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Changing Skill Requirements in Industry 4.0: A Study on Reskilling, Upskilling, and Managerial Challenges in Manufacturing Firms

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Abstract: The significance of reskilling, upskilling, and having good managers during the digital transition is discussed in this study, which analyses the influence of Industry 4.0 technologies on the manufacturing companies' skill requirements. The authors assert that the introduction of data-based systems, robots, and AI into the manufacturing process has transformed the industry in such a way that there is now a high demand for workers who not only have technical, cognitive, and soft skills but also possess a mix of these qualities. Digital communication, data interpretation, and cross-functional cooperation are now indispensable skills for the industry. The authors point out that most of the firms still face difficulties like a lack of willingness to adapt, inadequately trained staff, and the absence of skilled managers. This is where the reskilling and upskilling initiatives come into play, as they not only help the organisations to cope with the changing demands but also increase the digital capabilities of their workforce. The research encompassed worker readiness assessments, technological adoption, training programs, and managerial issues as the key factors to be examined. The quantitative analysis included a total of thirty-one respondents from manufacturing units located in the NCR region. The long-term competitiveness of organisations through the implementation of Industry 4.0 practices requires a commitment to continuous learning, efficient training, and strong management support. The findings indicated that, while the relationships between the variables were significant, the strength was not extremely high.

Keywords: Digital Competency, Industry 4.0, Managerial Challenges, Reskilling & Upskilling, Workforce Readiness.

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1. Introduction

1.1 Background: Industry 4.0 and the Transformation of Manufacturing Work

Industry 4.0 (I4.0) is characterised by the widespread adoption of innovative digital technologies, such as Artificial Intelligence, the Internet of Things (IoT), robots, and big data analytics in the manufacturing industry sector, which is still at its core. This shift is altering the entire process of product development, manufacturing, and delivery in the global supply chain. At first, it was regarded merely as a competitive advantage, but over the years, it has become a worldwide tech revolution with the core impacting factors being the likes of productivity, quality, and operational resilience (Hermann, 2016). The manufacturing sector has undergone a drastic change from its once heavy reliance on manual labour and mechanical systems to a state where the entire production process is directed by digital intelligence.

The transition towards more automated and connected setups has brought about a significant transformation in the job structure in the manufacturing sector. The tasks that depended on labour are slowly moving towards machines, thus requiring the engagement of workers with the machine, real-time data interpretation, and making machine-human interactions seamless. This transformation has added new complexity to the daily operations of the company as the workers are now expected to use tools like sensors, digital dashboards, and predictive analytics in their regular decision-making process

(Frank *et al*., 2019). The production operations are so data-driven that the entire workforce must be skilled in technology and possess good reasoning skills.

Industry 4.0 has made a new definition of organisational roles by dissolving the limitations between conventional technical areas. For example, the machine operators have started to work very closely with IT systems, and on the other hand, the maintenance workers will have to have a good comprehension of the automated control systems and digital diagnostic tools. This sharing of abilities reflects the trend of industries towards the multidisciplinary approach, where, besides the mechanical knowledge, nothing is effective (Clot *et al*., 2020). All these advancements point to the fact that firms need to rethink their human resource strategies to enable the workforce to face digitally supported work environments.

At the top management level, the change brought about by Industry 4.0 calls for a change in the way leaders are to behave. The managers now have immense importance in leading the digital transformation processes, technology selection that supports the corporate objectives, and employee acceptance of changing sectoral flows. Consequently, these tasks are going to require great skills in change management, technology planning, and cross-functional coordination. Therefore, the digital transformation happening in the manufacturing segment is not just technical; it is a human and organisational progression.

1.2 Emerging Skill Requirements in the Era of Industry 4.0

The change in the technology applied in the manufacturing sector has resulted in the development of new skill requirements that can be categorised as hybrid skill sets. Indeed, the staff working in the smart factory area are expected to be learners of three different sorts: basic technical knowledge, high-level digital skills, and software. The demand for those technical skills like programming, automation control, data analytics, mechatronics, and system integration has climbed as machines have reached this level of communication among themselves and with the human operator (Santos *et al.,* 2021). Such workers are supposed to get the logic behind algorithmic processes, be able to communicate through digital interfaces, and diagnose faults in the integrated production lines.

Furthermore, digital and technical skills, along with cognitive skills, have been made the most important in modern manufacturing jobs. The robot adoption has not only made the production line faster but also brought about a need for workers with advanced cognitive abilities. The workers still need to monitor the interactions, detect the anomalies, and decide the appropriate intervention based on data interpretation, even though the machines perform the tasks. All these cognitive skills have become particularly important for the company to be able to adapt to market changes through quality and quantity, as well as for preventing production losses during digital failures (Miró-Pérez, 2020).

Soft skills have shifted from being support materials to being the mainstay of performance in environments 4.0. Besides, collaboration, communication, adaptability, and continuous learning are digital systems' mainstay traits, as sometimes they might need multi-functional coordination to work. For instance, a machine operator may need to talk to IT experts, automation engineers, and data analysts to solve a problem. The communication expects clarity, teamwork, and open-mindedness to the learning, especially when the technologies are changing at a fast pace. The ability to collaborate with diverse teams, therefore, emerges as a significant factor for the readiness of the workforce.

The Fourth Industrial Revolution has led to a gradual transition towards lifelong learning as a prerequisite for the skilled workforce. Owing to the rapid technological advancements, workers should keep upgrading their competencies to be of any use. The manufacturing sector, which has been the source of unchanging job roles for decades, is now subject to changes within years or even months. This scenario compels both the workers to go for learning and the employers to establish structured development opportunities that are in line with the changing job requirements (Liao *et al.,* 2017). Thus, the process of skill development during Industry 4.0 is not a one-off event but an ongoing necessity for organisational survival.

1.3 Importance of Reskilling and Upskilling in Manufacturing Firms

Reskilling and upskilling are a necessity in the manufacturing industry during the process of digital change. Reskilling is the process that refers to the training of workers for new jobs, especially when robots take over processing, and some positions become redundant. Upskilling, conversely, aims at the highest possible use of existing talent, and that is why employees are trained to cope with the more advanced tech versions of their current jobs. Both methods are regarded as necessary in the creation of a professional team that can control, serve, and optimise digital production systems (Li *et al*., 2022). The companies that invest in their human resources ahead of time have fewer problems with adopting modern technology, and their productivity also goes up.

A major factor that makes reskilling and upskilling indispensable is the growing disparity in skills. The performance level required by the worker in the new tech environment and the skills demanded for the same are constantly changing with the development of technology. Most of the older factory workers have good mechanical work experience but lack the knowledge of digital systems. In the absence of training, these workers are likely to find it difficult to cope with new workflows, which would be the scenario of job insecurity for them, lower productivity, and even the whole organisation resisting change. Training interventions are the way forward as they help the workers to cope better with the changes, and at the same time, the company´s technological investments yield better returns (Demeter & Losonci, 2020).

While tackling skills shortages, reskilling and upskilling also help to eliminate the absenteeism problem and lower turnover rates. Scientific studies indicate that career development opportunities make workers more motivated, flexible, and committed to the organisation in general. This is especially important in places where the digital changeover may cause employment fears. Teaching and training will make the employees feel that the company values them, and it is also promising to keep them with the company going forward (Roy Ghatak & Garza-Reyes, 2024). Consequently, organisations not only develop the technical aspect needed but also the psychological aspect for the transformation to take place.

Skill development programs are ways to ensure that the manufacturing firms keep on improving and innovating. Staff with customer service training in data reading, problem-solving, and digital systems will be in a much better position to produce and implement innovative ideas. They will be able to point out where things are not working as they should, suggest areas where the use of technology might be increased, and collaborate with people from technology to create the most efficient and productive ways of doing things. Therefore, it can be concluded that retraining and upskilling are not just measures to be taken after dealing with change; they are pre-emptive advantages in the race to stay ahead in the already digitised industrial world.

2. Significance of the Study

The study is of utmost importance because it indicates the most significant requirement of reskilling and upskilling in manufacturing firms, which are being transformed by Industry 4.0. Modern technologies such as automation, IoT, AI, and cyber-physical systems are altering the tasks that workers perform, and the research provides extremely helpful insights into the ways in which people can have a positive interaction with the skills change. The results will enable the organisations to discover the skill gaps that are in the way of successful digital integration and to produce measures to create a workforce that is ready for the future. The company and HR leaders will get a clear picture of the difficulties they will encounter in the process of conducting continuous learning initiatives, ranging from limited resources to refusal of change. The government can base policy decisions on the findings for the setting up of training schemes that would fulfil not only the industrial needs but also the national skill development programs. Moreover, the study opens a new avenue for research in the academic circle by furnishing evidence from a systematic literature review on workforce capability building in the context of Industry 4.0. The outcome is that it helps to foster the sustainable growth of organisations by indicating strategic reskilling and upskilling as drivers of productivity, competitiveness, and innovation adoption in the manufacturing industry.

3. Review of Literature

3.1 Changing Skill Requirements in Industry 4.0

The rise of Industry 4.0 (I4.0) has significantly changed the skill requirements of the modern manufacturing industry. Continuous research indicates that interconnected technologies such as cyber-physical systems, industrial IoT, robotics, and data-driven automation demand a workforce that is not only digitally proficient but also able to think and act quickly (Park, 2022). Workers need to be able to comprehend, communicate, and work with automated environments, which implies that routine manual tasks will be phased out in Favor of higher-order analytical responsibilities. According to a systematic review conducted by Ghobakhloo (2020), rapid technological disruption is the main factor behind the increased demand for hybrid skillsets that combine digital literacy, engineering knowledge, data interpretation, and cross-functional communication. The likes of Yao *et al.* (2019) observe a gradual disappearance of traditional operational roles, while at the same time, roles that require high tech, such as automation supervisors, data technicians, predictive maintenance analysts, and robotic coordinators, are becoming increasingly prevalent. The trend is indicative of a shift in that skills have no longer become job-specific but rather continuously changing and evolving.

This very aspect is presented by Hellau *et al.* (2016), who not only identified I4.0 skills but also grouped them into four clusters: technical, methodological, social, and personal, saying that the ideal I4.0 worker must be at the same time a technician, an analytical person, a collaborator, and a self-directed learner. The transition of skill demand in developing countries is, in fact, a much more pronounced phenomenon. As reported by Priyono *et al.* (2020), many industries in the so-called emerging markets are experiencing broader discrepancies in the workforce skills since the present-day employees have extraordinarily little familiarity with automation and data technologies. Consequently, the Fourth Industrial Revolution (I4.0) is not just a matter of new skills; it is a complete transformation of what industrial workers are like.

3.2 Technological, Cognitive, and Soft Skills: A Thematic Classification

One of the key themes that runs across the literature is the technological capability that serves as the basis of Industry 4.0 readiness. Oke & Fernandes (2020) reveal that skills like sensor handling, basic programming, system integration, data visualisation, and machine diagnostics are now must-have skills in the smart factories. The authors opine that without the most basic digital skills, the employees would be in the dark as far as the IoT-enabled machines are concerned, and hence, could not be effective communication partners. Likewise, Raj *et al.* (2024) found that digital skills, digital tool proficiency, data analytics, and robotics operations are the most significant predictors of employee adaptability in the technologically advanced manufacturing setups. These skills put workers in a position to work along with machines, to regularly check the smoothness of the automated workflows, and to keep the production lines working at their peak. I4.0 goes beyond digital literacy and requires the next level of cognitive ability; thinking, complex problem-solving, and decision-making are among the top future skills. Academic research unequivocally supports this: Acerbi *et al.* (2022) showed that cognitive flexibility is the key quality that enables workers to cope with the unpredictable nature of the automated production processes.

The need for workers who can be able to spot process inefficiencies, analyse production data in real-time, and make decisions on their own, is growing across industries. According to Argyle *et al.* (2021), analytical reasoning is a vital quality for the staff who will be looking after the digital systems and reacting to the system's abnormalities promptly. The studies have produced different conclusions when it comes to I4.0 technology readiness, one of the conclusions being that technical skills alone are not enough, but rather the opposite, and that the workers should also have good interpersonal capabilities. For example, Barile *et al* (2023) point out that collaboration, adaptability, communication, and creative thinking are major factors that enable cross-disciplinary work in smart manufacturing teams. Tvenge and Martinsen (2020) opine that the cooperation between humans and machines will require a new type of workforce that will be able to work on both technological systems and human co-workers at the same time. Thus, it can be concluded that the soft skills are the ones that go hand in hand with digital abilities and make the workforce more agile.

3.3 Reskilling and Upskilling: Strategies for Workforce Transformation

Systematic reviews have consistently pointed out that the need for reskilling and upskilling is not optional; it is a necessity of a strategic kind (Sousa & Rocha, 2019). Reskilling employees is necessary when automation changes certain job roles, but it is also a source of continuous improvement for employees. Kim (2022) pointed out that digital transformation readiness in organisations is influenced by quality skill development programs. These programs may consist of structured training, on-the-job learning, mentoring, and simulation-based training. Manufacturers who are adopting I4.0 are using different strategies to make their workers fit for the future. Gyulai *et al.* (2023) think that the companies are making an investment in digital learning platforms, competency-based training, micro-learning modules, and the hybrid skill-development model, which combines technical and soft-skill training.

In the same way, Simões *et al.* (2021) indicated that systematic upskilling initiatives resulted in higher productivity, decreased machine downtime, and improved human-machine interaction. The study indicated that upskilling is only efficient if it is coordinated with organisational transformation, technology adoption, and support from management. Reskilling has its essentiality, but there are still numerous hurdles to overcome. Financial limitations, lack of digital infrastructure, low employee motivation, and absence of structured training frameworks are identified by Borovkov *et al*. (2021) as the most significant barriers. A case study conducted by Passalacqua *et al*. (2025) on European manufacturing firms disclosed that employees are often reluctant to take digital training because of the fear of job loss or lack of confidence in using technology.

3.4 Managerial and Organisational Challenges

The managers play imperative roles in facilitating the transition from conventional manufacturing to Industry 4.0. Agostini and Filippini (2019) in their research found that one of the major challenges for managers is the skill mismatch of the employees with modern technology. The other aspects are resistance to change by the workers, the need for job roles to be redesigned, and the company to be ready for an innovative culture. Similarly, a systematic review conducted by Moeuf *et al.* (2020) pointed out that small and medium-sized enterprises (SMEs) are having trouble with digital transitions due to the absence of structured human resource (HR) strategies and formalised training mechanisms, as well as having untrained supervisors to monitor digital operations. Thus, the onus is on the managers to synchronise their technology investment with their human workforce being ready. Jamwal *et al.* (2021) opine that the main managerial concern is the human-machine interface creation that would be safe, transparent, and efficient simultaneously. The managers are challenged to produce new leadership styles characterised by empowerment, decentralised decision-making, and continuous learning.

3.5 Research Gap

The existing literature on Industry 4.0 technologies has not been able to prepare a clear picture of the transformations in the skill requirements of the manufacturing sector due to the lack of a good definition in this area. There is a tendency for most studies to highlight the aspect of technology adoption while overlooking the human factor and workforce-readiness aspects of successful implementation that are especially important. The research on proper training for the workforce is very fragmented and often focuses solely on technical skill development without considering the supportive managerial, organisational, and behavioural issues. Also, there are very few studies that have documented how managers deal with problems such as resistance to change, inadequate training facilities, and skills being at variance with the required digital competencies. Moreover, most of such studies are conducted in developed economies, thus creating a lack of understanding of the specific limitations that the manufacturing industry in developing countries faces. The issue is quite unclear for companies on how to manage technological change and workforce development as an intricately linked process. Hence, a thorough and context-specific inquiry is deemed necessary to fill the gaps and provide a comprehensive picture of the changing skill requirements and managerial challenges in the industry 4.0 environment.

4. Objectives of the Study

- To examine the effect of Industry 4.0 technology adoption on changing skill requirements in manufacturing firms.
- To analyse how reskilling and upskilling initiatives influence employees' digital competency levels.
- To assess the impact of managerial challenges on the successful implementation of skill-development programs.
- To evaluate the relationship between training effectiveness and workforce readiness for Industry 4.0.

5. Hypotheses of the Study

- **H1:** Industry 4.0 technology adoption has a positive impact on changing skill requirements in manufacturing firms.
- **H2:** Reskilling and upskilling initiatives significantly improve employees' digital competency levels.
- **H3:** Managerial challenges affect the successful implementation of skill-development programs.
- **H4:** Training effectiveness has a relationship with workforce readiness for Industry 4.0.

6. Methodology

The geographical coverage of the current research encompassed the leading industrial locations of the National Capital Region (NCR), specifically Gurgaon, Noida, Faridabad, and Ghaziabad. The NCR is known to be one of India's most vibrant industrial areas, where the principal sectors are automotive, electronics, metal, and machinery, and the manufacturing plants in the region are very aggressively changing their technologies. It is the right place to investigate the impact of Industry 4.0 technologies on operations, skills, and overall workforce capabilities. The variances in industrialisation and the different degrees of digitalisation together make NCR an excellent place for studying the very processes of reskilling, upskilling, and the managerial challenges linked to technological shifts.

The research subjects will be employees and managers aged 21 and above who are working in medium and large manufacturing companies across the NCR. This population includes production operators, technicians, supervisors, HR professionals, and line managers who have direct access to the digital tools, automation systems, and training programs. Their views on the changing nature of job roles and skill expectations will enable them to give pertinent input on the transition of the workforce into the Industry 4.0 environment. The technical knowledge, education, and experience of the selected respondents will be remarkably diverse and will thus yield a comprehensive understanding of the impact of digitalisation on skill development, workplace demands, and managers' responsibilities.

For the study, a total of 130 respondents will make up the sample. The size of the sample is not only very dependable but also represents different functional levels well, thus enabling the statistical interpretation of workforce trends and organisational practices. The mixed sampling technique is employed, whereby stratified, purposive, and convenience sampling are used in combination. Stratification secures representation of respondents from job roles like operators, engineers, and managers; purposive sampling is directed at people who have direct exposure to Industry 4.0 technologies or are in a training program; and convenience sampling is done to select participants who are available and willing to respond under the terms of the organisation's permission. This method of sampling guarantees the emergence of a mix of participants who are not only diverse and relevant but also significantly analytic.

The research is grounded in a quantitative explanatory design, which will be employed to point out the existence of the relationship between, among others, the adoption of Industry 4.0 technology, re-skilling and up-skilling practices, managerial challenges, training effectiveness, and workforce readiness. The primary method for gathering data is a structured questionnaire that includes a five-point Likert scale to assess respondents' opinions on changing skill requirements, digital competency, organisational support, and training outcomes. Utilising this method of standardised measurement not only assures the respondents' clarity, comparability, and consistency but also renders the data amenable to descriptive and inferential statistical analyses as well.

Microsoft Excel and the Statistical Package for the Social Sciences (SPSS) are used to handle and analyse the data. Whereas SPSS enables the execution of sophisticated statistical methods, Excel handles data cleansing, coding, preliminary tabulating, and visual presentation. Mean, frequency, and standard deviation are examples of descriptive statistics that are employed to portray the demographics and overall impressions of the respondents. To examine the associations between the variables and assess the study hypotheses, inferential statistical procedures such as t-tests, chi-square, ANOVA, regression, and correlation are utilised. Independent variables, such as the efficacy of training or the rate of technological adoption, influence dependent variables, such as workforce readiness or skill gaps; regression analysis helps to reveal this relationship. When comparing groups, ANOVA and t-tests are useful, whereas correlation shows the strength of the relationship.

7. Result

7.1 Result Based on Demographics

"Table 1: Descriptive Statistics"

	N	Minimum	Maximum	Mean	Std. Deviation
Age	130	1	4	2.59	1.153
Gender	130	1	2	1.45	.499
Education	130	1	4	2.48	1.115
Job Role	130	1	4	2.63	1.101
Years of Experience	130	1	4	2.62	1.088
Have you worked with Industry 4.0 technologies	130	1	2	1.52	.501

Valid N (listwise)	130				

The participants hail from a diverse array of demographic and professional backgrounds, as shown by the descriptive facts of the sample (N = 130). "Based on the classification scheme, most of the participants fall into the middle age categories, as indicated by the mean age category (M = 2.59, SD = 1.15). With a mean of 1.45 and a standard deviation of 0.49, the sample is evenly split between males and females. An equal number of respondents in each qualification category have varying degrees of schooling (M = 2.48, SD = 1.11)." Respondents are performing a wide range of duties for their employers, as indicated by the average job-role score (M = 2.63, SD = 1.10). With years of experience, the sample contains persons with varying levels of professional tenure (M = 2.62, SD = 1.08). Almost half of the sample had expertise in the technologies, indicating an elevated level of knowledge and involvement, according to the last variable representing prior exposure to Industry 4.0 (M = 1.52, SD = 0.50).

"Table 2: Demographic Statistics"

		Frequency	Percent	Valid Percent	Cumulative Percent
Age	18–30 years	30	23.1	23.1	23.1
	31–40 years	33	25.4	25.4	48.5
	41–50 years	27	20.8	20.8	69.2
	Above 51 years	40	30.8	30.8	100.0
	Total	130	100.0	100.0	
Gender	Male	72	55.4	55.4	55.4
	Female	58	44.6	44.6	100.0
	Total	130	100.0	100.0	
Education	Diploma	34	26.2	26.2	26.2
	Graduate	30	23.1	23.1	49.2
	Postgraduate	36	27.7	27.7	76.9
	Technical Certification	30	23.1	23.1	100.0
	Total	130	100.0	100.0	
Job Role	Operator/Technician	28	21.5	21.5	21.5
	Supervisor	27	20.8	20.8	42.3
	Engineer/Executive	40	30.8	30.8	73.1
	Senior Management	35	26.9	26.9	100.0
	Total	130	100.0	100.0	
	1–3 years	27	20.8	20.8	20.8

Years of Experience	4–7 years	30	23.1	23.1	43.8
	8–12 years	39	30.0	30.0	73.8
	>12 years	34	26.2	26.2	100.0
	Total	130	100.0	100.0	
Have you worked with Industry 4.0 technologies?	Yes	62	47.7	47.7	47.7
	No	68	52.3	52.3	100.0
	Total	130	100.0	100.0	

There is a good representation of a wide range of ages, educational backgrounds, and occupational specialisations in the sample (N = 130). Half of the total respondents are in the 18–30 age bracket (23.1%) and the 31–40 age bracket (25.4%), although a sizeable proportion of individuals over the age of 51 (30.8%) also participate, indicating a mix of youthful and highly intelligent professionals. At 55.4% male and 44.6% female, the gender ratio is moderate. The respondents' educational backgrounds show a wide range of specialisations and degrees. The biggest category is that of people with postgraduate degrees (27.7%), followed by certificate holders (26.2%), and then graduates (23.1%). Academically and technically diverse workforces are characterised by this diversity.

Professional diversity is further demonstrated by the distribution of work roles and experience in the sample. Supervisors (20.8%), operators/technicians (21.5%), and top management (26.9% of the total) round out the top tier, with engineers and managers making up the biggest sector at 30.8%. With 30 per cent having 8-12 years of experience and 26.2% having more than 12 years, the sample is composed primarily of mid-to senior-level professionals, indicating a well-balanced distribution of experience. Furthermore, half of the respondents (52.3%) have never been exposed to Industry 4.0 technologies, whereas half (47.0%) have experience with them. The study's vast dataset is made possible by its well-distributed sampling, which ensures that it collects the opinions of both technologically experienced and novice individuals.

7.2 Based on Hypothesis

- **H1:** “Industry 4.0 technology adoption has a positive impact on changing skill requirements in manufacturing firms.”

“Table 3: Model Summary”

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df 1	df2	Sig. F Change
1	.209[a]	.044	.036	.71786	.044	5.862	1	128	.017

“a. Predictors: (Constant), Industry 4.0 Technology Adoption.”

Industry 4.0 technology usage explains “4.4% of the variance in the dependent variable, according to this model (R^2 =.044). But the regularised R^2 is only .036, which is far lower and indicates that there is not much explanatory power. A weak positive association between the predictor and the outcome variable is indicated by the correlation coefficient (R =.209). As the average distance of the observed values from the regression line, the standard error of the estimate is .71786, which represents the mean error of the forecast.” The change data show that the model is incredibly significant (F = 5.862, p

=.017), indicating that incorporating Industry 4.0 technology into forecasts yields a minor but noticeable advantage.

"Table 4: ANOVA"						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.021	1	3.021	5.862	.017[b]
	Residual	65.962	128	.515		
	Total	68.983	129			
"a. Dependent Variable: Changing Skill Requirements."						
"b. Predictors: (Constant), Industry 4.0 Technology Adoption"						

The regression model that attempts to quantify the effect of Industry 4.0 technology on skill development is confirmed by the findings of the ANOVA, which show an extraordinarily strong p-value ($F = 5.862$, $p = 0.017$). The model's variance explanation of 3.021 suggests that the independent variable contributes to the variability, but the error variance of 65.962 suggests that not all the variance has been accounted for. Even if it is tiny, the model expects a significant difference. The fact that the sum of all the squares comes out to 68.983 further proves this point. There has been a statistically significant effect of Industry 4.0 adoption on the changes in the sample's necessary skills, with a significance level below.05.

"Table 5: Coefficients"								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta (B)			Lower Bound	Upper Bound
1	(Constant)	3.660	.275		13.297	.000	3.116	4.205
	Industry 4.0 Technology Adoption	-.217	.090	-.209	-2.421	.017	-.394	-.040
"a. Dependent Variable: Changing Skill Requirements."								

A statistically significant negative connection between the adoption of Industry 4.0 technology and changing skill needs ($B = -0.217$, $p =.017$) is seen in the coefficients table. The unstandardized coefficient indicates that the changing skill needs' score will decrease by 0.217 units for every unit advancement in Industry 4.0 adoption. A little but noticeable negative is conveyed by the standardised beta value (-.209). Another piece of evidence supporting the effect's significance is the non-zero confidence interval (- 0.394 to -0.040). Without implementing Industry 4.0, the anticipated score for evolving skill sets will remain at 3,660. "Results suggest a weak but substantial correlation between Industry 4.0 technology adoption and subsequent skill set adjustments."

- **H2:** "Reskilling and upskilling initiatives significantly improve employees' digital competency levels."

"Table 6: Model Summary"									
Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.220[a]	.048	.041	.72723	.048	6.513	1	128	.012
"a. Predictors: (Constant), Reskilling & Upskilling Initiatives."									

Reskilling and upskilling activities contribute a tiny but statistically significant.041 to the dependent variable variance (R^2 =.048), according to the model summary. With a correlation coefficient of only.220, the interventions had a weak positive effect on the dependent variable. As a measure of the typical dispersion between predicted and observed results, the standard error of the estimate is.72723. The dependent variable is significantly related to reskilling and upskilling activities, according to the change statistics (F = 6.513, p =.012), but the total effect size is still tiny.

"Table 7: ANOVA"						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.444	1	3.444	6.513	.012[b]
	Residual	67.695	128	.529		
	Total	71.139	129			
"a. Dependent Variable: Employees' Digital Competency Levels."						
"b. Predictors: (Constant), Reskilling & Upskilling Initiatives."						

Evaluation of variance data (F = 6.513, p =.012) suggests that the regression model that investigated the impact of reskilling and upskilling programs on employees' levels of digital competency was statistically significant. "The regression sum of squares (3.444) represents the predictor-assigned variance, whereas the residual sum of squares (67.695) represents the unaccounted-for variance." With a total of 71.139 variables, the model encompasses a small but significant percentage of the range in digital competency levels. Since the significance value is less than.05, there is statistical evidence that reskilling and upskilling programs have a substantial impact on workers' levels of digital proficiency.

"Table 8: Coefficients"								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.695	.266		13.901	.000	3.169	4.221
	Reskilling & Upskilling Initiatives	-.220	.086	-.220	-2.552	.012	-.391	-.049
"a. Dependent Variable: Employees' Digital Competency Levels"								

The digital competency levels of employees are significantly lowered by the reskilling and upskilling programs, according to the table of coefficients (B = -0.220, p =.012). Taking a single-variable approach, we find that a one-unit increase in these programs would lead to a 0.220-unit drop in staff digital competency levels, according to the unstandardized coefficient. In addition, there is a small but notable negative association indicated by the standardised beta value (-.220). Since the confidence interval (- 0.391 to -0.049) does not include zero, the effect is uniform. A digital competency level of 3.695 (the value of the constant term) is anticipated under these conditions. At the end of the day, the model shows that the effect is significant (albeit weak) statistically.

- **H3:** Managerial challenges affect the successful implementation of skill-development programs.

"Table 9: Model Summary"

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.180[a]	.032	.025	.70931	.032	4.271	1	128	.041
"a. Predictors: (Constant), Managerial Challenges."									

Management issues accounted for 3.2% of the dependent variable's variation, according to the model summary (R^2 =.032). This was a small but noteworthy contribution, as indicated by the modified R^2 of.025. A weak positive association between management difficulties and the outcome variable is indicated by the correlation coefficient (R =.180). "The standard error of the estimate (.70931) shows the average discrepancy between the actual and anticipated values. The change statistics reveal that the model is significant (F = 4.271, p =.041)," confirming the hypothesis that management problems have an exceptionally low influence on the dependent variable.

"Table 10: ANOVA"

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.149	1	2.149	4.271	.041[b]
	Residual	64.400	128	.503		
	Total	66.549	129			
"a. Dependent Variable: Implementation of Skill-Development Programs"						
"b. Predictors: (Constant), Managerial Challenges"						

There was a statistically "significant relationship between managerial difficulties and the implementation of skill-development programs" in the regression model that examined this relationship (F = 4.271, p =.041), as revealed by "the analysis of variance (ANOVA) results". Meanwhile, the unaccounted variance is shown by the residual sum of squares (64.400), and the extent to which managerial issues contribute to the variability is shown by the regression sum of squares (2.149). The model explains a tiny but substantial portion of the total variation (66.549). Managerial difficulties significantly affect the efficacy of skill-development programs, as shown by the p-value being smaller than 05.

"Table 11: Coefficients"

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.647	.280		13.030	.000	3.093	4.200
	Managerial Challenges	-.187	.090	-.180	-2.067	.041	-.366	-.008

"a. Dependent Variable: Implementation of Skill-Development Programs"

According to the data displayed in the coefficients table, managerial obstacles impede the implementation of skill-development programs (B = -0.187, p =.041). According to the unstandardized coefficient, "the effectiveness of skill-development program implementation will decrease by 0.187 units for every one unit rise in management difficulties," with other factors being held constant. A conventional beta value of -.180 indicates a strong negative correlation, although it is tiny. To conclude that this effect is statistically significant, we need to look at the 95% confidence interval (- 0.366 to - 0.008) and see that zero is not there. An unchanged expected score of 3.647 for implementation is possible in the absence of management roadblocks. Despite a slight connection, the data show that skill-development programs are less effective when managers have more challenges.

- **H4:** "Training effectiveness has a relationship with workforce readiness for Industry 4.0."

"Table 12: Correlations"

		Training Effectiveness	Workforce Readiness for Industry 4.0
Training Effectiveness	Pearson Correlation	1	.182*
	Sig. (2-tailed)		.039
	N	130	130
Workforce Readiness for Industry 4.0	Pearson Correlation	.182*	1
	Sig. (2-tailed)	.039	
	N	130	130

"*. Correlation is significant at the 0.05 level (2-tailed)."

There is a weak but statistically significant positive relationship between training efficacy and workforce preparedness for Industry 4.0, according to the examination of the correlation coefficients (r =.182, p =.039). Although the association is still modest, this interpretation suggests that a workforce with better training would be more effective. By establishing a significance level of.05, we may provide further evidence that the association is not the result of chance alone. Despite modest correlations, the results show that training is still a vital component in employee preparedness for Industry 4.0 procedures and technology. The sample size for both variables was the same (N = 130).

8. Discussion

The study's results grant a detailed perspective of how the adoption of Industry 4.0 affects the capability of the workforce, the preparedness of the organisation, and the management duties of the manufacturing companies in the NCR area. The outcomes partly corroborate the theories, revealing that Industry 4.0 technologies have a significant impact on the skill requirements, but the connection is weak. This weak connection implies that while companies are investing in digitalisation and automation, the transition of skills among the workers is still terribly slow. A negative beta suggests that workers might be having a tough time adjusting their skills to the change of technology, which represents a mismatch between skills and technology. This is in line with global studies that maintain that employees frequently lack trust and knowledge about the new systems, thus creating the very gaps between technical investments and human capability. The demographic study also indicates the presence of a diverse workforce that has various levels of exposure to Industry 4.0, which causes skill adaptation to be uneven across distinct roles and levels of experience.

The study further reveals that reskilling and upskilling initiatives, though statistically significant, have a weak impact on improving digital competency levels. The negative coefficient implies that existing training mechanisms may not be sufficiently aligned with actual skill gaps or technological needs. This may be due to factors such as outdated training content, insufficient firsthand learning opportunities, or employee anxiety about using advanced technologies. Similarly, managerial challenges significantly hinder the implementation of skill-development programs, emphasising the crucial role of leadership in digital transformation. Resistance to change, lack of structured training frameworks, and limited managerial expertise in technology-driven environments are major barriers. The correlation between training effectiveness and workforce readiness is positive yet weak, suggesting that current training strategies contribute to readiness but are not robust enough to create transformative changes. Overall, the discussion highlights that Industry 4.0 success requires not only technical investments but also strong managerial support, a continuous learning culture, and the redesign of training programs to meet evolving workforce demands.

9. Conclusion

The study indeed reveals the influence of Industry 4.0 on manufacturing industry companies, especially in the areas of workforce skills, training, and management staff. The adoption of Industry 4.0 technology changes skill requirements significantly; however, the weak correlation hints that companies have not yet fully aligned the capabilities of their workforce with the expectations of the technology. This study calls for initiative-taking planning, well-defined roadmaps, and continuous skill improvement to close the widening digital skills gap. Reskilling and upskilling come out as necessary but not effectively utilised strategies, which means that manufacturing companies must change to more immersive, technology-connected, and competency-based training models to raise digital literacy to its real heights.

Management difficulties still create a significant obstacle that hampers the execution of effective skill-mapping programs. The research states that leadership must go through an evolution process to be able to apply management styles compatible with the digital world, to give communication priority, and to create an organisational culture that is open to innovation and change. The impact of the training on the workforce in terms of readiness is positive, but a weak correlation implies the need for redesigning training frameworks as a matter of priority. An all-inclusive approach is required for the successful implementation of Industry 4.0, where technology, humans, and management are seen as interconnected elements and are functioning in constructive collaboration. The manufacturing companies that will invest wisely in human resources, and at the same time, managerial support systems and the latest training methods, will bring themselves to the point where they can enjoy not only operational excellence and sustained competition but also long-lasting digital resilience.

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