

Skill-Based Talent Management and Ai-Powered Upskilling and Reskilling: Bridging Skill Gaps in the Future Workforce

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Abstract

The workforce skill requirements across industries have been fundamentally redefined by the fast transition brought about by Industry 4.0 technologies, which include automation, big data analytics, artificial intelligence (AI), and cyber-physical systems. In order to address dynamic and technology-driven skill gaps, traditional role-based talent management approaches are becoming less and less effective. Continuous learning and ongoing education are emphasised as essential components in preparing employees to adapt to the shifting demands of the industry. This study looks at how upskilling and reskilling programs driven by AI may close skill gaps in the industry 4.0 ecosystem to acquire the workforce ready for the future. Through the use of AI-enabled learning, ongoing competency development, and digital adaptability, the study creates a conceptual framework that connects skill-based talent management practices (an independent variable) with workforce agility and organisational success (dependent factors). In order to gather opinions from managers and workers in technology-intensive businesses, the study uses a quantitative research approach and standardised survey tools. AI integration in talent development procedures improves strategic workforce planning, decreases skill obsolescence, and promotes cultures of continuous learning.

Keywords: Skill-Based Talent Management, AI-Powered Upskilling, Reskilling, Industry 4.0, Future Workforce, Workforce Agility, Digital Transformation.

I. INTRODUCTION

Technological innovations like automation, robots, artificial intelligence, and data analytics are causing an unprecedented shift in the global workforce. Agile and competency-driven work cultures are replacing traditional hierarchical structures in organisations. Employees must constantly upgrade their skills to be relevant because job positions are becoming more and more flexible. According to predetermined job descriptions, traditional talent management techniques mostly concentrated on hiring, performance reviews, and succession planning. However, skill obsolescence has accelerated due to technological disruptions. Interdisciplinary competencies like as digital literacy, analytical thinking, flexibility, and teamwork are now required of employees. Lack of skills is becoming a significant obstacle to organisational innovation and productivity. The need for specialised technical skills has increased due to the rapid use of automation technologies, but human-centric abilities like creativity and emotional intelligence are also becoming more and more important. A revolutionary tool in workforce development is artificial intelligence. AI programs evaluate worker competencies, pinpoint areas in need of improvement, and provide tailored training programs. In order to close skill gaps and guarantee workforce sustainability, businesses are implementing skill-based talent management backed by AI-driven upskilling and reskilling programs. Artificial Intelligence (AI), robotics, big data analytics, and cloud computing are examples of Industry 4.0 technologies that have revolutionised employment trends and organisational structures worldwide. Businesses now function in more dynamic, technologically advanced settings where competitiveness and productivity are determined by abilities rather than job titles. Skill-centric workforce models are progressively replacing traditional talent management techniques that mostly concentrated on tenure and hierarchical positions. Rapid digital transformation has made skill gaps a significant organisational challenge. Research shows that employment skill requirements are changing at an unprecedented rate due to technology innovation, requiring ongoing workforce reskilling and upskilling activities. Global workforce studies predict that due to automation processes and the adoption of new technologies, about 50% of workers will need to retrain. Intelligent talent development systems will be supported by AI, which has become a disruptive force. AI-powered learning systems assess worker competencies, forecast skill gaps, and provide individualised training plans. As a result, firms looking to gain a sustained competitive edge now prioritise skill-based talent management backed by AI learning ecosystems. The use of artificial intelligence (AI) in talent management (TM) is already widely accepted as a significant area of study. Both "artificial intelligence" and "cognitive technologies"

are now widely used phrases in technology, research, and industry. The way that people and technology interact for company operations is greatly influenced by these technologies (Kuzior and Kwilinski 2022). Large investments in AI for talent management have already started to be made by businesses. After automating work procedures to enhance several activities, such as the recruitment and selection of suitable candidates, an HR technology start-up has "quietly become a billion-dollar unicorn" (Kelly 2021). Large international technology companies have already started integrating AI into their systems and operations, and they are presently hiring new employees (van der Lugt 2021). This suggests that AI will play a crucial role in organisations' talent management processes, underscoring the significance of the topic for further research. However, there are always a lot of people looking for jobs on the job market. Organisational approaches that give employees' competences, talents, and potential more weight than their set job positions are known as skill-based talent management. Its main objectives include competency mapping, agile workforce deployment, and the identification of transferable abilities. Organisations can flexibly assign talent according to project demands using skill-based frameworks, as opposed to traditional job-based arrangements. This strategy encourages cross-functional cooperation and increases workforce flexibility.

Concept of Skill-Based Talent Management

Skill-Based Talent Management (SBTM) represents a shift from traditional, job-based talent management toward an approach in which employees' actual skills, competencies, capabilities and potential are placed at the centre of talent decisions. While a skills-based approach concentrates on identifying the skills needed by the organization, evaluating employees' current capabilities, identifying skill gaps, and developing or redeploying employees to meet changing business requirements, traditional talent management frequently emphasizes job titles, qualifications, and organizational positions. Lawler and Ledford (1992) were among the early scholars to discuss a skill-based approach to human resource management, arguing that organizations can gain strategic benefits by moving beyond job-based systems and emphasizing employee skills and competencies. Their research demonstrated how crucial it is to match workforce competencies with organizational needs and proposed that skill-based systems can boost an organization's competitiveness. Collings and Mellahi (2009) developed a conceptual framework for strategic personnel management that focused on developing talent pools, differentiating HR methods, and methodically identifying key jobs. Even though their framework is more comprehensive than SBTM, it offers a crucial basis for a skill-based viewpoint since successful talent management necessitates that companies determine the competencies required for strategically significant positions and cultivate workers who have or can acquire those competencies. The skills-based approach has become

more popular in recent years due to the quick changes in technology and the workplace. Skills-first talent management, according to the World Economic Forum (2023), is a method that prioritizes skills and capabilities in hiring, training, pay, and internal mobility. It highlights how crucial it is to preserve accurate skill data and continuously train employees as organizational skills requirements change. Jooss et al. (2024) offer more concrete proof of the new skills-matching theory of talent management. According to their research, companies are putting more emphasis on talent management skills in response to shifts in the nature of work. This viewpoint places a strong emphasis on enhancing organizational agility through improved skill identification, development, and deployment as well as aligning available employee abilities with organizational requirements. The OECD (2026) goes on to define skills-first talent management as a process that includes identifying priority roles, defining necessary skills, using skills-based assessment and selection, and extending skills-based principles to career advancement, performance evaluation, and customized skill-development pathways. This shows that the current concept of SBTM is not limited to hiring but rather encompasses the entire employee lifecycle. AI has becoming especially significant in personalized learning, where learning materials and training exercises are tailored to each employee's needs. AI-based systems are able to assess an employee's current competencies and provide learning materials depending on inadequacies found. While more recent generative AI technologies are increasing potential for interactive and flexible learning, systematic research on AI-mediated personalized learning demonstrates that adaptive learning technologies can develop tailored learning pathways. Talent development, which enables businesses to go from a training strategy that is one-size-fits-all to one that is skills-based and employee-specific. AI is capable of continuously analysing learning and performance data and making recommendations for certain courses, simulations, tests, or practice exercises. Upskilling is the process of enhancing or expanding an employee's current talents to enable them to carry out present or future tasks more successfully. By determining the gap between an employee's existing skill set and the abilities needed for their current or future employment, AI can assist with upskilling. Tusquellas et al. (2024) list a number of uses of AI in corporate talent development, such as determining each person's unique training needs, creating individualized learning routes, and identifying future workforce skill requirements. Instead of giving every employee the same training, these features make AI very helpful for creating focused upskilling interventions. Reskilling and upskilling current employees is the most anticipated workforce approach for responding to AI-related transformation, according to the World Economic Forum's Future of Jobs Report 2025. According to the report, between 2025 and 2030, 77% of businesses surveyed intend to seek worker reskilling and upskilling. While human skills like

analytical thinking, creativity, resilience, and adaptability continue to be crucial, the fastest-growing skill categories are AI and big data, networks and cybersecurity, and technological literacy. Reskilling is creating significantly new skills that allow workers to perform various jobs, duties, or occupations. by evaluating new skill needs, comparing employee skills to future positions, and suggesting appropriate learning pathways. According to Pandya and Samuel (2026), AI is becoming more and more integrated into worker training through simulations, automated feedback, individualized learning pathways, and just-in-time support. Their research highlights the need for AI-enabled training to be in line with employee experience, contextual workplace practices, and adult learning concepts. A recent integrative synthesis by Mubarak, Tung, and Wibawanta (2026) also suggests AI-based personalized learning as a strategic response to organizational reskilling and upskilling requirements and concludes that AI-driven personalized learning has significant potential for addressing workforce competency gaps arising from digital transformation. Organizational applications are placing more emphasis on competency development and the transfer of training to strategic organizational objectives, according to a 2026 thorough assessment of AI-based personalized learning in professional development. The importance of skill gaps in the future workforce has grown due to the rapid changes in the nature of jobs brought about by technological revolution, artificial intelligence, automation, digitalization, demographic shifts, and the green transition. When workers' or job searchers' abilities fall short of what businesses and new professions need, there is a "skill gap." Therefore, the problem is not only a lack of people but rather a mismatch between the skills of the current workforce and changing skill requirements. According to the World Economic Forum (WEF, 2025), 63% of companies surveyed said that talent gaps would be a major hindrance to corporate transformation between 2025 and 2030. The analysis shows how quickly worker needs are changing, estimating that by 2030, over 40% of the skills needed for employment will have changed. Additionally, it predicts that by 2030, 59 out of every 100 workers will need to retrain or upskill. According to the ILO and OECD (2018), organizations as well as governments are under pressure to predict future skills due to technology advancements like artificial intelligence (AI), robotics, and digital technologies. The creation and execution of training programs can take a long period, which could cause a lag between the availability of people with the necessary training and the emergence of new skill requirements. The ILO (2023) highlights the need for workers to acquire the knowledge and abilities required to engage effectively in the digital economy and notes that digitalization is changing skill needs across occupations. The WEF (2025) similarly identifies AI and big data, networks and cybersecurity, and technological literacy among the fastest-growing skill areas. Organizations still need human skills including creativity, analytical

thinking, adaptability, resilience, leadership, and teamwork. Therefore, organizations increasingly require a combination of technical, digital, and human capabilities, so the future talent gap is not solely a technological issue. The WEF (2025) provides evidence of this challenge: although 59% of workers are expected to need upskilling or reskilling by 2030, 11 out of every 100 workers who require such development are not expected to receive it. This highlights a substantial gap between the need for workforce development and the actual availability of development opportunities.

Research Gap

Previous research has mainly focused on upskilling and reskilling, artificial intelligence, and skill-based talent management as distinct fields. There hasn't been much empirical study done on how AI-Powered Upskilling and Reskilling and Skill-Based Talent Management work together to reduce skill gaps. Furthermore, there is little proof that these strategies can handle the quickly evolving skill requirements under Industry 4.0 in developing industrial contexts. In order to close this gap, the current study looks at the individual and combined effects of AI-Powered Upskilling and Reskilling and Skill-Based Talent Management on the reduction of skill gaps.

Research Objectives

- To examine the influence of Skill-Based Talent Management on Skill-Gap Reduction among employees.
- To determine the influence of AI-Powered Upskilling and Reskilling on Skill-Gap Reduction among employees.
- To examine the combined influence of Skill-Based Talent Management and AI-Powered Upskilling and Reskilling on Skill-Gap Reduction among employees.

Hypothesis of the Study

Hypothesis 1

H₀₁: There is no significant relationship between Skill-Based Talent Management and Skill-Gap Reduction.

H₁₁: There is a significant positive relationship between Skill-Based Talent Management and Skill-Gap Reduction.

Hypothesis 2

H₀₂: There is no significant relationship between AI-Powered Upskilling and Reskilling and Skill-Gap Reduction.

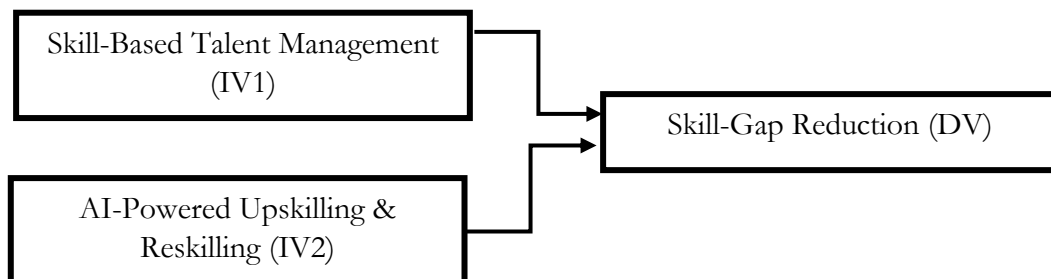
H₁₂: There is a significant positive relationship between AI-Powered Upskilling and Reskilling and Skill-Gap Reduction.

Hypothesis 3

H₀₃: Skill-Based Talent Management and AI-Powered Upskilling and Reskilling do not jointly have a significant positive influence on Skill-Gap Reduction.

H₁₃: Skill-Based Talent Management and AI-Powered Upskilling and Reskilling jointly have a significant positive influence on Skill-Gap Reduction.

Conceptual Framework



Research Methodology

The study adopts a descriptive and analytical research design to examine the role of Skill-Based Talent Management and AI-Powered Upskilling and Reskilling in reducing skill gaps among employees in the automotive industry of Ranipet District. A quantitative research approach is adopted. Primary data are collected from employees using a structured questionnaire based on a five-point Likert scale. Quantitative methods are used to measure the constructs and statistically test the proposed hypotheses. The target population comprises employees working in automotive and auto-component industries in Ranipet District, Tamil Nadu. The study focuses on employees who are exposed to changing technological requirements and therefore have relevant experience or awareness of skill development, upskilling, reskilling and talent-management practices. The study employs purposive sampling, respondents may be distributed across departments such as Production, Quality, Human Resources, Maintenance and related technical functions to obtain broader representation. A sample of 150 employees is selected for the study. Primary data are collected directly from employees of automotive and auto-component organizations in Ranipet District through a structured questionnaire. Secondary information is obtained from peer-reviewed journal articles, industry reports and credible institutional sources relating to Industry 4.0, Skill-Based Talent Management, Artificial Intelligence, upskilling, reskilling and workforce skill gaps.

A structured questionnaire is used as the principal data-collection instrument. The questionnaire consists of two sections.

Section A: Demographic and occupational information of respondents.

Section B: Statements measuring the three major constructs: Skill-Based Talent Management, AI-Powered Upskilling and Reskilling, Skill-Gap Reduction

Items are measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The collected data are analysed using IBM SPSS Statistics. The following statistical techniques are proposed: Cronbach's alpha, KMO & Bartlett's Test, Pearson Correlation, Simple Linear Regression, Multiple Linear Regression

Reliability Test (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha	Reliability Level
Skill-Based Talent Management Practices	15	0.835	Good
AI-Powered Upskilling and Reskilling Initiatives	20	0.940	Excellent
Bridging Skill Gaps in Future Workforce	15	0.925	Excellent

KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was 0.908, indicating excellent adequacy of the sample for conducting factor analysis. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 4050.709$, $df = 1225$, $p < 0.001$), demonstrating that significant correlations exist among the variables and that the correlation matrix is not an identity matrix. Therefore, the data are considered highly suitable for Exploratory Factor Analysis (EFA).

Hypothesis 1

H₀₁: There is no significant relationship between Skill-Based Talent Management and Skill-Gap Reduction.

Correlation

Variables	Skill-Based Talent Management	Skill-Gap Reduction
Skill-Based Talent Management	1	0.539**
Skill-Gap Reduction	0.539**	1
N	150	150

Note: Correlation is significant at the 0.01 level (2-tailed)

From the above table it is inferred that the Pearson correlation analysis shows a positive and statistically significant relationship between Skill-Based Talent Management (SBTM) and Skill-Gap Reduction (SGR). The Pearson correlation analysis revealed a moderate positive and statistically significant relationship between Skill-Based Talent Management and Skill-Gap Reduction ($r = 0.539$, $p < 0.001$, $N =$

150). This indicates that higher levels of Skill-Based Talent Management are associated with greater Skill-Gap Reduction among employees. Therefore, the proposed hypothesis is supported. Since the p-value is less than 0.01, the relationship is statistically significant at the 1% level. There is a significant positive relationship between Skill-Based Talent Management and Skill-Gap Reduction. Therefore H1 is accepted.

Hypothesis 2

H₀₂: There is no significant relationship between AI-Powered Upskilling and Reskilling and Skill-Gap Reduction.

Simple Linear Regression

Model / Variable	B	Std. Error	Beta (β)	t-value	Sig.
Constant	22.770	3.141	-	7.249	0.000
AI-Powered Upskilling and Reskilling	0.466	0.052	0.594	8.980	0.000

Model Summary: $R = 0.594$; $R^2 = 0.353$; Adjusted $R^2 = 0.348$, ANOVA: $F = 80.643$; $p < 0.001$, Dependent Variable: Skill-Gap Reduction, $N = 150$

From the above table it is inferred that the simple linear regression results indicate that AI-Powered Upskilling and Reskilling has a significant positive influence on Skill-Gap Reduction. The standardized regression coefficient ($\beta = 0.594$) indicates a moderate positive influence, while the t-value of 8.980 is statistically significant ($p < 0.001$). The overall regression model is also statistically significant ($F = 80.643$, $p < 0.001$). The R^2 value of 0.353 indicates that AI-Powered Upskilling and Reskilling explains 35.3% of the variation in Skill-Gap Reduction. Therefore, the findings provide sufficient evidence to reject the null hypothesis and support H2. Therefore, H2 is accepted, and the null hypothesis is rejected.

Hypothesis 3

H₀₃: Skill-Based Talent Management and AI-Powered Upskilling and Reskilling do not jointly have a significant positive influence on Skill-Gap Reduction.

Multiple Linear Regression

Model / Variable	B	Std. Error	Beta (β)	t-value	Sig.	VIF
Constant	10.525	3.834	-	2.745	0.007	
Skill-Based Talent Management (SBTM)	0.446	0.090	0.340	4.927	0.000	1.259
AI-Powered Upskilling & Reskilling (AIUR)	0.345	0.054	0.440	6.372	0.000	1.259

Model Summary: $R = 0.667$; $R^2 = 0.444$; Adjusted $R^2 = 0.437$; Std. Error = 7.72348
ANOVA: $F = 58.803$; $p < 0.001$, $N = 150$

From the above table it is inferred that the multiple regression analysis indicates that Skill-Based Talent Management and AI-Powered Upskilling and Reskilling jointly have a significant positive influence on Skill-Gap Reduction. The overall regression model is statistically significant ($F = 58.803$, $p < 0.001$). The model produced an R value of 0.667, indicating a moderately strong positive relationship between the combined predictors and Skill-Gap Reduction. The R^2 value of 0.444 shows that 44.4% of the variation in Skill-Gap Reduction is explained jointly by Skill-Based Talent Management and AI-Powered Upskilling and Reskilling. The adjusted R^2 is 0.437, indicating that 43.7% of the variance is explained after adjustment.

Both predictors have statistically significant positive coefficients:

- Skill-Based Talent Management: $\beta = 0.340$, $t = 4.927$, $p < 0.001$
- AI-Powered Upskilling & Reskilling: $\beta = 0.440$, $t = 6.372$, $p < 0.001$

Regression Equation

$$\text{Skill-Gap Reduction (Y)} = 10.525 + 0.446(\text{SBTM: } X_1) + 0.345(\text{AIUR: } X_2)$$

Y = Skill-Gap Reduction (SGR)

X_1 = Skill-Based Talent Management (SBTM)

X_2 = AI-Powered Upskilling and Reskilling (AIUR)

For every 1-unit increase in SBTM (X_1), SGR (Y) increases by 0.446 units, holding AIUR constant. For every 1-unit increase in AIUR (X_2), SGR (Y) increases by 0.345 units, holding SBTM constant. 10.525 is the expected value of SGR when both X_1 and X_2 are zero.

Among the two predictors, AI-Powered Upskilling and Reskilling has the stronger relative influence on Skill-Gap Reduction because its standardized beta ($\beta = 0.440$) is higher than that of Skill-Based Talent Management ($\beta = 0.340$). The VIF value of 1.259 for both predictors is low, indicating that there is no serious multicollinearity problem between the independent variables. The Variance Inflation Factor (VIF) values for Skill-Based Talent Management and AI-Powered Upskilling and Reskilling were 1.259, with a tolerance value of 0.794. Since the VIF values are well below the commonly accepted threshold of 5, the results indicate that multicollinearity is not a concern among the independent variables. Since $p < 0.001$, the null hypothesis is rejected and the alternative hypothesis is supported. Both Skill-Based Talent Management and AI-Powered Upskilling and Reskilling significantly and positively contribute to Skill-Gap Reduction, with AI-Powered Upskilling and Reskilling showing the stronger relative contribution.

Findings

Hypothesis Statement	Statistical Test	Result
H1: Skill-Based Talent Management has a significant positive influence on Skill-Gap Reduction.	Correlation	Accepted
H2: AI-Powered Upskilling and Reskilling has a significant positive influence on Skill-Gap Reduction.	Simple Linear Regression	Accepted
H3: Skill-Based Talent Management and AI-Powered Upskilling and Reskilling jointly have a significant positive influence on Skill-Gap Reduction.	Multiple Linear Regression	Accepted

Implications of the Study

- The findings suggest that HR policies should shift from traditional job-based talent management towards a skill-based approach. Organizations should establish systematic skill inventories, competency mapping, regular skill-gap assessments and skill-based career development policies. HR departments can also integrate AI-based tools into learning and development to identify individual training needs, recommend personalized learning pathways and track employee progress. Policies should encourage continuous upskilling and reskilling to ensure workforce readiness for technological changes.
- For the automotive industry, the findings highlight the need to prepare employees for Industry 4.0 technologies such as AI, automation, robotics, IoT and advanced manufacturing systems. Automotive organizations should combine skill-based talent management with AI-enabled training to address emerging technical and digital skill shortages. This approach can improve workforce adaptability, technological readiness, productivity and organizational competitiveness while reducing the risk of skill obsolescence.
- The findings emphasize the importance of continuous employee development rather than one-time training. Employees should receive opportunities for personalized upskilling and reskilling based on their existing capabilities and future job requirements. AI-powered learning platforms can provide individualized training, continuous feedback and development recommendations. This can help employees acquire new technical, digital and problem-solving skills, improve career readiness and adapt effectively to changing workplace requirements.

Future Research Directions

Future research can extend the present study in several ways.

- Studies can examine the proposed framework across different industries, such as IT, electronics, pharmaceuticals, banking and logistics, to determine whether the findings vary across sectors.
- Future studies can use a larger sample size and broader geographical coverage to improve the generalizability of the findings.
- Researchers can incorporate additional variables such as employee engagement, organizational readiness, digital literacy, learning agility and organizational support to provide a more comprehensive understanding of skill-gap reduction.
- Future studies can compare different generations, job roles and skill categories and examine the effectiveness of specific AI technologies, such as generative AI, adaptive learning systems and AI-based skills analytics, in developing a future-ready workforce.

II.CONCLUSION

A paradigm shift in human resource development is represented by skill-based talent management backed by AI-powered reskilling and upskilling. Organisations must transition from old role-based structures to competency-driven workforce strategies as Industry 4.0 speeds up workplace transformation. AI-enabled immersive training environments, predictive skill analytics, and personalised learning improve worker flexibility. In order to promote lifelong learning cultures and close skill gaps, organisations, legislators, and educational institutions must constantly collaborate. In the end, workforce sustainability and organisational resilience in the future economy will depend on how well AI is integrated with human-centric talent management techniques.

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