Rural Innovation and Sustainable Business Models for Viksit Bharat 2047: A Data-Driven Analysis of ERP, Automation, and Machine Learning Adoption in Indian Industries

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Abstract: ***The rise of Industry 4.0 technologies, such as Enterprise Resource Planning (ERP), industrial automation, and machine learning (ML), has revolutionized the competition in the industrial sectors in India. However, the uptake of these technologies in rural and semi-urban industrial systems is still empirically under-investigated, although they can be a driver for inclusive growth and sustainable industrial business change. The present empirical study focuses on the adoption trends, productivity impacts and sustainability benefits of ERP, automation and ML integration in the Indian industry sector, especially within the rural and peri-urban manufacturing and agribusiness clusters in Odisha. The study is based on structured survey data of 312 respondents from five industry verticals within the context of Viksit Bharat 2047 vision. The research uses Structural Equation Modeling (SEM) and multiple hierarchical regression to validate a conceptual model specifically created for the rural context, the Rural Digital Technology Adoption Model (RDTAM) through seven tested pathways. The findings reveal that ERP adoption has a significant impact on enhancing the coordination of the supply chain ($\beta = 0.423$, $p < 0.001$), automation has a significant impact on reducing the operational cost and increasing the productivity ($\beta = 0.398$, $p < 0.001$), and ML enabled predictive analytics has a significant impact on the quality of strategic decisions taken ($\beta = 0.374$, $p < 0.001$). More importantly, the intensity of technology use shows a positive and significant impact on rural enterprise sustainability outcomes ($\beta = 0.356$, $p < 0.001$) and this impact is mediated by digital capability development. The study provides theoretical and policy interventions and a roadmap for industrial digitization in relation to rural innovation imperatives of Viksit Bharat 2047.***

Keywords: ERP Systems, Industrial Automation, Machine Learning, Rural Innovation, Sustainable Business Models, Viksit Bharat 2047, Industry 4.0, Indian Industries, Digital Technology Adoption

1. Introduction

The 4th industrial revolution has brought about a structural transformation in the way organizations, irrespective of their sectors, create, manipulate and utilize information for competitive advantage (Schwab, 2016). Three digital technologies – Enterprise Resource Planning systems, industrial automation and machine learning – are three mutually reinforcing technologies that have shown transformative potential when combined in the areas of organizational efficiency, quality of decision making and long-term sustainability (Ghobakhloo, 2020). Although initially the adoption of these technologies was limited to large metropolitan companies and technology-intensive industries, the spread of technologies to smaller companies in rural and semi-urban areas has increased due to policy measures, cost reductions in cloud-based systems, and the need for economic recovery after the pandemic. (Bai et al., 2021)

The Indian industrial context is particularly learning rich for analyzing this diffusion trajectory. The potential for successful technology adoption is high, given the number of registered MSMEs in India (around 63.4 million, mostly in the rural and semi-urban areas), and the national goal to boost the contribution of manufacturing to GDP to 25% by 2025 under the Make in India initiative (Ministry of MSME, 2022). The vision of Viksit Bharat 2047, the umbrella development plan to make India a developed economy by the 100th Independence Day, clearly emphasizes technological modernization of rural industries, decentralized innovation ecosystems and the development of sustainable business models that reduce the productivity gap between the urban and rural areas (NITI Aayog, 2023).

The geographical context of this inquiry is the State of Odisha, which is home to a fast diversifying industrial sector, including agro-processing, textiles, light engineering, minerals, and IT enabled services. The state has more than 280,000 registered MSMEs and has been an active beneficiary of various digitization initiatives by the central government such as PM Vishwakarma, Digital India, and Odisha MSME Development Policy 2022 (Government of Odisha, 2022). However, there is limited empirical evidence on the level of ERP, automation and ML adoption and its drivers and impact in this context.

This study fills this gap with four contributions: (1) development of a contextually grounded conceptual model for technology adoption and sustainability outcomes in rural industrial settings, Rural Digital Technology Adoption Model (RDTAM); (2) robust empirical evidence from a multi-sector primary survey; (3) quantification of the productivity, decision-quality and sustainability impact of ERP, automation and ML adoption in Odisha industrial clusters; and (4) actionable policy recommendations aligned with the

Viksit Bharat 2047 framework. The paper goes from thirteen sections, beginning with literature review up to conclusion.

2. Literature Review

The research on ERP systems has grown significantly during the last decade, starting with implementation success/failure studies and moving to more nuanced studies focusing on value realization after ERP implementation. Kumar et al. (2019) explored ERP adoption in the Indian SMEs and revealed that the companies which have higher intensity of supply chain integration got more efficiency gains from ERP deployment than the companies that used ERP as a standalone administrative tool. This has been corroborated by Khare and Shrivastava (2021) in the rural industrial context, who found the challenges for adoption of these technologies in rural industrial areas to be infrastructure and digital literacy of the owners, and vendor support, which is especially weak in Odisha's non-metropolitan manufacturing clusters.

Shukla and Bansal (2021) examined ERP implementation readiness of rural MSMEs in India by using the Technology Acceptance Model (TAM) (Davis, 1989), and concluded that perceived usefulness (PU) and top management support (TMS) were the most significant factors affecting adoption intention, while perceived ease of use (PEU) was also dependent on prior experience with IT as much as it could be mistakenly thought. They found that the barrier to ERP adoption isn't necessarily lower when the interface is simplified, and that there is a need for continued support to implement ERP.

Due to Industry 4.0 policy discourse, literature on the subject of industrial automation in manufacturing with developing economy has increased significantly. Kamble et al. (2018) suggested a sustainable Industry 4.0 framework that correlates automation, cyber-physical systems, and IoT with environmental and economic sustainability outcomes. Lee et al. (2015) have given basic theoretical foundations to this framework with their cyber-physical systems (CPS) architecture, and Oztemel and Gursev (2020) have performed a detailed bibliometric analysis of literature on Industry 4.0, finding process automation and smart manufacturing sub-domains to be the ones with the most consistent empirical evidence to support productivity improvement.

In the context of Indian manufacturing in particular Luthra and Mangla (2018) assessed the challenges to Industry 4.0 adoption in emerging economy supply chains, and found skill gap, capital constraint, regulatory uncertainty, and fragmented industrial ecosystems as the four major barriers. Drawing specifically on the case of Odisha, Singh et al. (2019) analysed the adoption of automation in manufacturing clusters and found that the automation penetration rate was 28% higher in manufacturing clusters with common digital infrastructure embedded in industry associations than in the individual enterprises.

In industrial applications, machine learning has been the subject of an exponentially increasing volume of research. Jordan and Mitchell (2015) offered a seminal scientific overview of the ML trends and listed the three industrial domains that promise the greatest near-term impact of ML: predictive maintenance, demand forecasting and quality control. Jain et al. (2022) tested this framework in the Indian MSMEs' supply chains, where it was found that ML-based demand forecasting led to an average inventory holding cost reduction of 22.4% among the surveyed firms, with higher cost reductions for firms that had a longer tenure and larger data assets.

The relationship between the adoption of digital technology and the sustainability of enterprises in rural areas of India has been investigated by Prasad and Sharma (2020), who found positive associations between digital enablement and enterprise sustainability through the intermediation of market information and supply chain linkages. The theorisation of sustainability dimensions of technology adoption in industrial settings has been done through various lenses. Ghobakhloo (2020) has suggested a holistic approach to connect Industry 4.0 technologies to economic, social and environmental sustainability. In the case of manufacturing in developing economies, Yadav et al. (2020) operationalized this framework and concluded that the sustainability returns from the adoption of Industry 4.0 were the highest when it was coupled with the workforce upskilling and governance quality improvement. Viksit Bharat 2047 policy architecture that works in synchrony with rural industrialization, workforce development and sustainability provides an institutional landscape that is close to this theoretical prediction.

Wamba et al. (2017) investigated the impact of big data analytics which is closely related to the adoption of ML on performance, and they found that there is a significant impact mediated through dynamic capabilities (Teece et al., 1997). This lens of dynamic capabilities is especially relevant to rural businesses that need to use analytics tools to adapt in changing agricultural and commodity markets. Viksit Bharat 2047 programs explicitly target to reduce the adoption gap for analytics between large and small and medium enterprises, and this gap is indeed observed in ransbotham et al., (2017).

3. Scope of the Study

The geographical scope of the study is limited to the industrial clusters of Odisha where the respondents were selected from five districts with varying industrial profile namely Khurda (IT enabled services and light manufacturing), Cuttack (Agro-processing and textile), Sambalpur (Engineering goods and minerals processing), Ganjam (Agro-processing, cashew and seafood) and Balasore (Pharmaceutical and chemical).

The industry verticals are agro-processing and food manufacturing, textile and handloom, engineering goods and light fabrication, pharmaceutical and health products manufacturing, IT enabled services and digital commerce. The thematic scope covers three technology areas: ERP systems (cloud ERP, SAP, Oracle, and native Indian ERP solutions); industrial automation (process automation, robotic process automation, and IoT-based monitoring); and machine learning applications (predictive analytics and demand forecasting algorithms and quality control). Operational efficiency, supply chain performance, quality of decision-making, productivity of workers and enterprise sustainability orientation are outcomes of interest.

Large-scale integrated manufacturing complexes (turnover > ₹500 crore) are not included in the study as they have different dynamics of technology adoption and pure-play software or IT companies are excluded because ERP or ML adoption are not production-facing innovations but internal tools for their use.

4. Conceptual Model: Rural Digital Technology Adoption Model (RDTAM)

The current study is under the theoretical background of Rural Digital Technology Adoption Model (RDTAM). The RDTAM is based on a combination of Technology Acceptance Model (Davis, 1989), Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and Dynamic Capabilities Framework (Teece et al., 1997) and suggests that technology adoption in rural industrial settings is a three stage transformation process:

Stage 1- Adoption Antecedents: Infrastructure availability, perceived technology usefulness, managerial digital orientation, policy incentive availability and peer-enterprise adoption visibility are the enablers for ERP, automation, and ML adoption in rural industrial settings.

Stage 2- Technology Integration Mechanisms: Enterprise digital capability (workforce IT literacy, data governance maturity, system integration depth) exists between stage 1 and the technology integration of its production, supply chain, finance or customer management functions.

Stage 3- Sustainable Business Outcomes: Integrated technology deployment results in tangible improvements in operational efficiency, supply chain coordination, decision quality, workforce productivity, and enterprise sustainability - the ability to sustain competitiveness, efficiency and inclusivity in the economy aligned with the vision of Viksit Bharat 2047.

Financial constraint intensity and regulatory environment quality are moderating constructs that affect the level of conversion efficiency of the adoption antecedents to the integration outcomes. Control variables in the structural model include industry vertical and enterprise size.

5. Research Objectives

- To explore the current penetration levels of ERP, automation, and ML technologies across Odisha's rural and semi-urban industrial clusters.
- To examine the impact of ERP adoption on supply chain coordination and operational efficiency in the surveyed industrial enterprises.
- To assess the effect of industrial automation on workforce productivity and operational cost reduction.
- To evaluate the contribution of ML-based predictive analytics to strategic decision-making quality in rural manufacturing and agribusiness contexts.

6. Research Hypotheses

H1: ERP adoption intensity is positively and significantly associated with supply chain coordination performance in Odisha's rural industrial enterprises.
H2: Industrial automation adoption is positively associated with workforce productivity and operational cost efficiency.
H3: Machine learning application breadth is positively associated with strategic decision-making quality and predictive capability.
H4: Enterprise digital capability significantly mediates the relationship between technology adoption intensity and sustainable business outcomes.
H5: Financial constraint intensity negatively moderates the positive relationship between technology adoption and productivity outcomes.
H6: Combined ERP, automation, and ML adoption is positively associated with enterprise sustainability orientation and long-term competitive viability.
H7: Alignment of enterprise technology adoption strategies with Viksit Bharat 2047 rural innovation policy targets enhances sustainable business model development outcomes.

7. Sampling Design

A stratified proportional random sampling technique was employed across five industry verticals and five geographic districts, ensuring representativeness along both dimensions simultaneously. The sampling frame comprised all registered industrial units in the five target districts with annual turnover between ₹10 lakh and ₹500 crore and documented adoption of at least one digital technology tool. Four organizational strata were defined: enterprise owners and top management (n = 58), middle management and functional heads (n = 87), technical/IT supervisors and system users (n = 102), and skilled production workers with operational technology exposure (n = 65), yielding a target sample of N = 312.

The minimum sample requirement was determined using Cochran's (1977) formula at a 95% confidence level and ±5% margin of error, generating a minimum threshold of 246. The study oversampled by 26.8% to manage anticipated attrition. Final usable responses numbered 284 after removing 28 incomplete instruments, yielding an effective response rate of 91.0%. Sub-sector distribution was as follows: agro-processing (n = 62), textiles and handloom (n = 54), engineering goods (n = 68), pharmaceutical manufacturing (n = 58), and IT-enabled services (n = 42). Female enterprise representatives and workers constituted 34.2% of the sample, reflecting the higher feminization of agro-processing and textile enterprises.

Table 1: Sample Distribution by Industry Vertical and Respondent Category

Industry Vertical	Top Mgmt.	Mid. Mgmt.	Tech/IT Staff	Prod. Workers	Total
Agro-Processing & Food	13	19	18	12	62
Textiles & Handloom	11	16	16	11	54
Engineering Goods	14	22	21	11	68
Pharmaceutical Mfg.	12	18	18	10	58
IT-Enabled Services	8	12	13	9	42

Total (N = 284 usable)	58	87	86	53	284

8. Data Collection

Structured questionnaires were used to gather primary data from January to May 2024. There were a total of 58 items in the instrument which were spread across nine thematic scales: ERP adoption intensity (8 items), automation adoption breadth (7 items), ML application depth (7 items), enterprise digital capability (8 items), supply chain coordination (6 items), operational cost efficiency (5 items), decision-making quality (6 items), enterprise sustainability orientation (6 items), and financial constraint intensity (5 items- moderator scale). A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to measure all items.

The instrument development process involved four stages: the first was the generation of the items from the technology adoption, ERP, automation, and ML literature; the second was the validation of the instrument by the expert panel comprising seven experts (four academic researchers and three industry digitization consultants) who evaluated the items for relevance, representativeness, and domain coverage; the third was pilot testing with 38 respondents from non-sample enterprises in Bhubaneswar, and the fourth was the refinement of nine items for better understanding and contextual fit (Cronbach's alpha range: 0.80–0.93 across scales). A questionnaire was translated into Odia for the production worker respondents according to the back-translation method as outlined by Brislin (1970) and the accuracy of the Odia translation was checked by two bilingual reviewers.

Data were gathered in three different modes – (i) self-administered online questionnaires with managerial respondents who were digitally literate, (ii) structured telephone interviews with middle management respondents who were not digitally literate, and (iii) interviewer-administered paper questionnaires with production workers. The high effective response rate (91.0%) was achieved by using two follow-up rounds at 3-week intervals. For contextual triangulation, objective secondary sources like MSME Ministry data portals, Annual Survey of Industries reports at state level and District Industrial Centre records have been used.

9. Research Methodology

The study is based on the positivist epistemology, with a cross-sectional explanatory quantitative design. Descriptive and reliability analysis, correlation analysis, and hierarchical regression analysis were performed in IBM SPSS Statistics 27.0, while confirmatory factor analysis (CFA) and structural equation modeling (SEM) were performed in AMOS 26.0. The analytical framework included 4 stages of sequential analysis:

Stage 1: Data preparation: screening for missing values (listwise deletion for < 2% missing; scale mean imputation for isolated missing values); common method variance (Harman's single factor test); outlier detection (Mahalanobis distance, d^2, $p < 0.001$); and normality assessment (skewness, $|sk| < 3$; kurtosis, $|ku| < 10$).

Stage 2: Measurement Model (CFA): Convergent validity was assessed using Average Variance Extracted (AVE ≥ 0.50) and composite reliability (CR ≥ 0.70). Using the Fornell-Larcker (1981) criterion and Heterotrait- Monotrait (HTMT) ratios (with a conservative cut-off of 0.85 as suggested by Henseler et al., 2015), the discriminant validity was confirmed. Model fit was conducted following Hu and Bentler's (1999) suggestion of using two indices.

Stage 3: Structural Model (SEM)- Seven hypothesized paths were simultaneously estimated. Fit indices reported: χ^2/df (≤ 3.0), CFI (≥ 0.95), TLI (≥ 0.90), RMSEA (≤ 0.08), and SRMR (≤ 0.08). Path coefficients, standard errors, and t-values were given for all hypothesized relationships.

Hayes (2018) PROCESS macro (Model 4, 95% bias-corrected confidence intervals, 5,000 bootstrap resamples) was used to test mediation. Moderation was explored with hierarchical regression with mean centered interactions (Aiken and West, 1991). The results of Harman's single factor test showed that the maximum single factor accounted for 24.3% of the total variance, which is below the 50% cut-off point, suggesting that common method bias should not affect the results.

10. Analysis and Interpretation

10.1. Respondent Profile and Descriptive Statistics-

The 284 usable responses comprised 65.8% male and 34.2% female respondents. Age distribution: 18.7% aged 25 to 34 (mainly IT enabled services and tech staff); 46.1% aged 35 to 49 (core management and supervisory strata); and 35.2% aged 50 and over (mainly enterprise owners and senior managers). Qualification level: 38.4% graduate degree; 29.6% postgraduate qualification; 32.0% diploma, vocational or secondary qualification. Enterprise size distribution: 41.2% micro (< ₹1 crore turnover), 34.5% small (₹1–10 crore), 24.3% medium (₹10–500 crore). The mean enterprise age was 14.7 years (SD = 8.4 years), indicating a well-established industrial base with a wealth of operational data but also the potential for legacy systems to be in use.

The highest mean score (4.02, SD = 0.61) was found in pharmaceutical manufacturing, whereas agro-processing had the lowest (2.87, SD = 1.08), with significant variation across the sectors, depending on the level of regulatory documentation requirements and degree of formalization in the supply chain. The breadth of automation adoption was greatest in engineering goods (3.94, SD = 0.73) and least in handloom textiles (2.41, SD = 0.96) where the artisanal nature of production and the cultural value of handloom work limited its adoption. The depth of ML application was also generally low across verticals (grand mean = 2.94, SD = 0.89), highlighting the early stage of adoption of ML in this industrial population.

Table 2: Construct-Level Descriptive Statistics and Reliability Indices

Construct	Items	Mean	SD	α	CR	AVE
ERP Adoption Intensity	8	3.41	0.84	0.893	0.907	0.579
Automation Adoption Breadth	7	3.19	0.91	0.878	0.892	0.562
ML Application Depth	7	2.94	0.89	0.871	0.886	0.549
Enterprise Digital Capability	8	3.08	0.93	0.904	0.917	0.583
Supply Chain Coordination	6	3.52	0.78	0.869	0.884	0.558
Operational Cost Efficiency	5	3.44	0.81	0.856	0.874	0.581
Decision-Making Quality	6	3.29	0.86	0.877	0.891	0.567
Enterprise Sustainability Orient.	6	3.17	0.88	0.882	0.896	0.572
Financial Constraint Intensity	5	3.63	0.79	0.847	0.865	0.562

Note. α = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted. All values are above minimum thresholds (Hair et al., 2019).

10.2 Measurement Model Fit-

CFA of the nine-construct measurement model yielded acceptable fit statistics: $\chi^2(df = 692) = 1{,}624.8$, $\chi^2/df = 2.35$, CFI = 0.964, TLI = 0.957, RMSEA = 0.069 (90% CI: 0.060–0.078), SRMR = 0.055. All the standardized factor loadings ranged from 0.70 to 0.88. AVE values were between 0.549 and 0.583 showing convergent validity. The HTMT values for all constructs were below 0.85, and the discriminant validity was obtained for all the construct pairings according to Fornell-Larcker criterion. The highest inter-construct correlation was ERP Adoption Intensity and Enterprise Digital Capability ($r = 0.63$) which did not pose a threat to discriminant validity under either criterion.

10.3 Structural Model and Hypothesis Results-

The structural model demonstrated satisfactory fit: $\chi^2/df = 2.54$, CFI = 0.958, TLI = 0.950, RMSEA = 0.074 (90% CI: 0.065–0.083), SRMR = 0.061. The model accounted for 51.8% of the variance in enterprise sustainability orientation ($R^2 = 0.518$) and 47.4% of the variance in the quality of decision-making ($R^2 = 0.474$). Complete results of hypothesis testing are shown in Table 3.

Table 3: Structural Path Coefficients and Hypothesis Testing Summary

Hyp.	Path Relationship	β	SE	t-value	p-value	Result
H1	ERP Adoption → Supply Chain Coordination	0.423	0.072	5.875	< 0.001	Supported
H2	Automation → Workforce Productivity/Cost Eff.	0.398	0.069	5.768	< 0.001	Supported
H3	ML Application → Decision-Making Quality	0.374	0.074	5.054	< 0.001	Supported
H4	Digital Capability → Sustainability (Mediation)	0.287	0.066	4.348	< 0.001	Supported
H5	Financial Constraint (mod.) × ERP → Productivity	-0.218	0.063	-3.460	< 0.01	Supported
H6	Tech. Adoption → Enterprise Sustainability	0.356	0.071	5.014	< 0.001	Supported
H7	Policy Alignment → Sustainable Biz Model Dev.	0.311	0.068	4.574	< 0.001	Supported

Table 4: Mediation Analysis- Enterprise Digital Capability as Mediator

Effect Component	β Estimate	SE	BCCI 95% Lower	BCCI 95% Upper	Inference
Direct: Tech. Adoption → Sustainability	0.214	0.057	0.103	0.325	p < 0.001
Indirect: via Digital Capability	0.142	0.031	0.083	0.205	p < 0.001
Total Effect	0.356	0.071	0.217	0.495	p < 0.001
Mediation Type	—	—	Partial Mediation	—	Confirmed

Note. BCCI = Bias-Corrected Confidence Interval; 5,000 bootstrap iterations (Hayes, 2018).

11. Results and Discussion

The comprehensive support offered by all seven hypotheses in a well-fitting structural model of the framework forms a strong empirical validation of the RDTAM framework. The direct impact of H1 was the highest (0.423, $p < 0.001$) which revealed ERP adoption as the most important factor for coordination in the supply chain in the industrial clusters of Odisha. The qualitative follow-up interviews conducted with 12 enterprise owners indicated that there were three main coordination mechanisms – real-time inventory visibility in multi-location operations, automatic supplier order generation based on pre-set reorder thresholds, and centralized dispatch documentation which, on average, reduced shipment errors by 31% as reported by the enterprise owners. The results are comparable with Kumar et al., (2019) and an extension of their results for smaller rural companies.

The results for H2 support ($\beta = 0.398$, $p < 0.001$) confirm the productivity and cost efficiency benefits of automation. The greatest productivity gains were for process automation (mean increase 18.7% in engineering goods and pharmaceutical sub-sectors) and IoT based quality monitoring (mean decrease 14.2% defect rates in pharmaceutical manufacturing). As far as the benefits of robotic process automation are concerned, the use of RPA was found to be more beneficial in large enterprises that had formal administrative processes, whereas the same was not observed in micro-enterprises, which is consistent with the findings of Luthra and Mangla (2018) that document the scale dependency of automation returns.

The results of the H3 ($\beta = 0.374$, $p < 0.001$) indicate that the level of ML application is an important factor in improving the quality of decision-making in the aspects of demand forecasting, inventory management and predictive maintenance scheduling. The agro-processing sector experienced the highest perceived positive change in decision quality as a result of the use of ML, suggesting that accurate demand forecasting can be crucial when production is seasonal. This is in accordance with Jain et al. (2022), who have analyzed the same in a detailed rural multi-sector scenario, and highlights the importance of digitization of value chains in the agricultural sector as an integral component of Viksit Bharat 2047.

The mediation analysis (H4) showed that enterprise digital capability partially mediates the technology adoption–sustainability relationship (indirect effect = 0.142, 95% BCCI: 0.083–0.205). The direct effect of technology adoption after mediation ($\beta = 0.214$, $p < 0.001$) suggests that there is some sustainability impact due to technology adoption that is not related to capability development, possibly because of the structural change of the process. The mediated pathway is also important, however, with a 66% greater sustainability return on technology investment when capability is developed as compared to when technology is adopted without capability development. This calculation, (0.356 – 0.214) / 0.214, can be directly translated for the design of government digitisation funding.

The significant negative moderation effect of financial constraint intensity (H5: $\beta = -0.218$, $p < 0.01$) confirms the productivity attenuating effect of ERP and ERP related technology adoption in the presence of financial constraint. Simple slopes analysis revealed that the technology–productivity relationship was quite strong for enterprises with low financial constraint ($\beta = 0.549$, $p < 0.001$) but significantly reduced yet still positive for enterprises with high financial constraint ($\beta = 0.198$, $p < 0.05$). This finding implies that technology adoption programmes should be tied to financial support measures and that it should not be assumed that technology investment will result in returns that will cover the cost of technology adoption capital.

H6 ($\beta = 0.356$, $p < 0.001$) and H7 ($\beta = 0.311$, $p < 0.001$) together support the notion that technology adoption leads to enterprise sustainability orientation and the impact of technology adoption is strengthened if it is in line with national policy frameworks. The scores for enterprises that explicitly mentioned Viksit Bharat 2047 targets in their digitisation roadmap were significantly higher for enterprise sustainability orientation (mean = 3.74 vs. 2.94 for enterprises that did not mention the policy, $p<0.001$) indicating the need for policy-practice coherence in translating technology investment to sustainable industrial outcomes.

12. Implications and Recommendations

12.1 Managerial Implications

It is recommended that enterprise owners and managers in rural and semi-urban industrial clusters of Odisha should focus on ERP as a basic technology investment as it has been proven to provide benefits in coordinating the supply chain and it is an enabler to downstream automation and integration of ML. To mitigate investment risk and to gradually develop organisational capabilities, a phased adoption roadmap is recommended, which starts with cloud ERP implementation, then process automation and finally ML analytics deployment. Based on the analysis results that showed the difference in benefits by enterprise size, the automation–productivity relationship presented in H2 suggests that targeted investment in process automation should be made before RPA.

The mediation finding (H4) has a crucial managerial implication: Only 60% of the sustainability return can be realized with technology investment without parallel workforce digital capability development. Digital literacy programs for production workers and supervisory staff should be part and parcel of any technology adoption project, rather than as an add-on training activity. Since there is significant negative moderation by financial constraints (H5), companies with capital constraints should look for technology adoption in consortium or shared-infrastructure models through the District Industry Association and the sector specific cluster development programs.

12.2 Policy Implications

The rate of ERP adoption, the level of automation penetration and the depth of ML applications should be made explicit indicators of MSME performance in national and state policy frameworks, which can then be monitored and used to guide the improvement of the program. The documented negative moderation by financial constraints strongly suggests that credit accessibility in the Pradhan Mantri MUDRA Yojana (PMMY) scheme should be enhanced for technology-specific investments with documented milestones towards digitization, and with concessional interest rates. The National Skill Development Corporation (NSDC) should create Industry 4.0 digital skills courses tailored to the needs of rural MSME owners and workers, instead of using courses that have been created for urban employees in the IT sector.

Technology adoption incentives (capital subsidy, reimbursement of ERP licensing, and infrastructure grant for technology) should be included explicitly in the Odisha Industrial Policy Resolution and Odisha MSME Development Policy and should be available only on a cluster-level basis, where network effects, as in Singh et al. (2019), have been observed. The creation of a Rural Digital Enterprise Index to monitor the five dimensions of technology-adoption and capability, as identified and validated in the RDTAM framework, and which are common elements of state industrial performance dashboards, would be beneficial in the policy coordination for Viksit Bharat 2047.

12.3 Academic Implications

The RDTAM model validated in this study offers a theoretically informed and empirically tested model for the future research on adoption of digital technology in rural industrial context. Scientists need to replicate the model for other Indian states that have similar MSME ecosystems- the comparison cases of Jharkhand, Chhattisgarh and Madhya Pradesh are particularly instructive- and for other developing economies in a process of rural industrialization. There is a great need for longitudinal panel designs that follow the same enterprises through the various stages of technology adoption to support causal inference. Multi-source data designs that combine objective production records, ERP system log data and financial performance data with perceptual survey instruments would overcome the weaknesses associated with cross-sectional self-report designs.

13. Conclusion

This empirical study has revealed through rigorous structural equation modeling and the validation of the Rural Digital Technology Adoption Model that ERP systems, industrial automation and machine learning adoption all independently and collectively help in the supply chain performance, operational efficiency, decision quality and enterprise sustainability in rural and semi-urban industrial clusters of Odisha. The study's main result, namely that technology adoption intensity has a positive impact on enterprise sustainability orientation, offers strong empirical evidence for the policy investments the Indian government is making in industrial digitization as a means for inclusive and sustainable economic growth.

The mediating effect of enterprise digital capability and the negative moderating effect of financial constraints suggest that more complex policy packages than technology diffusion programs are needed for sustainable rural industrialization: investment in digital infrastructure, human capability, and financial accessibility must all occur at the same time. It is the organizations and policymakers who understand these interdependencies and who plan on integrated interventions who will be best placed to make the ambitious vision of Viksit Bharat 2047 into tangible industrial reality in rural areas.

In the midst of India's rapidly evolving technological landscape, the challenges of rural development, and the imperative for sustainability, one thing is evident from this study: ERP, automation, and machine learning are not the technologies of tomorrow's metropolitan future, but the tools for rural industrial transformation that can be deployed now, only if we will and if we have the institutional framework to do so in an inclusive way.

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