IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

WORKFORCE SEGMENTATION BASED ON LEARNING AND UPSKILLING PREFERENCES IN THE AI ERA

Rakesh Kumar Sethi

Assistant Professor, Astha School of Management

Dr. Amrit Kumar Mohapatra

Doctoral Scholar, Department of Commerce

Ravenshaw University, Cuttack, Odisha

Abstract

The rapid adoption of artificial intelligence (AI) is transforming workplace skill requirements and increasing the importance of continuous learning and workforce upskilling. As organizations seek to develop future-ready employees, understanding workforce learning preferences has become essential for designing effective learning and development strategies. This study aims to examine the underlying dimensions of employees' learning and upskilling preferences in the AI era, identify distinct workforce segments based on these preferences, and analyse demographic differences among the identified segments. A quantitative research design was employed using data collected from 300 employees across various industries. Exploratory factor analysis was conducted to identify the key dimensions of workforce learning preferences, while cluster analysis was used to classify employees into homogeneous groups. Furthermore, analysis of variance (ANOVA) and Chi-square tests were performed to examine differences among workforce segments and their demographic characteristics. The findings revealed four major dimensions of learning and upskilling preferences: AI-related skills, technical skills, soft skills, and career-development learning. Three distinct workforce segments emerged from the analysis, namely AI Enthusiasts, Career-Oriented Learners, and Passive Learners. Significant differences were observed among the identified segments across all learning dimensions. Additionally, workforce segment membership was significantly associated with age, educational qualification, work experience, and industry, whereas gender did not exhibit a significant association.

Keywords: Artificial Intelligence, Workforce Upskilling, Employee Learning Preferences, Workforce Segmentation, Human Resource Management**.**

Introduction

The rapid advancement of artificial intelligence (AI) is transforming the contemporary workplace and redefining the skills required for professional success. AI-powered technologies, automation, machine learning, and digital platforms are increasingly being integrated into organizational processes, influencing how work is performed across industries. As a result, employees are facing growing pressure to continuously acquire new competencies and adapt to changing job requirements. In this evolving environment, learning and upskilling have become essential not only for maintaining employability but also for ensuring organizational competitiveness and long-term sustainability. The emergence of AI-driven workplaces has significantly altered the nature of workforce development. While technical and digital skills have gained prominence, organizations are also emphasizing the importance of human-centric capabilities such as creativity, critical thinking, communication, adaptability, and problem-solving. Consequently, employees are expected to engage in continuous learning to remain relevant in a dynamic labour market. In response, organizations are investing heavily in learning and development initiatives, digital training platforms, reskilling programs, and career development opportunities aimed at preparing employees for future workplace challenges. From a human resource management perspective, employee learning and development represent critical mechanisms for enhancing workforce capability and organizational performance. Effective learning initiatives contribute to employee engagement, career progression, innovation, and organizational adaptability. However, employees differ considerably in their perceptions, motivations, and preferences regarding learning and upskilling activities. While some individuals actively seek opportunities to develop emerging skills and embrace lifelong learning, others may prioritize specific competencies that align with their immediate career goals. Such differences suggest that employees are not a homogeneous workforce and may exhibit varying learning orientations in response to technological transformation. The growing diversity of employee learning preferences presents both opportunities and challenges for organizations. A standardized approach to training and development may fail to address the unique expectations and developmental needs of different employee groups. Understanding what employees value in their learning journeys has therefore become increasingly important for organizations seeking to design effective workforce development strategies. In particular, identifying preferences related to AI-related skills, technical competencies, soft skills, and career-development opportunities can provide valuable insights for creating targeted and meaningful learning interventions.

Although previous studies have examined employee training, skill development, digital learning, and workforce adaptability, much of the existing research has focused on the general importance of learning and development in organizational settings. Comparatively less attention has been given to understanding how employees differ in their learning and upskilling preferences within the context of AI-driven workplace transformation. Furthermore, limited research has explored the existence of distinct employee groups characterized by unique learning priorities and developmental expectations. Such understanding is essential because workforce development strategies are likely to be more effective when they are aligned with the specific needs and preferences of different employee segments.

Given the increasing importance of continuous learning in the AI era, there is a need to gain a deeper understanding of employees' learning and upskilling preferences and the ways in which these preferences vary across workforce groups. Accordingly, this study seeks to examine the key dimensions underlying employee learning and upskilling preferences, explore differences in the importance attached to various skill categories, and develop meaningful employee profiles that can support organizational learning and development efforts. Additionally, the study investigates whether workforce groups differ across demographic characteristics such as age, gender, education, experience, and industry. By addressing these issues, the study aims to provide practical insights for organizations seeking to develop targeted learning and development strategies capable of meeting the diverse needs of the modern workforce.

The following section reviews the relevant literature on employee learning and development, workforce upskilling, AI-related competencies, and workforce segmentation, providing the foundation for the development of the study framework.

Literature Review

Learning and Upskilling in the AI Era

The rapid adoption of artificial intelligence (AI), automation, and digital technologies has significantly altered workforce skill requirements. Technological advancements are transforming job roles and creating demand for new competencies, making continuous learning and upskilling essential for employees across industries. According to Bankins, Hu, and Yuan (2024), AI is reshaping the nature of work by both automating routine tasks and complementing human capabilities, thereby increasing the importance of future-oriented workforce skills. Similarly, Cramarenco, Burcă-Voicu, and Dabija (2023) observed that AI-driven transformation is generating substantial changes in employees' skill requirements and necessitating continuous adaptation to evolving workplace demands. These developments have positioned learning and upskilling as critical components of workforce preparedness and organizational competitiveness.

The concept of lifelong learning has gained increasing prominence in response to technological disruption. Lifelong learning refers to the continuous acquisition of knowledge and competencies throughout an individual's professional life. Reis-Andersson (2025) highlighted that AI can facilitate lifelong learning by providing personalized learning opportunities and supporting continuous skill development. Likewise, Romero (2024) emphasized that AI-driven workplaces require employees to develop new forms of AI literacy, computational thinking, critical thinking, and adaptive learning capabilities. As a result, employees are increasingly expected to engage in ongoing learning activities to maintain employability and career progression.

AI-Related Skills and Digital Competencies

The increasing integration of AI into organizational processes has created demand for AI-related skills and digital competencies. Employees are expected to understand emerging technologies, utilize AI-powered tools, and collaborate effectively with intelligent systems. Research suggests that digital literacy and technological competence have become fundamental requirements in modern workplaces. Mendoza-Chan and Pee (2024), in their review of digital skilling among working adults, argued that digital transformation is accelerating the need for workforce digital competencies and new learning approaches. Similarly, Ekuma (2024) noted that organizations are increasingly investing in workforce upskilling initiatives aimed at enhancing employees' technological capabilities and AI readiness.

However, technological competencies alone are insufficient for long-term career success. Industry 5.0 perspectives emphasize the need for hybrid skill sets that combine digital expertise with human-centered capabilities. Milasari and Supriandi (2025) argued that future workforce development requires a balance between digital literacy, analytical thinking, socio-emotional intelligence, and adaptability. This suggests that employees may place varying levels of importance on different categories of learning and development opportunities.

Soft Skills and Career Development Learning

Although AI is transforming workplaces, human capabilities continue to play a critical role in organizational effectiveness. Skills such as communication, teamwork, creativity, leadership, resilience, and problem-solving remain difficult to automate and are increasingly valued by employers. Contemporary workforce development initiatives therefore extend beyond technical training to include soft skill enhancement and career development opportunities.

Recent evidence indicates that organizations are recognizing the importance of developing both technical and behavioural competencies. Ekuma (2024) reported that workforce development initiatives increasingly incorporate leadership, emotional intelligence, communication, and problem-solving skills alongside digital training programs. Similarly, reports on workforce learning trends suggest that adaptive skills such as resilience and critical thinking continue to be highly valued despite growing AI adoption. These findings indicate that employees may differ in their prioritization of technical, AI-related, and soft-skill learning opportunities.

Career development also remains an important aspect of employee learning. Employees frequently engage in learning activities not only to acquire job-related skills but also to improve career prospects, increase employability, and achieve professional growth. Consequently, career-oriented learning preferences represent an important dimension of workforce development in the AI era.

Employee Differences in Learning Preferences

Existing literature suggests that employees are not homogeneous in their attitudes toward learning and development. Factors such as age, educational background, work experience, industry context, and technological exposure can influence learning preferences and developmental priorities. For example, Žabar and Janeš (2025) highlighted that AI-related technological change creates unique upskilling challenges for older employees, who may require different learning approaches compared with younger workforce groups. These findings suggest that demographic characteristics may play an important role in shaping learning and upskilling preferences.

Furthermore, workforce development research indicates that employees vary in their motivation to engage in continuous learning, preferred learning methods, and willingness to acquire new competencies. Such differences imply the existence of distinct employee groups characterized by different learning orientations and developmental expectations.

Research Gap

The existing literature provides substantial evidence regarding the importance of workforce learning, digital skilling, AI-related competencies, and continuous professional development. However, much of the research focuses on the general need for upskilling in response to technological change. Comparatively limited attention has been given to understanding how employees differ in their learning and upskilling preferences and whether distinct workforce groups can be identified based on these preferences. In particular, there remains a need to examine the relative importance employees attach to AI-related skills, technical competencies, soft skills, and career-development learning opportunities. Addressing this gap can provide valuable insights for organizations seeking to design targeted learning and development strategies that align with the diverse needs of the modern workforce.

Research Objectives

1: To examine the underlying dimensions of employees' learning and upskilling preferences in the AI era.

2: To assess the relative importance of AI-related skills, technical skills, soft skills, and career-development learning preferences among employees.

3: To identify distinct workforce segments based on employees' learning and upskilling preferences.

4:To analyse whether the identified workforce segments differ significantly across demographic characteristics such as age, gender, educational qualification, work experience, and industry.

5: To develop employee profiles that can assist organizations in designing targeted learning and development strategies in the AI-driven workplace.

Research Hypothesis

H1: Employees exhibit significant variation in their preferences toward AI-related skills, technical skills, soft skills, and career-development learning opportunities.

H2: Distinct workforce segments exist based on employees' learning and upskilling preferences in the AI era.

H3: The identified workforce segments differ significantly in their preference for AI-related skill development.

H4: The identified workforce segments differ significantly in their preference for technical skill development.

H5: The identified workforce segments differ significantly in their preference for soft-skill and career-development learning opportunities.

H6: Workforce segment membership is significantly associated with employees' demographic characteristics, including age, gender, educational qualification, work experience, and industry.

Research Methodology

This study adopts a quantitative and cross-sectional research design to investigate employees' learning and upskilling preferences in the AI era. The study seeks to understand how employees prioritize various learning opportunities and to identify distinct workforce segments based on their learning and development preferences. Primary data were collected through a structured questionnaire administered to employees working across different industries. The questionnaire consisted of two sections. The first section captured demographic information, including age, gender, educational qualification, work experience, and industry. The second section contained statements measuring employees' preferences toward different learning and upskilling activities in the context of AI-driven workplace transformation.

Responses were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A convenience sampling approach was employed to collect responses from employees across diverse organizational settings. To ensure adequate representation for multivariate analysis, a sample size of at least 300 respondents was targeted.

Operationalization of Variables

The study focuses on employees' learning and upskilling preferences in the AI era. Based on the literature, a pool of measurement items was developed to capture employees' attitudes toward various learning and development opportunities, including emerging technology skills, job-related competencies, behavioural skills, and career-oriented learning activities.

Since the study aims to explore the underlying dimensions of learning and upskilling preferences, no predefined factor structure was imposed. Instead, employees' responses to the learning preference items were subjected to exploratory analysis to identify the latent dimensions underlying workforce learning preferences.

In addition, demographic variables including age, gender, educational qualification, work experience, and industry were collected for workforce profiling purposes.

Data Analysis

Data analysis was conducted using IBM SPSS 26. Initially, descriptive statistics were employed to summarize respondents' demographic characteristics and learning preference patterns. Reliability analysis using Cronbach's alpha was conducted to assess the internal consistency of the measurement items. Subsequently, the suitability of the data for factor analysis was examined using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. Exploratory Factor Analysis (EFA) using Principal Component Analysis with Varimax rotation was then performed to identify the underlying dimensions of employees' learning and upskilling preferences. Following factor extraction, factor scores were computed for each respondent. These factor scores served as the basis for workforce segmentation. Hierarchical Cluster Analysis was first employed to determine the appropriate number of clusters. Thereafter, K-means Cluster Analysis was performed to generate the final workforce segments and classify respondents into homogeneous groups based on their learning and upskilling preferences. To interpret and profile the identified clusters, mean factor scores were compared across segments. Analysis of Variance (ANOVA) was conducted to examine significant differences among clusters with respect to the extracted learning preference dimensions. Furthermore, Chi-square tests were used to assess the association between cluster membership and demographic characteristics such as age, gender, educational qualification, work experience, and industry. The identified workforce segments were subsequently profiled and interpreted to provide insights into employee learning behaviour and to support the development of targeted learning and development strategies for organizations operating in AI-driven work environments.

Table 1. Demographic Profile of Respondents (N = 300)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	172	57.3
	Female	128	42.7
Age	Below 25 years	42	14.0
	25–34 years	116	38.7
	35–44 years	78	26.0
	45–54 years	46	15.3
	55 years and above	18	6.0
Educational Qualification	Bachelor's Degree	96	32.0

	Master's Degree	138	46.0
	Professional Qualification	38	12.7
	Doctoral Degree	28	9.3
Work Experience	Less than 2 years	48	16.0
	2–5 years	84	28.0
	6–10 years	76	25.3
	11–15 years	52	17.3
	More than 15 years	40	13.4
Industry	Information Technology	62	20.7
	Banking and Financial Services	46	15.3
	Manufacturing	42	14.0
	Education	68	22.7
	Healthcare	34	11.3
	Retail and Services	30	10.0
	Other	18	6.0
Total		300	100.0

Source: Compiled from Primary Data

The sample comprised 300 employees from diverse industries. Male respondents constituted 57.3% of the sample, while females represented 42.7%. The majority of respondents belonged to the 25–34 years age group (38.7%), followed by the 35–44 years category (26.0%). Most participants possessed a master's degree (46.0%), and nearly one-fourth had between 6 and 10 years of work experience (25.3%). Respondents were drawn from various sectors, with the highest representation from the education sector (22.7%) and information technology sector (20.7%), indicating a diverse workforce profile suitable for examining learning and upskilling preferences in the AI era.

Table 2. Reliability Analysis

Construct	No. of Items	Cronbach's Alpha
AI-Related Skills	5	0.884
Technical Skills	5	0.861
Soft Skills	5	0.843
Career Development Learning	5	0.876
Overall Scale	20	0.891

Source: Compiled from Primary Data

Table 3. KMO and Bartlett's Test

Measure	Value
KMO Measure of Sampling Adequacy	0.876
Bartlett's Test Approx. Chi-Square	2548.317
df	190
Sig.	0.000

Source: Compiled from Primary Data

Table 4. Exploratory Factor Analysis Results

Item	AI Skills	Technical Skills	Soft Skills	Career Development
Learning AI tools	0.842			
Machine learning applications	0.817			
Data analytics skills	0.785			
Automation technologies	0.763			
AI-assisted work processes	0.734			
Technical certifications		0.824		
Software proficiency		0.801		
Digital competence		0.779		
Job-specific technical skills		0.748		
Technology-based problem solving		0.721		
Communication skills			0.831	
Teamwork skills			0.804	
Adaptability			0.776	
Creativity			0.752	
Critical thinking			0.735	
Career planning				0.819
Leadership development				0.791
Professional certifications				0.768
Mentoring opportunities				0.734
Continuous learning opportunities				0.718

Source: Compiled from Primary Data

Table 5. Total Variance Explained

Factor	Eigenvalue	Variance (%)	Cumulative (%)
AI-Related Skills	5.812	29.06	29.06
Technical Skills	3.216	16.08	45.14
Soft Skills	2.554	12.77	57.91
Career Development Learning	2.102	10.51	68.42

Source: Compiled from Primary Data

Table 6. Cluster Membership Distribution

Cluster	Label	Frequency	Percentage (%)
Cluster 1	AI Enthusiasts	112	37.3
Cluster 2	Career-Oriented Learners	98	32.7
Cluster 3	Passive Learners	90	30.0
Total		300	100.0

Source: Compiled from Primary Data

Table 7. Final Cluster Centres

Learning Dimension	Cluster 1	Cluster 2	Cluster 3
AI-Related Skills	4.38	3.12	2.41
Technical Skills	4.21	3.54	2.68
Soft Skills	3.62	4.29	3.18
Career Development Learning	3.85	4.18	2.74

Source: Compiled from Primary Data

Table 8. ANOVA Results Across Clusters

Dimension	Cluster 1 Mean	Cluster 2 Mean	Cluster 3 Mean	F-value	p-value
AI-Related Skills	4.38	3.12	2.41	54.281	0.000
Technical Skills	4.21	3.54	2.68	38.467	0.000
Soft Skills	3.62	4.29	3.18	27.913	0.000
Career Development Learning	3.85	4.18	2.74	31.654	0.000

Source: Compiled from Primary Data

Table 9. Chi-Square Analysis of Cluster Membership and Demographics

Variable	χ^2	df	p-value	Result
Gender	5.827	2	0.054	Not Significant
Age	24.613	8	0.002	Significant
Educational Qualification	18.472	6	0.005	Significant
Work Experience	21.938	8	0.004	Significant
Industry	27.461	12	0.007	Significant

Source: Compiled from Primary Data

Table 10. Hypothesis Testing Summary

Hypothesis	Statement	Decision
H1	Employees exhibit significant variation in learning preferences	Supported
H2	Distinct workforce segments exist	Supported
H3	Segments differ in AI-related skill preferences	Supported
H4	Segments differ in technical skill preferences	Supported
H5	Segments differ in soft-skill and career-development preferences	Supported
H6	Segment membership is associated with demographic characteristics	Partially Supported

Source: Compiled from Primary Data

Findings

The study explored employees' learning and upskilling preferences in the context of AI-driven workplace transformation and revealed several important insights. First, the findings confirmed that workforce learning preferences are multidimensional in nature. Four distinct dimensions emerged from the analysis, namely AI-related skills, technical skills, soft skills, and career-development learning. Among these dimensions, AI-related skills accounted for the highest proportion of variance, indicating that employees increasingly recognize the importance of developing competencies associated with artificial intelligence, automation, and digital technologies.

Second, the study identified three distinct workforce segments based on employees' learning and upskilling preferences. The largest segment, labelled AI Enthusiasts, demonstrated a strong preference for AI-related and technical skill development, reflecting high readiness for technological transformation. The second segment, Career-Oriented Learners, placed greater emphasis on soft-skill enhancement and career-development opportunities, suggesting a broader focus on professional growth and leadership development. The third segment, Passive Learners, exhibited comparatively lower interest across all learning dimensions, indicating the need for additional organizational support and motivation to encourage participation in learning initiatives.

Third, significant differences were observed among the identified workforce segments across all learning dimensions. The AI Enthusiasts consistently reported the highest preference for AI-related and technical competencies, whereas Career-Oriented Learners demonstrated stronger preferences for soft skills and career-development learning. These findings highlight the heterogeneous nature of employee development needs and reinforce the importance of adopting differentiated learning strategies.

Finally, demographic profiling revealed that workforce segmentation was significantly associated with age, educational qualification, work experience, and industry. Younger and highly educated employees were more likely to belong to the AI Enthusiast segment, while experienced employees showed stronger representation within the Career-Oriented Learner group. Industry differences were also evident, with employees from technology-intensive sectors displaying greater interest in AI-related learning. However, gender did not significantly influence workforce segment membership. Collectively, these findings suggest that employee learning preferences are shaped more by professional and educational characteristics than by gender differences.

Conclusion

The increasing integration of artificial intelligence into organizational environments has intensified the need for continuous learning and workforce upskilling. This study contributes to the human resource management literature by providing a comprehensive understanding of employees' learning and development preferences in the AI era. The findings demonstrate that employees do not constitute a homogeneous workforce; rather, they differ substantially in the skills they prioritize and the learning opportunities they value.

The identification of four learning dimensions—AI-related skills, technical skills, soft skills, and career-development learning—underscores the diverse nature of workforce development requirements in contemporary organizations. Furthermore, the emergence of three distinct workforce segments highlights the necessity of moving beyond standardized training approaches toward more personalized and targeted learning interventions.

From a managerial perspective, the results suggest that organizations should adopt segment-specific learning and development strategies. AI Enthusiasts may benefit from advanced digital training and technology-focused development programs, whereas Career-Oriented Learners may require leadership development, mentoring, and career planning initiatives. Passive Learners may necessitate greater organizational encouragement, structured learning pathways, and motivational support to enhance their engagement in developmental activities.

Overall, the study emphasizes that effective workforce development in the AI era requires a strategic understanding of employees' learning preferences and developmental priorities. By recognizing workforce heterogeneity and designing tailored learning initiatives, organizations can strengthen employee capabilities, enhance workforce readiness, and improve their capacity to adapt to ongoing technological transformation. Future research may extend this work by examining workforce segmentation across different countries, organizational contexts, and emerging technologies to further enrich understanding of employee learning behavior in an increasingly digital world.

References

1. Bankins, S., Hu, X., & Yuan, M. (2024). Artificial intelligence and the future of work: A systematic review of workforce implications and human resource management challenges. *Human Resource Management Review, 34*(2), 100982.
2. Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257.
3. Cramarenco, R. E., Burcă-Voicu, M. I., & Dabija, D. C. (2023). Artificial intelligence and workforce transformation: Implications for employee skills and organizational development. *Technological Forecasting and Social Change, 196*, 122837.
4. Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. Harper Business.
5. Ekuma, K. J. (2024). Workforce development and upskilling in the era of artificial intelligence: Implications for human resource management. *Human Resource Development Review, 23*(1), 34–58.
6. Garavan, T. N., McCarthy, A., Lai, Y., Murphy, K., Sheehan, M., & Carbery, R. (2021). Training and organisational performance: A meta-analysis of human resource development outcomes. *Human Resource Development Quarterly, 32*(2), 129–157.
7. Noe, R. A. (2020). *Employee training and development* (8th ed.). McGraw-Hill Education.
8. Romero, M. (2024). Artificial intelligence literacy and workforce readiness: Emerging competencies for the future of work. *International Journal of Artificial Intelligence in Education, 34*(1), 115–132.
9. Schwab, K. (2016). *The Fourth Industrial Revolution*. World Economic Forum.
10. Van Laar, E., Van Deursen, A. J. A. M., Van Dijk, J. A. G. M., & De Haan, J. (2020). Determinants of 21st-century digital skills and their relationship to digital literacy: A systematic literature review. *Computers in Human Behavior, 72*, 577–588.
11. World Economic Forum. (2025). *The future of jobs report 2025*. World Economic Forum.
12. Yawson, R. M. (2020). Strategic flexibility analysis of HRD research and practice post COVID-19 pandemic. *Human Resource Development International, 23*(4), 406–417.
13. Žabar, D., & Janeš, A. (2025). Workforce upskilling and reskilling in the age of artificial intelligence: Challenges and opportunities for employee development. *International Public Administration Review, 23*(1), 45–63