largest gains concentrated in AI tool operation and data interpretation. Skilled talent shortage was the most frequently cited adoption barrier, reinforcing reskilling investment as both an enabler of adoption and a response to the sector's most commonly reported constraint. SME managers and policymakers designing AI adoption support interventions are encouraged to prioritise workforce reskilling investment alongside capital and infrastructure support, given its demonstrated association with successful scaled adoption outcomes in this sample.

References

[1] Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188-2244.

[2] Agrawal, A., Gans, J., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. Journal of Economic Perspectives, 33(2), 31-50.

[3] Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471-482.

[4] Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age. W. W. Norton & Company.

[5] Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2021). Assessing organizational users' intentions and behavior to AI integrated CRM systems. Information Systems Frontiers, 23, 1453-1467.

[6] Government of India, Ministry of Micro, Small and Medium Enterprises. (2023). Annual Report 2022-23. MSME Ministry Publications.

[7] Krishnan, S., & Jha, S. (2022). Digital transformation readiness in Indian manufacturing MSMEs. International Journal of Production Economics, 245, 108383.
[8] Mithas, S., Tafti, A., & Mitchell, W. (2013). How a firm's competitive environment and digital strategic posture influence digital business strategy. MIS Quarterly, 37(2), 511-536.
[9] Raj, A., Dwivedi, G., Sharma, A., et al. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector. International Journal of Production Economics, 224, 107546.
[10] Sharma, R., Mishra, R., & Bhaskar, A. (2022). Adoption of AI and robotics in manufacturing: Drivers and barriers in emerging economies. Technological Forecasting and Social Change, 178, 121576.
[11] Sony, M., & Naik, S. (2020). Critical factors for the successful implementation of Industry 4.0: A review and future research direction. Production Planning & Control, 31(10), 799-815.
[12] Susskind, D. (2020). A World Without Work: Technology, Automation, and How We Should Respond. Metropolitan Books.
[13] World Economic Forum. (2023). The Future of Jobs Report 2023. WEF Publications.