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RESEARCH ARTICLE

Reskilling for Smart Manufacturing: A Structural Equation Modelling Analysis of Digital Literacy, Training Infrastructure, and Learning Culture in India

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Abstract

As the manufacturing industry moves from traditional factories to smart factories in Industry 4.0, the workforce needs to practice reskilling and lifelong learning. This study examines the significance of reskilling in this change in terms of Digital Literacy, training resources and the learning culture. This research used a quantitative method and collected data from 285 (n) Indian manufacturing employees. The hypotheses were tested using Structural Equation Modelling (SEM). It demonstrates that Digital Literacy ($\beta = 0.38$, $p < 0.001$), training resources ($\beta = 0.44$, $p < 0.001$) and learning culture ($\beta = 0.33$, $p < 0.001$) of the organisation have a significant influence on reskilling. Also, reskilling effectiveness significantly positively affects Smart Manufacturing Environment performance ($\beta = 0.60$, $p < 0.001$). Mediation analysis reveals that reskilling effectiveness has a partial mediating effect on the impact of organisational factors on performance. This research reveals the importance of investing in systematic training infrastructure, digital literacy and learning cultures to increase the capability of the workforce and pursue operational efficiency in smart factories. This research adds to the body of literature by generating empirical insights in the Indian context and provides guidelines for managers and policymakers to develop reskilling plans to meet the demands of Industry 4.0.

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INTRODUCTION

The world is seeing a shift in manufacturing industries with the introduction of Industry 4.0 or the Fourth Industrial Revolution (4IR). This revolution involves the blending of emergent digital technologies like Artificial Intelligence (AI), Internet of Things (IoT), robotics, cloud computing and big data analytics with manufacturing processes. Smart factories use networks of cyber-physical systems to integrate monitoring, predictive maintenance, adaptive decision-making, and increased efficiency, unlike conventional manufacturing environments. This enables the efficient exchange of information between machines, processes and humans, thereby enhancing productivity and competitiveness.

These technological advancements, although providing numerous advantages, are also redefining conventional professions and skills in manufacturing. Manual skills and repetitive jobs are being replaced by automation, resulting in a decline in traditional skills. This results in a growing need for a workforce with blended skills that encompass technical know-how, digital fluency, creativity and flexibility. This underscores the need for workforce changes to enable effective workforce-technology interactions. In developing countries like India, the shift towards smart manufacturing adds to the complexity. While technology uptake is growing, there is a marked upskilling gap. There is a lack of digital skills and exposure among the workforce to thrive in a tech-enabled environment. Lack of formal training opportunities, weak industry-academia partnerships and inequalities in skills development programs also contribute to this gap. Consequently, companies need to link technology investments with targeted workforce initiatives to harness the potential of Industry 4.0. Thus, reskilling and lifelong learning play a pivotal role in sustainable industrial innovation. Reskilling is about teaching workers new skills needed for changing job profiles, while lifelong learning is about helping them build skills throughout their working life. Both strategies address workforce flexibility and employability and foster innovation within a changing manufacturing environment.

This Study Aims to:

- Analyse the impact of digital literacy, investment in training, and a learning culture on reskilling effectiveness.
- Understand the effect of reskilling effectiveness on Smart Manufacturing Environment performance.
- Investigate the mediating role of reskilling effectiveness between organizational/individual factors and performance.

Need for the Study

The advent of Industry 4.0 technologies has transformed the manufacturing sector, resulting in the need for reskilling. One of the challenges resulting from this transition is the skills gap. Current reports indicate a massive skill gap in India, with a report estimating the need for 103 million skilled workers and currently only having 74 million skilled workers. Moreover, employability is a significant issue, with only around 42.6% of graduates deemed employable in 2024 because of a lack of both technical and soft skills. For advanced manufacturing, the issue is further exacerbated by the need for hybrid skills for Industry 4.0, which requires a mix of digital and technical skills. Research points to a 60-73% shortfall between supply and demand in emerging positions such as data analytics, AI and automation. This is compounded by a lack of vocational training, with only 4.7% of the workforce in India receiving formal training, far less than developed countries. Furthermore, nearly 71% of manufacturing firms say current training programs do not align to industry needs, highlighting shortcomings in policies with respect to skills requirements. This limitation impacts the successful integration of new technologies: less than 35% of firms are at advanced stages of digital transformation. And the pace of technological evolution is increasing, with almost 40% of job-relevant skills set to change by 2026, while the majority of employers cite skill shortages as a growth impediment. Such changing dynamics suggest that reskilling is no longer a choice but a necessity to stay competitive and provide an agile workforce in smart manufacturing environments. While there is a severe skills deficit, little empirical research has been done on the role of reskilling in enhancing the Smart

Manufacturing Environment in developing economies like India. So, this study is significant to address this gap by providing a systematic and empirical study of the impact of reskilling on industrial development.

Scope of the Study

This study examines the impact of reskilling in facilitating the shift of manufacturing to smart factories under Industry 4.0. It seeks to explore the influence of factors such as Digital Literacy, training opportunities and the learning culture on the effectiveness of reskilling and their impact on Smart Manufacturing Environment performance. This study is confined to India, offering insights into reskilling challenges in an emerging economy where industrialisation is rapid, and there are significant skill gaps. It focuses on employees of large manufacturing industries such as automotive, electronics and heavy engineering industries, which are technology-intensive. A quantitative approach is used in this study with Structural Equation Modelling (SEM) to study the relationship between variables and direct and indirect effects. The inclusion of individual skills and workforce support mechanisms in an integrated model provides insights into how reskilling contributes to improving efficiency, productivity and other operational and performance metrics in smart factories. Overall, the study is both analytical and applied and has implications for industry practitioners, policymakers and researchers in designing reskilling programs for the workforce of Industry 4.0.

LITERATURE REVIEW

Workforce Reskilling and Transformation in Industry 4.0

Recent research underlines the fact that Industry 4.0 has broadened the focus from skills specific to jobs to multi-skills that include technical, digital and cognitive skills. Studies show reskilling initiatives improve employee and company performance. However, these reports are theoretical or lack empirical evidence, particularly in developing countries. Moreover, although reskilling is advocated as critical, little research has explored how reskilling leads to specific performance improvements in smart factories. Although there is broad agreement that reskilling has become essential in Industry 4.0 environments, previous studies report differing outcomes regarding its effectiveness. Several researchers argue that reskilling initiatives improve employee adaptability, innovation capability, and organisational performance by equipping workers with digital and cognitive competencies. Conversely, other studies indicate that reskilling programs frequently fail to produce the expected outcomes due to inadequate training design, resistance to change, insufficient managerial support, and limited employee engagement. Furthermore, while studies conducted in developed economies report strong positive associations between reskilling initiatives and organisational competitiveness, empirical evidence from emerging economies remains limited and often inconsistent due to differences in technological readiness and institutional support systems. These contrasting findings indicate the need for further empirical investigation into the mechanisms through which reskilling contributes to smart manufacturing performance.

Training Infrastructure and Organisational Support

Training infrastructure has been recognised as a key facilitator of reskilling. Research shows that firms with well-developed training infrastructure, including simulation and online training, perform better. Although numerous studies report that organisations with advanced training infrastructure experience superior workforce performance and higher technology adoption rates, other studies present contradictory evidence. Some researchers argue that investments in digital learning platforms and simulation-based training do not automatically improve employee competencies unless the training content is aligned with organisational objectives and emerging skill requirements. Studies in several emerging economies reveal that many training initiatives fail because they are implemented as short-term interventions without continuous learning mechanisms and managerial support. Therefore, training infrastructure should be viewed not merely as a technological investment but as an integrated organisational capability that facilitates continuous learning and workforce transformation.

Organisational Learning Culture

A learning organisation refers to an environment where knowledge is shared, innovation is encouraged, and employees are developed. Evidence indicates that firms with a strong learning culture are more effective in undergoing technological change. But there is a lack of empirical research on the direct influence of learning culture on reskilling programs. Additionally, the interplay between learning culture and individual skills in influencing Reskilling Effectiveness needs further investigation. Prior studies generally suggest that organisations characterised by strong learning cultures exhibit greater adaptability and innovation during technological transitions. However, empirical findings remain inconclusive. Some studies indicate that learning-oriented cultures significantly enhance employee participation in reskilling initiatives and improve organisational performance. In contrast, other studies argue that a supportive learning culture alone is insufficient to generate meaningful outcomes unless employees possess adequate digital competencies and access to structured training opportunities. These divergent findings suggest that organisational learning culture may operate in conjunction with other individual and organisational factors rather than functioning independently, thereby justifying the integrated framework proposed in this study.

Smart Manufacturing Environment Performance and Skill Integration

The integration of human and technology skills is becoming a key factor in Smart Manufacturing Environment performance. Technological investments are critical, but recent research shows that workforce readiness plays a crucial role in operational performance. But there is a gap in empirical studies explicitly linking reskilling effectiveness to performance using sophisticated statistical methods like Structural Equation Modelling.

Recent Empirical Evidence from India and Emerging Economies

Recent empirical studies from India and other emerging economies have highlighted the growing importance of workforce reskilling in facilitating Industry 4.0 adoption. According to the World Economic Forum (2023), nearly 44% of workers' core skills are expected to change within the next five years, making continuous learning and reskilling essential for organisational sustainability. In India, the India Skills Report (2025) revealed that although digital transformation initiatives are accelerating across manufacturing sectors, significant gaps remain in employees' competencies related to automation, data analytics, artificial intelligence, and smart manufacturing systems.

Empirical evidence from Indian manufacturing organisations indicates that digital literacy significantly influences employees' ability to adapt to new technologies and participate effectively in technology-enabled work environments. NASSCOM (2024) reported that organisations investing in structured digital learning programs demonstrated higher employee productivity, innovation capability, and technology adoption rates compared to firms with limited reskilling initiatives. Similarly, a study conducted among manufacturing employees in India found that training infrastructure and organisational support significantly improved workforce readiness for Industry 4.0 implementation.

Evidence from other emerging economies further supports these findings. Research conducted in Malaysia, Indonesia, and Brazil demonstrates that organisations with strong learning cultures and continuous training systems achieve better employee adaptability and operational performance during digital transformation. However, these studies also indicate that technological investments alone do not guarantee successful implementation unless accompanied by effective workforce development strategies. Employees lacking digital competencies often struggle to utilise advanced technologies despite the availability of sophisticated manufacturing systems.

Although previous studies acknowledge the importance of Digital Literacy, training infrastructure, and learning culture, limited empirical research has examined their combined influence on reskilling effectiveness and Smart Manufacturing Environment performance within a unified framework. Furthermore, evidence from the Indian manufacturing

context remains relatively scarce, creating a need for comprehensive empirical investigations that explain how organisational and individual factors contribute to workforce transformation in Industry 4.0 environments.

The review of previous studies reveals considerable variation in findings concerning the effectiveness of reskilling initiatives, training infrastructure, and organisational learning mechanisms across different industrial and national contexts. The inconsistencies in empirical evidence indicate that the relationships among these variables are not yet fully understood, particularly in emerging economies such as India. Consequently, there is a need for a comprehensive empirical model that simultaneously examines these factors and explains their collective influence on reskilling effectiveness and Smart Manufacturing Environment performance.

The theoretical foundations of this study are rooted in Human Capital Theory, Technology Acceptance Model (TAM), and Organisational Learning Theory. Human Capital Theory explains how investments in employee education and training improve productivity and organisational competitiveness. TAM suggests that digital literacy influences employees' willingness to adopt emerging technologies and participate in reskilling initiatives. Organisational Learning Theory emphasises continuous learning, knowledge sharing, and adaptive capabilities that facilitate workforce transformation in technology-intensive environments. The integration of these perspectives provides a comprehensive explanation of reskilling effectiveness in smart manufacturing contexts.

Research Gap

Although more literature is being written on Industry 4.0 and employee change, gaps exist. To begin with, the literature is mostly descriptive and does not provide empirical evidence. Second, individual (digital literacy) and organisational factors (training support and learning culture) are not holistically implemented in a framework. Third, the possibility of Reskilling Effectiveness mediating the relationship between these factors and Smart Manufacturing Environment performance has not been analysed much, particularly in the Indian manufacturing industry.

Hypothesis

Our review of the literature and identified research gaps led to the following hypotheses: Digital literacy supports employee understanding and acceptance of new technology and thus enhances learning and reskilling.

H1: Digital Literacy has a significant positive impact on Reskilling Effectiveness.
H2: Training Infrastructure has a significant positive effect on Reskilling Effectiveness.
H3: Organisational Learning Culture has a significant positive effect on Reskilling Effectiveness.
H4: Reskilling Effectiveness significantly influences Smart Manufacturing Environment Performance.
H5: Reskilling Effectiveness is a mediator between Digital Literacy and Smart Manufacturing Environment Performance.
H6: Reskilling Effectiveness has a significant positive effect on Smart Manufacturing Environment Performance.
H7: Reskilling Effectiveness has a mediating effect on the impact of Organisational Learning Culture on Smart Manufacturing Environment Performance.

Conceptual Framework

The conceptual model of this study explains the relationship between the individual skills, organisational support mechanisms, reskilling effectiveness, and Smart Manufacturing Environment performance in the age of Industry 4.0. The framework is based on key constructs of Human Capital Theory, the Technology Acceptance Model (TAM) and organisational learning theory to come up with an empirical model. It implies that reskilling effectiveness, which has an influence on Smart Manufacturing Environment performance, is a precursor to digital literacy, training mechanisms, and organisational learning climate. Further, reskilling effectiveness is a mediating construct between individual and organisational factors and performance.

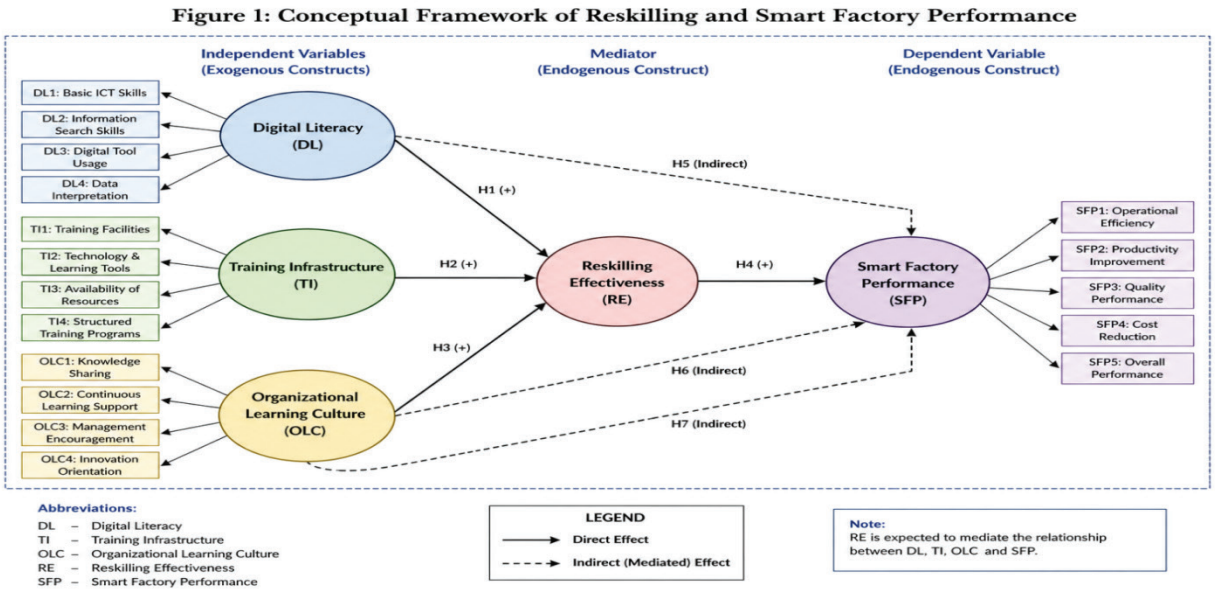


Figure 1. Conceptual framework of reskilling and smart factory performance.

Table 1. Respondent characteristics

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	196	68.8
	Female	89	31.2
Age	Below 30 years	82	28.8
	31–40 years	121	42.5
	Above 40 years	82	28.8
Industry Type	Automotive	110	38.6
	Electronics	95	33.3
	Heavy Engineering	80	28.1
Work Experience	Less than 5 years	87	30.5
	5–10 years	118	41.4
	More than 10 years	80	28.1
Job Position	Supervisory Level	115	40.4
	Middle Management	102	35.8
	Senior Management	68	23.8

RESEARCH METHODOLOGY

This paper is empirical and rigorous, as it aims to explore the role of reskilling in the transformation to smart factories in the manufacturing sector within the notion of Industry 4.0. The study employed a systematically developed and validated questionnaire instrument to ensure the reliability, content validity, and contextual appropriateness of the measurement scales used in assessing the proposed constructs.

Research Design

The research design used is descriptive and analytical. The descriptive part will be used to explain the status quo of Digital Literacy, reskilling and organisational learning in manufacturing. It investigates the perceptions and experiences of training and skills amongst the employees. The analytical aspect dwells on the interrelationships of the key variables that include digital competency, training and learning infrastructure, organisational learning, reskilling effectiveness and Smart Manufacturing Environment performance. The research is based on Structural Equation Modelling (SEM), which is used to test the direct and indirect relationships between latent

variables and provides a comprehensive perspective of the proposed model.

Sample Size: A sample of 285 individuals from a manufacturing industry (automotive, electronics and heavy engineering) is used. This sample size is deemed sufficient for SEM analysis, meeting the criteria for multivariate statistical methods and providing good statistical power.

Sampling Technique: The study employed a convenience sampling technique to collect data from employees working in manufacturing organisations undergoing digital transformation initiatives. Probability sampling was not feasible because obtaining comprehensive sampling frames and unrestricted organisational access was difficult due to confidentiality policies, operational schedules, and limited permissions for employee participation in surveys. Similar challenges have been reported in organisational and Industry 4.0 studies where researchers encounter practical constraints in accessing employees involved in technology-driven transformation initiatives. Convenience sampling was considered appropriate because it enabled the collection of primary data from respondents possessing direct experience with digital technologies, reskilling initiatives, and smart manufacturing practices.

Furthermore, the approach facilitated timely data collection across multiple manufacturing sectors, including automotive, electronics, and heavy engineering industries. To improve the representativeness of the sample, efforts were made to include respondents from different age groups, job positions, levels of work experience, and industrial sectors. Such diversification helped capture varying perceptions and experiences regarding reskilling effectiveness and Smart Manufacturing Environment performance. The final dataset comprised 285 valid responses, which satisfied the recommended sample size requirements for Structural Equation Modelling (SEM) and provided adequate statistical power for hypothesis testing. All participants were asked to voluntarily participate in the study and were given a brief description of the study.

Anonymity of responses and confidentiality of information were ensured, and the data were used only for research purposes. Exploratory factor analysis was used to perform Harman's Single Factor Test. The variance explained by the first factor was 32.45%, which is less than 50%, suggesting that there is no common method bias. Also, a full collinearity test (VIF) was conducted using Smart PLS. The results show that the VIF values are less than the suggested cut-off value of 3.3, which also indicates the absence of common method bias.

Data Analysis

The analysis was based on responses obtained from 285 manufacturing employees representing different age groups, organisational positions, and industry

Table 2. Descriptive statistics

Construct	Mean	Std. Deviation
DL	3.82	0.71
TI	3.95	0.68
OLC	3.88	0.73
RE	4.02	0.66
SFP	4.05	0.64

Table 3. Mean scores of study constructs

Construct	Mean
Digital Literacy (DL)	3.82
Training Infrastructure (TI)	3.95
Organisational Learning Culture (OLC)	3.88
Reskilling Effectiveness (RE)	4.02
Smart Manufacturing Environment Performance (SFP)	4.05

Table 4. Reliability analysis

Construct	Cronbach's Alpha
DL	0.86
TI	0.88
OLC	0.89
RE	0.91
SFP	0.90

Table 5. Factor loadings

Construct	Item	Factor Loading
DL	DL1	0.78
DL	DL2	0.82
DL	DL3	0.85
DL	DL4	0.80
TI	TI1	0.81
TI	TI2	0.84
TI	TI3	0.86
TI	TI4	0.83
OLC	OLC1	0.79
OLC	OLC2	0.85
OLC	OLC3	0.87
OLC	OLC4	0.82
RE	RE1	0.88
RE	RE2	0.90
RE	RE3	0.87
SFP	SFP1	0.86
SFP	SFP2	0.89
SFP	SFP3	0.88
SFP	SFP4	0.84

sectors, thereby ensuring adequate diversity in the sample characteristics. The analysis was done in SPSS for preliminary analyses and AMOS for Structural Equation Modelling and Confirmatory Factor Analysis, structural model testing and mediation.

All factor loadings are above the recommended threshold of 0.70, ensuring high reliability of indicators

Table 6. Model fit indices

Fit Index	Value	Recommended
CFI	0.93	> 0.90
TLI	0.92	> 0.90
RMSEA	0.06	< 0.08
χ^2/df	2.45	< 3

Table 7. Convergent validity

Construct	CR	AVE
DL	0.89	0.68
TI	0.91	0.72
OLC	0.90	0.70
RE	0.93	0.76
SFP	0.92	0.74

Figure 2. Measurement Model (Confirmatory Factor Analysis)

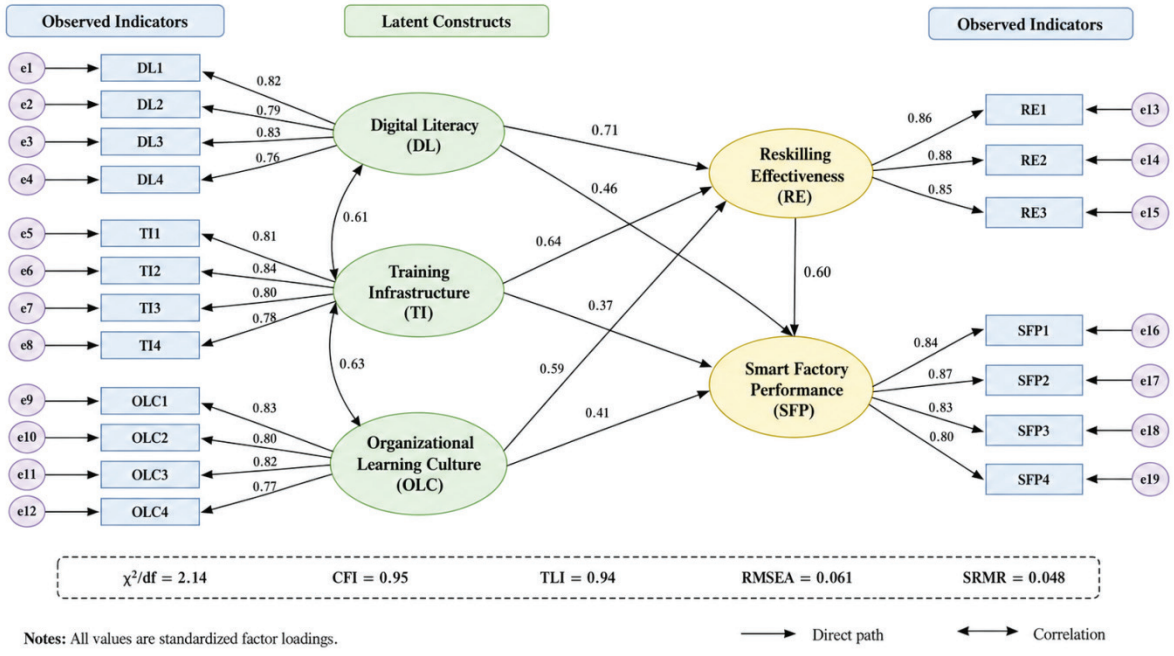


Figure 2. Measurement model (confirmatory factor analysis).

Table 8. Structural model results

Path	Standardized β	t-value	p-value	Result
DL → RE	0.38	5.21	0.000	Supported
TI → RE	0.44	6.02	0.000	Supported
OLC → RE	0.33	4.88	0.000	Supported
RE → SFP	0.60	7.10	0.000	Supported

Table 9. Coefficient of determination (R^2 values)

Endogenous Variable	R^2 Value
Reskilling Effectiveness (RE)	0.58
Smart Manufacturing Environment Performance (SFP)	0.62

Table 10. Mediation analysis (bootstrapping)

Relationship	Indirect Effect	p-value	Result
DL → RE → SFP	0.23	0.001	Partial Mediation
TI → RE → SFP	0.26	0.000	Partial Mediation
OLC → RE → SFP	0.20	0.002	Partial Mediation

and good representation of the latent constructs in the observed variables.

Confirmatory Factor Analysis (CFA)

The measurement model is well fit, suggesting that the observed variables are a good representation of their latent constructs.

FINDINGS

The results of the SEM provide strong empirical evidence for the conceptual model and yield useful theoretical and practical insights. To begin with, we have established a strong link between digital literacy and reskilling efficacy. This finding aligns with the Technology Acceptance Model, which says that people who have better skills in technology are more likely to effectively embrace new technologies. Highly digital-literate people are more likely to become agile learners, who will enjoy greater benefits of reskilling programs. This observation is a continuation of earlier studies such as Viswanath Venkatesh (2003) that emphasise the role of perceived ease of use and tech familiarity in enhancing the learning process. Second, the most important factor that led to successful reskilling was training infrastructure. This aligns with the Human Capital Theory, which indicates that investment in training in organisations positively influences their productivity and learning. Formal training programs, simulation and digital platforms enable employees to learn and acquire the required skills within a short period to boost reskilling initiatives. Third, firm culture of learning influences the outcomes of reskilling. Reskilling is supported by a culture of constant learning, knowledge spread and innovation. This finding promotes the concept of learning organisations that seek to encourage the process of continuous improvement and social learning to transform their workforce. Fourth, the effectiveness of reskilling has a positive impact on Smart Manufacturing Environment performance. It implies that investments in technology should be supported by the development of human capital to achieve outcomes. Reskilled workers contribute towards improvement of productivity, efficiency, and quality of smart factories. Finally, the mediation outcome suggests that reskilling effectiveness is a key mediator between individual abilities and organisational support systems and performance. It suggests that reskilling effectiveness is mediated by Digital Literacy, learning infrastructure, and learning culture. These findings illuminate the fact that reskilling is not only an operational practice, but also a critical element in enhancing performance within Industry 4.0.

The findings demonstrate that successful implementation of Industry 4.0 technologies depends not only on technological investments but also on workforce preparedness and organisational learning capabilities. Training infrastructure emerged as the most influential determinant of reskilling effectiveness, suggesting that organisations should prioritise investments in structured learning systems and digital learning platforms. Furthermore, the significant mediating role of reskilling effectiveness indicates that digital literacy and learning culture improve smart factory performance primarily through their ability to enhance workforce competencies. These findings reinforce the proposition that human capital development constitutes a strategic capability for

achieving sustainable competitive advantage in smart manufacturing environments.

DISCUSSION OF FINDINGS

The findings indicate that digital literacy has a significant positive effect on reskilling effectiveness ($\beta = 0.38$, $p < 0.001$). This suggests that employees possessing higher digital competencies are more capable of understanding and adapting to emerging technologies associated with Industry 4.0. Digital literacy enables employees to effectively participate in training programs, learn new technologies, and apply acquired knowledge in their work environment. This finding is consistent with the Technology Acceptance Model (TAM), which proposes that individuals with greater technological familiarity are more willing to adopt and use new technologies. The result also supports previous studies that identified digital competencies as a critical requirement for workforce transformation and smart manufacturing readiness.

The findings of the study provide strong empirical support for the proposed conceptual model and demonstrate that both individual and organisational factors significantly contribute to workforce reskilling in smart manufacturing environments. Training Infrastructure emerged as the strongest predictor of Reskilling Effectiveness ($\beta = 0.44$, $p < 0.001$), indicating that investments in digital learning platforms, simulation-based training, and structured skill development programmes substantially enhance employee readiness for Industry 4.0 technologies. Digital Literacy also exhibited a significant positive effect on Reskilling Effectiveness ($\beta = 0.38$, $p < 0.001$), suggesting that employees possessing higher levels of digital competence are better able to understand, adopt, and effectively utilise emerging technologies. Similarly, Organisational Learning Culture significantly influenced Reskilling Effectiveness ($\beta = 0.33$, $p < 0.001$), emphasising the importance of continuous learning, knowledge sharing, and collaborative work environments in facilitating successful workforce transformation.

Furthermore, Reskilling Effectiveness had a strong positive impact on Smart Factory Performance ($\beta = 0.60$, $p < 0.001$), indicating that organisations with effectively reskilled employees are more likely to achieve improvements in productivity, operational efficiency, and overall manufacturing performance. The coefficient of determination values further demonstrate the explanatory power of the proposed model, with Digital Literacy, Training Infrastructure, and Organisational Learning Culture jointly explaining 58% of the variance in Reskilling Effectiveness ($R^2 = 0.58$), while Reskilling Effectiveness explained 62% of the variance in Smart Factory Performance ($R^2 = 0.62$). Moreover, the mediation analysis revealed that Reskilling Effectiveness partially mediated the relationships between Digital Literacy (indirect effect = 0.23, $p = 0.001$), Training Infrastructure (indirect effect = 0.26, $p < 0.001$), Organisational Learning Culture (indirect effect = 0.20, $p = 0.002$), and Smart Factory Performance. These findings indicate that technological investments alone are insufficient for achieving superior manufacturing outcomes unless supported by systematic workforce development initiatives and continuous learning mechanisms. Overall, the results reinforce the propositions of Human Capital Theory, Technology Acceptance Model, and Organisational Learning Theory by demonstrating that strategic investments in employee capabilities constitute a critical determinant of sustainable competitive advantage in Industry 4.0 environments.

Recommendations

The following recommendations can be made based on the results:

For Manufacturing Organizations

- Set aside Training Budgets: Companies should budget 5-10% of yearly HR or operational expenses on employee reskilling and digital training programs.
- Provide Reskilling and Upskilling: Roll out quarterly reskilling programs on new technologies like AI, IoT, and automation.
- Set up Futuristic Training Centres: Set up simulation labs, virtual Organisational Learning Cultures

and real-time Smart Manufacturing Environment training modules.
- Enhance Digital Literacy: Implement Digital Literacy training and certification for all employees.
- Promote the Culture of Learning: Value knowledge sharing, cross-departmental cooperation and innovation efforts through rewards and endorsement.

For Policymakers

- Enhance Skill Building Programs: Customise national skill development initiatives to meet Industry 4.0 needs and new technologies.
- Promote Industry–Academia Collaboration: Encourage collaborations to develop skills curricula and training programs.
- Provide Financial Incentives: Provide subsidies or tax incentives for companies reskilling their workers.
- For Educational Institutions
- Integrate Industry 4.0 Curriculum: Offer classes on data analytics, AI, automation and IoT in technical and management degrees.
- Create Adaptive Learning Formats: Offer short-term and online certification courses for lifelong learning.
- Enhance Practical Exposure: Encourage internships, projects and partnerships with industry.

CONCLUSION

The current change towards smart factories of Industry 4.0 is a paradigm shift in manufacturing, as technological advancement must be coupled with human development. We find that Reskilling Effectiveness is a key indicator of Smart Manufacturing Environment performance, which supports the idea that human capital growth is important in maintaining industrial growth.

Theoretical Contribution

This study contributes to the literature as it bridges the gap between the Human Capital Theory, Technology Acceptance Model (TAM) and organisational learning theories. It develops the previous knowledge by testing the mediating role of reskilling effectiveness in mediating between digital literacy, Training Infrastructure and, learning culture and Smart Manufacturing Environment performance in an emerging economy.

Managerial Contribution

Practically, the research implies that companies should not focus on technology adoption but on reskilling. Digital Literacy programs and training platforms, as well as learning cultures, can result in increased efficiency and productivity. In shifting industrial environments, managers must focus on reskilling as a strategic activity, but not as a cost centre, to remain competitive. In conclusion, firms that match technology and human capital are more likely to achieve a sustainable competitive advantage in smart manufacturing. Not only is reskilling necessary, but it is at the core of business strategy.

Limitations of the Study

The present research provides valuable evidence of the usefulness of reskilling in facilitating the transition to smart factories, but there are drawbacks in the research. First, this research design is cross-sectional, and the data were collected at a single point in time. This constrains the research in its ability to identify shifts in employee competencies as well as company performance. Future research can be conducted using longitudinal designs to assist in comprehending causality and the long-term effects of reskilling programs. Second, the study adopted convenience sampling because of practical difficulties in obtaining comprehensive sampling frames and gaining unrestricted access to manufacturing employees involved in Industry 4.0 initiatives. Although efforts were made to include respondents from different manufacturing sectors, job positions, and experience levels, the possibility of sampling bias cannot be entirely ruled out. Consequently, the findings should be generalised with caution and primarily reflect the experiences of employees working in Indian manufacturing organisations undergoing digital transformation. Third, the study is restricted to India, which may restrict the externalisation of the results. Disparities in technological readiness, skills

related to the industry and institutional settings of the various countries can affect the extent to which the results can be generalised. Fourth, the research is premised on self-reported data collected through questionnaires. Although the validity of the data was given through statistical techniques, including Common Method Bias (CMB) testing, the possibility of a response bias and social desirability bias cannot be eliminated. Fifth, the measurement strategy of Likert scales is adopted in the study, which can be subject to measurement weakness, central tendency, acquiescence and personal interpretations of the responses given by the participants. This may affect the accuracy and precision of the responses and measurement. Finally, the research has only considered a limited number of variables, including digital literacy, Training Infrastructure and organisational learning culture. In the model, other factors are not put into consideration, including leadership, readiness to technology, readiness to organizational and engagement. Further, the research embraces a quantitative research design using Structural Equation Modelling, which might not fully capture the context and qualitative nature of reskilling practices.

Future Scope of the Study

Even though the current study is a valuable contribution to the comprehension of the role of reskilling in facilitating the creation of smart factories against the backdrop of Industry 4.0, there are future study opportunities.

To start with, this study is founded on cross-sectional data at a given moment. It is possible to conduct longitudinal research to examine the effect of reskilling programs on outcomes and performance in the long term. Such studies will assist us in better understanding the sustainability and long-term outcomes of reskilling programs in rapidly evolving manufacturing environments.

Second, the analysis is limited to a couple of manufacturing sectors in India. Further research studies can expand the geographical boundaries by conducting studies in various countries, particularly the developed and the developing ones, to emphasise the significance of the institutional, technological and cultural factors in defining the success of reskilling and the performance of smart factories.

Third, the present research examines a few constructs, among them being digital literacy, Training Infrastructure and learning culture. The variables that could be added to future research are management support, employees' interest, preparedness for technology (readiness) and flexibility and innovation within organisations to have a more comprehensive picture.

Fourth, new technologies such as Artificial Intelligence (AI), machine learning and digital twins are becoming more commonplace in organisations, so future research can explore the ways in which learning systems and adaptive learning platforms using AI can be used to facilitate reskilling efforts to a higher degree. These can boost the individualised learning process and effectiveness of skill acquisition.

Fifth, future studies can investigate industry-specific effects by examining particular areas within the economy (a car, a drug, electronics) where the nature of technology that the industry adopts and skills required may vary. This will be able to give more industry-specific results.

Lastly, future research may use mixed-method research methodologies that combine quantitative research methods like Structural Equation Modelling (SEM) with qualitative research methods like case studies and interviews to obtain a more in-depth perspective of reskilling programs and issues.

In general, future research may expand by adding more variables to the research design and by taking into account the new trends in the sphere of technology in order to understand workforce development in the smart manufacturing ecosystems better.

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