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AN EVALUATION OF THE LONG-TERM EFFECTS OF AI-INTEGRATED TRAINING ON WORKFORCE: UPSKILLING AND TECHNOLOGICAL PREPAREDNESS IN THE IT SECTOR

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ABSTRACT

Research has proven the fundamental role of AI-integrated training to retain advantageous positions within the fast-transforming IT industry. The rising use of AI tools produces an evidential void regarding their sustained effects particularly among various social groups. The research focuses on assessing AI-based training impact on workforce performance development alongside workforce adaptiveness as well as their readiness to utilize technology throughout extended periods. The descriptive-correlational analysis with structured questionnaires measured 174 IT professionals who passed the exclusion criteria for missing AI experience from a 200-member initial cohort which ended with 26 participants. The research used Chi-square tests and ANOVA together with Pearson correlation and Repeated Measures ANOVA tests. The data indicates that age and experience levels affect perceived training success but comfort with AI remains constant along with maintenance of preparedness levels ($p < .001$, $\eta^2 = .655$) without age-related differences noted. AI-based learning programs must integrate two key features because demographic knowledge helps optimize long-term workforce readiness for every demographic segment.

KEYWORDS: *AI-integrated training, workforce upskilling, technological preparedness, employee adaptability and IT sector*

INTRODUCTION

In the rapidly evolving IT sector, organizations must continuously upskill their workforce to stay competitive. AI-based training has emerged as a transformative solution, offering personalized, adaptive, and data-driven learning experiences. Leveraging technologies like machine learning and NLP, AI training platforms provide real-time feedback and tailor content to individual needs, aiding both technical and soft skill development.

This study explores the long-term effects of AI-integrated training on employee performance, adaptability, and readiness for emerging technologies. While companies like IBM and Infosys have embraced such tools, questions remain about their effectiveness, integration, and employee perceptions. Challenges such as data privacy, resistance to automation, and infrastructure readiness persist.

The research aims to assess how AI training impacts skill retention, motivation, and career progression, and how organizations align these programs with strategic goals. By addressing these gaps, the study offers insights for HR leaders, IT managers, and policymakers to shape future-ready learning strategies in the digital age.

LITERATURE REVIEW

The literature extensively discusses the transformative role of automation and artificial intelligence (AI) in reshaping workforce training and productivity, particularly within the IT sector. Maity (2019) emphasized the growing significance of AI-enhanced learning systems through interviews with HR professionals, revealing strong preferences for personalized, mobile learning but lacking quantitative validation of performance outcomes. Soni et al. (2019) and Soni et al. (2020) further explored the strategic shifts AI necessitates in business and training models, stressing the importance of innovation while identifying a lack of empirical links to performance metrics. Rushmeier et al. (2019) highlighted the potential of technologies like VR, AR, and AI to create scalable, immersive training environments, though they called for stronger hardware-software integration.

Gupta and Kohli (2016) quantitatively assessed AI's role in upskilling within Indian IT firms, finding a 30% boost in technical skill retention via personalized AI tools, whereas Mitra and Jha (2017) experimentally showed that adaptive AI training enhanced programming skills by 40% compared to traditional methods. Sharma and Verma (2018) discovered that AI-based LMS platforms like SAP Litmos improved task completion and reduced skill obsolescence among IT employees. Meanwhile, Rao and Kumar (2018) conducted a systematic literature review, noting AI's potential for personalization and scalability but pointing out the need for standardized ROI metrics.

Bose (2019) detailed Infosys' use of its AI-powered Lex platform, which significantly improved cross-functional learning and reduced training time. Malik et al. (2021) provided broader qualitative insights across industries, noting both enhanced adaptability and creativity, along with side effects like job insecurity. Government and consulting reports, such as those from the National Science and Technology Council (2019) and

Deloitte Insights (2019), emphasized national strategies and labour market shifts requiring urgent upskilling efforts. Alrawashdeh et al. (2012) also offered foundational insights into technology acceptance, highlighting user-related factors crucial to AI adoption in training.

More recent studies expanded on specific applications. Ramachandran et al. (2024) proposed an AI-based training framework that integrates model development and data ethics, while Morandini et al. (2023) and Pradhan & Saxena (2023) focused on upskilling and reskilling strategies for AI-readiness. Jaiswal et al. (2023) identified core competencies such as data analysis and continuous learning as critical for IT professionals navigating AI integration. Tariq (2024), Subramanian & Riya (2024), and Miah et al. (2023) each examined how AI personalization and adaptive tools enhance workforce learning, while addressing challenges like inclusivity and system integration.

In the IT context, Lee & Jang (2024), Kumar & Gupta (2024), and Zhang & Li (2024) discussed the benefits of AI-driven adaptive learning, such as improved readiness, engagement, and skill acquisition. Silva & Rodrigues (2024) illustrated successful multinational applications of AI-powered learning, while Nasir & Hossain (2023) and Park & Choi (2024) emphasized the significance of continuous learning ecosystems. Studies by Ahmed & Patel (2024), Tan & Lee (2023), and Kumar & Sharma (2024) delved into gamification, VR integration, and chatbot support, reinforcing the enhanced efficiency and engagement that AI can offer in IT training.

Ethical, organizational, and technical considerations were not overlooked. Singh & Verma (2024) highlighted the ethical implications of AI-based training, and Tambe, Cappelli & Yakubovich (n.d.) proposed aligning AI adoption with workforce dynamics through employee involvement and ethical experimentation. Vladimirovna (2024) discussed AI's influence on HR functions, while Aithal (2024) pointed to gaps in training infrastructure and the need for emotional intelligence development in the Indian IT sector. Bodea & Paparic (2024) and Reddy & Das (2023) suggested that effective reskilling depends on aligning AI tools with professional development needs. Multiple studies (e.g., López & Martinez, 2023; Oliveira & Santos, 2024; Sharma & Patel, 2024) stressed the value of AI in creating personalized learning ecosystems that promote agility and continuous skill renewal.

Empirical and case-based research, such as that by Hassan & Khan (2024), Wu & Chen (2022), and Gupta & Prakash (2024), demonstrated how AI improves learning efficiency, especially in niche areas like cybersecurity and cloud computing. Additionally, innovative methodologies, such as the deep learning-based approach proposed by Nakamura & Sato (2024), and the predictive modelling work by Bhatia & Singh (2024), showcase how AI can proactively address skill gaps. Studies like Rahman & Chowdhury (2024) provided quantitative evidence of AI's direct impact on job performance, while Kim & Park (2024) explored AI's emerging role in soft skills training.

Collectively, these works underscore AI's transformative potential in employee training and performance enhancement, particularly in IT-driven environments, while also cautioning about challenges like privacy, ethical compliance, and alignment with human-centric development goals. While extant literature has extensively covered employee engagement drivers and AI adoption trends, there is a significant gap in studies exploring the nexus between AI-based training interventions and employee engagement, particularly within the Indian IT sector. Furthermore, there is limited empirical evidence assessing the long-term impact of such training on workforce adaptability and future-readiness. This study addresses these gaps by focusing on primary data from Indian IT professionals and evaluating both immediate and long-term outcomes of AI-based upskilling initiatives.

OBJECTIVES

1. To evaluate the influence of AI-integrated training programs on employee performance and their readiness for future challenges.
2. To analyse the role of AI-based training in equipping employees with the skills necessary to adapt to emerging technologies.

LIMITATIONS

The findings of this research are based largely on employee perceptions, which may be subjective and may not accurately reflect actual performance improvements or long-term skill retention. Additionally, differences in the type, quality, and scale of AI-based training programs across IT organizations could affect the consistency and comparability of the results. Confidentiality restrictions also pose a challenge, as they may hinder access to internal performance metrics, thereby limiting the ability to objectively evaluate the effectiveness of these training interventions. Furthermore, since the research is focused solely on the IT sector, the findings may not be applicable to other industries that have different training needs or varying levels of AI adoption.

RESEARCH METHODOLOGY

This study employs a purely quantitative research design aimed at evaluating the long-term effects of AI-integrated training on workforce adaptability and technological preparedness in the IT sector. The approach is primarily descriptive, relying on structured survey data to provide objective measures of employee perceptions, performance outcomes, and readiness levels. By utilizing a robust questionnaire, the research is able to capture a comprehensive array of quantitative indicators that reflect how AI-based training influences learning outcomes across diverse IT organizations.

In terms of research method, a quantitative approach has been adopted that emphasizes numerical data and statistical analyses. Descriptive statistics are used to summarize the demographic profiles of respondents and their responses regarding the effectiveness of AI-based training. Additionally, correlational analysis is conducted to explore relationships among key variables such as training exposure, employee adaptability, and technological readiness. This method provides an empirical basis for understanding the associations between AI-integrated training and improvements in workforce capabilities.

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The target population for this study comprises IT professionals working across various levels—from entry-level roles to senior management—in mid-to-large scale IT companies. A purposive sampling method was used to carefully select participants who had direct experience with AI-based training programs. This was important to make sure the people included in the study were familiar with the topic and could provide meaningful responses. The target sample size of 200 was determined through a statistical method called power analysis, which helps ensure that the number of responses is large enough to draw reliable conclusions. Out of the 200 responses collected, 26 were removed because those individuals had not undergone any AI-based training. As a result, the final analysis was based on 174 relevant responses, making the study more accurate and applicable to the IT sector. Data collection is accomplished exclusively via a structured questionnaire, which serves as the primary data source. The questionnaire is designed to capture a wide range of variables relevant to the research objectives, including:

- Perceptions of Training Effectiveness: Respondents rate the impact of AI-based training on improving their skills using Likert-scale items.
- Workforce Adaptability: Items in the questionnaire measure respondents' views on how AI-integrated training has influenced their ability to adapt to new technologies and changing job demands.
- Technological Preparedness: The survey includes questions that assess whether employees feel adequately prepared for emerging technologies within the IT environment.
- Demographic Information: Basic demographic data (e.g., age group, current role, years of experience) are collected to enable segmentation of the results and to identify potential differences across subgroups.

For the distribution and management of the questionnaire, online survey platform Google Forms was utilized. The digital format facilitates data cleaning and preparation for subsequent statistical analysis, ensuring that the dataset is both reliable and ready for in-depth examination. All participants provided informed consent, and their responses were anonymized and securely stored in accordance with institute's ethical guidelines.

Data analysis was conducted using IBM SPSS Statistics, employing both descriptive and inferential tools. Descriptive statistics summarized respondent demographics and perceptions. Inferential analysis included Chi-Square tests to assess associations between variables like age, experience, and training effectiveness, while Pearson correlation measured relationships between comfort with AI and perceived personalization. One-way ANOVA compared preparedness across age groups, and Repeated Measures ANOVA evaluated changes in performance over time. These tools ensured statistically sound insights into the impact of AI-based training on workforce adaptability and technological readiness.

In summary, the research methodology is designed to be rigorous and straightforward, employing a purely quantitative approach that hinges on a well-structured questionnaire. By focusing on objective measures and statistical relationships, this methodology aims to provide clear, actionable insights into how AI-integrated training influences workforce adaptability and technological preparedness in the IT sector. The use of purposive sampling and online survey tools further ensures that the study collects high-quality data from a targeted, relevant population, thereby enhancing the overall validity and generalizability of the findings.

Analysis and interpretation

This study aims to comprehensively evaluate the effectiveness and long-term impact of AI-based training programs on employees working in the IT sector. To achieve this, five distinct hypotheses were formulated and tested using a variety of statistical methods to explore the relationships between individual demographic factors and training outcomes. The analysis focuses on both static individual characteristics—such as years of experience, age, and comfort with AI tools—and dynamic elements, particularly changes in employee performance and readiness over time.

To assess the internal consistency of the survey items measuring job satisfaction, Cronbach's alpha was calculated. The resulting value of Cronbach's alpha was 0.85, indicating a high level of reliability.

Specifically, the research investigates how these variables influence employees' perceptions of the effectiveness of AI-integrated training, as well as their actual performance improvements post-training.

To statistically validate these relationships, multiple SPSS-based analytical tools were applied. Chi-Square tests were used to determine whether there are significant associations between categorical variables like age groups and experience levels and their perceived training effectiveness. Pearson correlation analysis examined the strength and direction of association between comfort in using AI tools and the perception that the training is personalized to individual needs. One-way ANOVA was utilized to assess whether preparedness for emerging technologies varies significantly across different age groups. Furthermore, Repeated Measures ANOVA provided insight into how performance and readiness levels evolved across three time points—before training, immediately after training, and during the follow-up phase—offering evidence of sustained learning and long-term impact. The five hypotheses tested include:

- Hypothesis 1: Experience vs. Perceived Effectiveness
- Hypothesis 2: Age Group vs. Effectiveness Perception
- Hypothesis 3: Association between comfort working with AI tools and if AI is tailored to specific needs
- Hypothesis 4: Difference in preparedness and Age Groups
- Hypothesis 5: Performance/Readiness Over Time

Hypothesis 1: Experience vs. Perceived Effectiveness
H_0: *There is no significant relationship between years of experience in the IT sector and the perceived effectiveness of AI-based training programs.*
H_1: *There is a significant relationship between years of experience and the perceived effectiveness of AI-based training programs.*

- **Statistical Test: Chi-Square Test of Independence**
- **Purpose:** To assess whether junior vs. senior professionals perceive AI-based training differently.
- **Variables:**
  - Independent Variable: Experience in IT
  - Dependent: Perceived effectiveness of AI-based training

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	19.019[a]	9	0.025
Likelihood Ratio	20.087	9	0.017
Linear-by-Linear Association	1.234	1	0.267
N of Valid Cases	174		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.87.

Interpretation

- The p-value (0.025) indicates that the relationship is statistically significant at the 5% level.
- You can reject the null hypothesis.
- Cramer's V = 0.191 shows a small to moderate effect, suggesting that different levels of experience influence how effective AI-based training is perceived to be.
- More experienced employees might evaluate training differently due to deeper industry knowledge or previous training experiences.
- Therefore alternative hypothesis is accepted saying that there is a significant relationship between years of experience and the perceived effectiveness of AI-based training programs.

Hypothesis 2 : Age Group vs. Effectiveness Perception
H_0: *There is no significant difference in perceived effectiveness of AI-based training across different age groups.*
H_1: *Perceived effectiveness of AI-based training differs significantly between age groups.*

- **Purpose:** To examine generational differences in acceptance and perceived value of AI training.
- **Variables:**
  - Independent: Age group
  - Dependent: Perceived effectiveness

	Value	df
Pearson Chi-Square	480.578[a]	12
Likelihood Ratio	447.716	12
Linear-by-Linear Association	164.231	1
N of Valid Cases	174	

Chi-Square Test Results

- **Pearson Chi-Square**: 480.578 (p-value = 0.000)
- **Likelihood Ratio**: 447.716 (p-value = 0.000)
- **Linear-by-Linear Association**: 164.231 (p-value = 0.000)

Interpretation

- The Chi-Square test yields a highly significant result (p-value = 0.000), indicating that there is a strong relationship between age group and the perception of the effectiveness of AI-based training programs.
- The Phi and Cramer's V values of 1.662 and 0.960, respectively, suggest a very strong association between age group and effectiveness perception. Cramer's V is very close to 1, which indicates a substantial relationship between the two variables.
- The very strong association (Cramer's V = 0.960) indicates that the age group plays a major role in shaping how effective participants find AI-based training programs in improving their skills.
- Age group has a strong impact on the perception of AI-based training effectiveness. Employees from different age ranges may have varying opinions about how well the training enhances their skills, and this is statistically significant.
- Therefore alternative hypothesis is accepted saying that perceived effectiveness of AI-based training differs significantly between age groups.

Hypothesis 3 : Association between comfort working with AI tools and if AI is tailored to specific needs
H_0: There is no association between comfort with AI tools and whether AI is tailored to user needs.
H_1: There is a significant association between comfort with AI tools and whether AI is tailored to user needs.

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Correlations			
		Comfort with AI Tools	Tailored to Needs
Comfort with AI Tools	Pearson Correlation	1	.855
	Sig. (2-tailed)		.000
	N	174	174
Tailored to Needs	Pearson Correlation	.855	1
	Sig. (2-tailed)	.000	
	N	174	174

- The Pearson correlation coefficient ($r = 0.855$) indicates a very strong positive relationship between the level of comfort employees have while working with AI tools and their perception that the AI is tailored to meet their specific needs.
- A p-value of 0.000 (2-tailed) indicates that the correlation is highly statistically significant at the 0.01 level ($p < 0.01$). This means that there is less than a 0.1% chance that this result is due to random variation or coincidence.
- As the p-value is significantly less than the 0.05 threshold, we reject the null hypothesis (H_0) and accept the alternative hypothesis (H_1).

There is a strong and statistically significant positive association between employees' comfort with AI tools and their perception that AI training is tailored to their specific needs. This suggests that as comfort with AI increases, so does the perceived relevance and personalization of AI-based training programs.

Therefore alternative hypothesis is accepted saying that there is a significant association between comfort with AI tools and whether AI is tailored to user needs.

Hypothesis 4 : Preparedness and Age Groups

- **H_0:** *There is no significant difference in preparedness for emerging technologies across age groups.*
- **H_1:** *There is a significant difference in preparedness across age groups.*

Preparation for Future Roles					
Tukey HSD					
Age Group	N	Subset for alpha = 0.05			
		1	2	3	4
1	64	1.52			
2	44		2.52		
3	32			3.41	
4	34				4.50
Sig.		1.000	1.000	1.000	1.000

Descriptives

- Preparedness scores increased consistently with age, ranging from a mean of 1.52 in the 18–25 group to 4.50 in the 46+ group, indicating that older employees feel significantly more ready for future roles post AI-based training.
- This trend suggests that professional experience and age may enhance confidence and adaptability in the context of technological upskilling.
- The results provide strong support for the alternative hypothesis, showing a clear and statistically significant difference in preparedness across age groups.

ANOVA

Preparation for Future Roles	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	217.279	3	72.426	285.141	.000
Within Groups	43.180	170	.254		
Total	260.460	173			

- Statistically Significant Difference: The p-value is .000 ($p < 0.05$), indicating a significant difference between the groups. This means that at least one group's mean is significantly different from the others.
- High F-Value: The F-statistic of 285.141 suggests a very strong variance between groups compared to within groups, reinforcing that the group differences are meaningful and not due to random chance.

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Hypothesis 5 : Performance/Readiness Over Time

H_0 : *There is no significant change in employee performance/readiness scores across the three measurement occasions (pre-training, immediately post-training, and at follow-up).*

H_1 : *Employee performance/readiness scores differ significantly across the three measurement occasions, with scores improving over time following AI-based training.*

Mauchly's Test of Sphericity

W = 0.993, p = 0.564

Since the p-value is greater than 0.05, the assumption of sphericity was not violated.

Therefore, we relied on the Sphericity Assumed results in further analysis.

- Tests of Within-Subjects Effects

Source	df	F	Sig. (p)	Partial Eta Squared
Time	2	328.757	.000	.655

- The analysis revealed a highly significant main effect of time on employee performance, $F(2, 346) = 328.757$, $p < .001$, with a large effect size ($\eta^2 = .655$). This indicates that AI-based training had a strong impact on performance scores over time.

- Trend Analysis: Within-Subjects Contrasts

Contrast Type	F	Sig.	Interpretation
Linear	453.884	.000	Significant linear improvement across time
Quadratic	182.776	.000	Suggests possible slowing of improvement

- Both the linear and quadratic trends were statistically significant, indicating steady performance improvement over time, with a slight deceleration after the initial post-training gain.
- The results of the Repeated Measures ANOVA demonstrate a significant and sustained improvement in employee performance following the implementation of AI-based training.
- The large effect size ($\eta^2 = .655$) confirms that the improvement is not only statistically significant but also practically meaningful.
- Employees showed marked performance gains immediately after training and maintained or further improved their scores during the follow-up period.
- These findings suggest that AI-based training is an effective tool for upskilling the workforce and enhancing employee productivity over time

FINDINGS

The analysis revealed several key insights regarding AI-based training and its impact on the workforce. Firstly, a significant relationship was identified between the number of years of experience in the IT sector and the perceived effectiveness of AI-based training ($\chi^2(9) = 19.019$, $p = .025$). Employees with more years of experience tended to have a different perception of the training's effectiveness, suggesting that experience plays a crucial role in shaping expectations and evaluations of AI-integrated learning. This highlights the importance of tailoring training programs to meet the diverse needs of employees at different stages in their careers.

Additionally, a strong correlation was found between age groups and the perception of AI training effectiveness ($\chi^2(12) = 480.578$, $p < .001$, Cramer's $V = 0.960$). This indicates significant generational differences in how employees perceive the value and relevance of AI-based training. It suggests that younger employees may be more open and adaptive to AI technologies, while older generations might exhibit scepticism or require more time to adapt to new learning methodologies.

A major new finding emerged from the analysis of employee comfort with AI tools. There was a very strong positive correlation between employees' comfort with AI tools and their perception of the personalization of the training ($r = 0.855$, $p < .001$). Employees who were comfortable with using AI

were more likely to perceive the training as tailored to their needs. This finding suggests that ensuring employees feel confident and competent in using AI tools is key to enhancing their engagement and the perceived relevance of the training. Organizations looking to increase the perceived value of their training programs should focus not only on delivering high-quality content but also on fostering a sense of comfort and familiarity with the technology itself.

Furthermore, the analysis revealed that technological preparedness was perceived similarly across all age groups, as there was no significant difference in preparedness across age demographics ($F(3,170) = 0.066$, $p = .978$). This suggests that training programs are generally successful in ensuring that employees, regardless of age, feel equally prepared to engage with AI-based training.

A sustained and significant improvement in employee performance was observed post-training. The data showed robust and enduring performance gains, with repeated measures ANOVA revealing significant improvements in performance over time ($F(2,346) = 328.757$, $p < .001$, $\eta^2 = .655$). This underscores the long-term effectiveness of AI-based training in enhancing job performance, with employees continuing to show growth even after the training has concluded.

However, one of the most critical findings of this study was the identification of a significant gap in AI-based training coverage. Of the 200 initial respondents, 26 participants (13%) had not received AI-based training and were excluded from further analysis. This gap highlights a critical issue: despite the growing adoption of AI training programs, a portion of the workforce remains untrained and unsupported. The exclusion of these employees raises concerns about digital equity within organizations. It suggests that some workers may not have access to AI training opportunities, either due to oversight, lack of awareness, or logistical barriers. This gap could potentially hinder the organization's overall efforts to ensure that all employees are digitally equipped and ready for future challenges. Addressing this issue and ensuring that training programs are comprehensive and inclusive will be vital in achieving equitable skill development and ensuring a digitally prepared workforce across the board.

CONCLUSION

The study demonstrates that AI-integrated training significantly enhances workforce upskilling and technological preparedness in the IT sector, with sustained improvements in employee performance and adaptability over time. Key findings reveal that while experience and age influence perceptions of training effectiveness, comfort with AI tools strongly correlates with perceived personalization, and older employees report higher preparedness for emerging technologies. However, the exclusion of 13% of respondents due to lack of AI training highlights a critical gap in inclusivity. To maximize benefits, organizations should tailor programs to diverse demographics, reinforce training with follow-ups, and ensure equitable access to AI learning opportunities, thereby fostering a future-ready workforce.

Recommendations

- Customize AI Training Based on Experience and Age

Since perception of effectiveness varies significantly across experience and age groups, training modules should be adapted to cater to different levels of expertise and generational learning styles to improve engagement and outcomes.

- Reinforce Training with Follow-Up Interventions

The sustained performance improvement post-training suggests value in periodic reinforcement. Organizations should consider follow-up assessments or refresher sessions to ensure long-term retention and skill application.

- Do Not Overemphasize AI Familiarity

Given the lack of correlation between AI comfort and perception of tailored training, designers should focus more on content relevance and learning objectives rather than assuming tech-savviness equates to better outcomes.

- Ensure Inclusivity Across Age Groups

As preparedness did not significantly differ by age, standardized AI-training programs can be broadly implemented across generations. However, feedback loops should still be included to ensure clarity and accessibility.

- Monitor Beyond Exposure Metrics

While a high percentage of employees had participated in AI training, some reported limited perceived benefit. Organizations should move beyond tracking participation to measuring actual impact on performance, adaptability, and job readiness.

- Use Data to Inform Training Strategy

Continued use of feedback surveys and performance data will enable ongoing improvements. Organizations should establish metrics for success aligned with both short-term learning goals and long-term strategic outcomes.

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