JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Leveraging Artificial Intelligence for Employee Performance Management in Manufacturing Units with Special Reference to Hyderabad city

[1]Mr. Mohammed Abdul Lateef Siddiqui, [2] Dr. Nikhat Sultana, [3] Mr. Mohammad Sirajuddin
[1,2,3]Assistant Professor
[1,2] Amjad Ali Khan College of Business Administration, Hyderabad, Telangana, India
[3] CMR College of Engineering and Technology, Hyderabad, Telangana, India

Abstract: *The manufacturing sector is undergoing a revolution in the era of Industry 4.0 due to the incorporation of Artificial Intelligence (AI) into employee performance management systems. With an emphasis on Hyderabad, this study investigates the possibilities and real-world effects of using AI to improve employee performance management in manufacturing facilities. The study looks at how AI-powered tools, like real-time monitoring systems, machine learning algorithms, and predictive analytics, can be used to monitor performance indicators, spot skill gaps, tailor training, and increase worker productivity. The study assesses the adoption rates, perceived advantages, and difficulties of implementing AI in human resource functions through a qualitative and quantitative analysis of a subset of Hyderabad's manufacturing facilities. According to the research, AI can greatly enhance decision-making procedures, encourage impartial performance reviews, and assist strategic.*

IndexTerms **- Artificial Intelligence (AI), Employee Performance Management, Manufacturing Sector, Leverage, AI Powered tools, Predictive Analytics.**

I. Introduction

The intersection of digital technologies and human capital management is changing how businesses function and compete in today's ever-changing industrial landscape. Artificial Intelligence (AI) is a key component of contemporary manufacturing ecosystems as the fourth industrial revolution, or Industry 4.0, places an emphasis on automation, smart systems, and data-driven decision-making. Although artificial intelligence (AI) has historically been used to improve supply chain logistics, production lines, and quality control, its application in human resource management (HRM), specifically in employee performance management (EPM), is receiving more and more attention.

Goal-setting, performance monitoring, feedback systems, training, and succession planning are just a few of the many activities that fall under the umbrella of employee performance management, which aims to increase both individual and organizational effectiveness. These procedures have historically mainly depended on human intervention and subjective assessments, which frequently results in bias, inefficiencies, and limited scalability. By enabling real-time data analysis, automated performance tracking, and predictive insights, artificial intelligence (AI) provides a revolutionary alternative that improves objectivity and strategic

Large amounts of employee data, including task completion rates, attendance, training logs, peer reviews, and even behavioural patterns, can be analyzed by AI-powered systems to produce insights that can be put to use. These insights can be used to identify high-potential employees or underperformers, forecast future performance trends, and suggest customized development plans in addition to assessing current performance. For manufacturing facilities, where worker productivity and skill alignment are directly linked to operational efficiency, such capabilities are essential.

In order to stay competitive in both local and international markets, manufacturing facilities in Hyderabad, one of India's fastest-growing industrial and technological centers, are increasingly looking into digital solutions. The city is a desirable site for manufacturing companies in a variety of industries, including electronics, heavy machinery, pharmaceuticals, and the automotive sector, thanks to its strong infrastructure, skilled labor pool, and proactive industrial policies. To encourage a more flexible, effective, and innovative workforce, these companies must reconsider their talent management plans as the competition heats up.

The purpose of this study is to look into how Hyderabad manufacturing facilities are using AI technologies to manage employee performance. It will examine the perceived advantages and difficulties, gauge the degree of AI adoption to date, and analyze how AI affects HR procedures and organizational effectiveness. Additionally, the study aims to comprehend these units' readiness for integrating AI in terms of staff readiness, data management, and digital infrastructure..

The study adds to the larger conversation on AI in HRM by providing a region-specific and industry-focused analysis. It also offers useful insights for policymakers, HR professionals, and business executives. The results should help manufacturing companies in Hyderabad and elsewhere create AI-based performance management systems that are efficient, moral, and long-lasting.

II. LITERATURE REVIEW

Rao, M. R. M. (2025) over the past ten years, there has been a lot of scholarly interest in the integration of artificial intelligence (AI) into human resource management (HRM), especially in relation to performance management. AI applications in HR are now being used more and more for predictive workforce analytics, employee performance evaluation, and training needs assessment. These applications are no longer just used for payroll automation or recruitment.

H. Mehrabi et al., (2025) AI can help reduce human bias in performance reviews. It was discovered that by emphasizing objective measurements over subjective opinions, AI algorithms standardize evaluations. Algorithmic transparency and fairness are still issues, though.

Bhatia, S., Arora, V., & Batra, S. (2024) despite an increasing amount of research highlighting AI's potential to improve employee performance management, there are still few empirical studies that concentrate on low-to-mid skill manufacturing roles. The majority of current research focuses on IT or white-collar settings. Furthermore, there aren't many studies that look at the long-term organizational and psychological effects of AI-enabled monitoring, which calls for more research.

Bhatia, M., et al (2024) by contrasting current employee performance data with task or role-specific benchmarks, AI is also being used to perform skill gap analyses. Artificial intelligence (AI) systems can determine which employees are performing poorly and why by using methods like decision trees and clustering. Then, using collaborative filtering techniques or reinforcement learning, personalized training pathways can be suggested. This has made it possible to specifically upskill workers in manufacturing contexts, particularly in industries going through automation-driven transitions.

Uraon, R. S., & Kumarasamy, R. (2024) Conventional performance reviews frequently suffer from prejudices and imprecise feedback. Artificial Intelligence (AI)-powered Natural Language Processing (NLP) tools are being used to standardize and organize feedback from supervisor comments, peer evaluations, and performance reviews. These tools can pinpoint areas for improvement or employee discontent by analyzing tone, intent, and sentiment. This is especially important in manufacturing because multilingual and multicultural workforces can make communication difficult.

Kumar, P. N., et al (2024) numerous scholars have highlighted how AI is revolutionizing contemporary HR tasks. By using data-centric methods to track, assess, and improve employee performance, AI technologies help businesses minimize human biases and increase decision accuracy. Similarly, Min et al. (2019) contend that AI improves strategic HRM by using real-time analytics and feedback mechanisms to match workforce capabilities with organizational goals..

Chakramakkil Sathian, T. (2024) According to Pulakos et al. (2015), traditional performance appraisal methods are frequently criticized for being time-consuming, subjective, and out of step with changing business requirements. These drawbacks are addressed by AI-based systems, which use machine learning algorithms to provide individualized development plans and continuously monitor performance indicators.

Jain, R., et al (2024) In order to further enhance performance evaluation metrics, particularly for performance management, which is still in its infancy, natural language processing, or NLP, is being utilized more and more to analyze employee feedback, communication patterns, and engagement levels. This disparity emphasizes the necessity of conducting regional research to examine AI-based HR system readiness, adoption hurdles, and strategic opportunities.

Ranganath, I. V. S., et al (2024) notwithstanding its benefits, there are drawbacks to using AI in employee performance management. The literature has extensively addressed issues related to algorithmic bias, transparency, data privacy, and employee acceptance. For responsible implementation, ethical AI frameworks and regulatory compliance are therefore crucial.

Pandey, N., et al., (2023) AI-enabled continuous feedback systems are replacing conventional annual assessments. Real-time performance analytics are provided by chat bots and natural language processing (NLP) tools. AI-powered coaching has been shown to increase worker engagement and productivity in assembly-line settings.

Jarrahi, M. H., et al (2023) Human resource management (HRM) procedures are increasingly incorporating artificial intelligence (AI) to improve the precision and effectiveness of decision-making. By facilitating real-time performance tracking and predictive analytics, artificial intelligence (AI) applications like machine learning, natural language processing (NLP), and computer vision have completely changed employee evaluation techniques. In manufacturing industries, where operations are heavily data-driven and performance metrics are closely linked to output and quality standards, these capabilities are especially pertinent

Tyagi, P., et al (2023) in the manufacturing industry, where accuracy and productivity are crucial and performance management is essential. According to studies, AI tools can forecast changes in labor demand, track machine-human interactions, and spot skill gaps. But they also warn that employee training, change management programs, and a supportive digital infrastructure are necessary for the effective application of AI in manufacturing HRM..

Singh, S., et al (2023) research on the adoption of AI in Indian manufacturing hubs like Hyderabad is scarce but expanding. According to reports from the Telangana State Industrial Infrastructure Corporation (TSIIC) and the Confederation of Indian Industry (CII), many Hyderabad-based businesses are implementing automation in their production processes, but AI is not yet being used in human resources.

Sirajuddin, M. M., et al (2023) few empirical studies have been carried out in the context of Indian manufacturing units, especially in regional centres like Hyderabad, despite the fact that the body of existing literature provides a solid foundation for understanding AI's role in HRM and performance management. By examining the real-world implementation, advantages, and difficulties of AI-driven employee performance management systems in Hyderabad's manufacturing industry, this study aims to close this gap.

Floridi et al., (2022) the incorporation of affective computing and emotional AI into performance management is gaining traction. These systems use physiological markers, voice tones, and facial recognition to gauge not only productivity but also emotional engagement. These tools promise a more comprehensive understanding of worker performance, but they are still in the experimental stage. Furthermore, ethical AI frameworks with a focus on human-centered design, accountability, and transparency are being developed specifically for manufacturing settings.

Li et al., (2022) in the meantime, NLP tools examine unstructured employee feedback to determine levels of engagement and morale (Rana & Sharma, 2022). Managers can shift from reactive performance evaluations to proactive performance improvement tactics with the aid of these AI-powered tools.

Rana, S., & Singh, S. (2022) in performance management, predictive analytics is becoming more and more popular, especially in labor-intensive industries. According to studies, AI models can predict employee training needs, labor shortages, and even mental exhaustion. With this information, manufacturing companies can better allocate labor, cut down on downtime, and increase worker productivity. Additionally, AI makes it easier to set dynamic goals by modifying performance standards in response to shifts in workload, equipment efficiency, and environmental factors.

S. Agrawal (2022) AI models use previous data to forecast patterns in employee performance. Emphasize how training requirements, fatigue levels, and skill gaps can be identified using predictive analytics. Manufacturing companies that use AI-driven insights report lower attrition and better labour planning.

Dwivedi et al., (2021) notwithstanding its benefits, there are serious ethical issues with using AI in performance management. If bias in algorithmic decision-making is not adequately addressed, it can sustain workplace disparities. Furthermore, employees may object to ongoing monitoring and data tracking, particularly if they feel that it is intrusive. Concerns about privacy, data security, and transparency continue to be major obstacles to the use of AI-based performance tools. Additionally, there aren't many regulations that specifically address AI monitoring in blue-collar workplaces.

Westerman, J. W. et al., (2021) AI-based performance systems have been piloted by a number of manufacturing companies with encouraging results. To enhance performance, Siemens, for instance, uses AI to evaluate operator-machine interactions and deliver real-time alerts. Toyota has used artificial intelligence (AI) tools to assess worker ergonomics and task efficiency, enhancing worker safety and productivity. These case studies demonstrate how AI's contribution to the development of intelligent and sustainable performance management systems is becoming increasingly acknowledged.

Balasubramanian & Fernandes, (2021) Although AI increases productivity; little is known about how it affects employees' mental health. Performance reviews based on surveillance may cause anxiety, a loss of autonomy, and problems with trust. The necessity of open communication and staff participation in the development and implementation of AI systems is emphasized by research. Perceived fairness, output explains ability, and alignment with organizational objectives is all strongly connected with trust in AI tools.

Mitra, N. (2021) Real-time, objective, and context-aware evaluation metrics are made possible by AI. Based on past data, machine learning algorithms have been used to forecast attrition, absenteeism, and performance declines. Without the need for direct human intervention, computer vision systems—which are frequently combined with shop floor cameras—evaluate worker productivity, safety compliance, and ergonomics

Ghosh, R, et al (2020) in the past, post-hoc productivity reviews, standardized checklists, and manual supervision were the mainstays of performance management in manufacturing. Nevertheless, subjectivity and feedback delays are common problems with these approaches. Manufacturing facilities have begun implementing sensor-based monitoring and real-time data collection in order to evaluate operator efficiency, error rates, and task completion times as a result of the emergence of Industry 4.0 technologies. By automating the analysis of intricate datasets and spotting patterns that conventional methods might miss, artificial intelligence has further simplified this process.

Aggarwal & Kapoor, (2020) according to this research implementing AI for performance management had many organizational advantages, such as enhanced employee accountability, decision-making and greater transparency. For example, supervisors can now concentrate on coaching instead of administrative tracking thanks to real-time dashboards and automated scoring systems. AI-based performance insights also help create customized development plans, which improves employee retention and engagement..

Porter, T., et al (2020) numerous studies have demonstrated how useful AI is for resource optimization and workforce scheduling. AI can recommend the best team setups, break times, and task rotations to increase output by examining past productivity data and current task completion rates. By preventing burnout, performance management not only guarantees equitable workload distribution but also enhances employee morale and health.

Tambe et al. (2019) Ensuring fairness and equity has become crucial as AI systems have a greater impact on evaluations and hiring decisions. According to research, if AI systems are trained on unbalanced datasets, they may inadvertently replicate preexisting workplace biases. Particular care must be taken to guarantee that performance algorithms do not discriminate on the basis of role, gender, or shift patterns in manufacturing facilities where gender representation is frequently skewed.

III. OBJECTIVES

- To examine the current level of adoption of Artificial Intelligence (AI) technologies in employee performance management systems within manufacturing units in Hyderabad.
- To analyze the effectiveness of AI-based tools in enhancing the accuracy, objectivity, and efficiency of performance evaluation processes in the manufacturing sector.
- To identify the key benefits experienced by manufacturing organizations through the implementation of AI-driven performance management systems.
- To explore the challenges and limitations faced by manufacturing units in Hyderabad in adopting AI for performance management, including technological, organizational, and ethical concerns.

IV. HYPOTHESIS

- H_1: The adoption of AI in employee performance management significantly improves the accuracy and objectivity of performance evaluations in manufacturing units.
- H_2: There is a positive correlation between the use of AI tools and overall employee productivity in Hyderabad-based manufacturing firms.
- H3: AI-driven performance management systems are perceived more favourably by and there is an association between Performance Evaluation and Digital Infrastructure
- H_4: The primary barriers to AI adoption in performance management are lack of technical expertise and inadequate digital infrastructure in manufacturing units in Hyderabad.

V. Research Methodology

With particular reference to Hyderabad, this section describes the methodology used to examine the function of artificial intelligence (AI) in employee performance management in manufacturing facilities. To guarantee that both quantitative and qualitative insights are recorded and to provide a thorough grasp of AI's influence in this field, a mixed-methods approach has been chosen.

VI. Research Design

A descriptive and exploratory research design is used in the study. While exploratory elements try to comprehend underlying perceptions, difficulties, and possible future applications of AI in performance management, descriptive elements try to capture the current state of AI adoption.

VII. Research Approach

A **mixed-methods approach** will be used:

- **Quantitative** data will be collected through structured surveys distributed among HR professionals, managers, and employees working in manufacturing units.
- **Qualitative** insights will be gathered through semi-structured interviews and focus group discussions to explore deeper perceptions and experiences.

VIII. Population and Sampling

- **Target Population:** HR managers, line managers, and employees from small, medium, and large-scale manufacturing units located in Hyderabad.
- **Sampling Technique:** To guarantee representation from a variety of manufacturing sectors, a stratified random sampling technique will be used (e.g., pharmaceuticals, electronics, automotive).
- **Sample Size:** Depending on accessibility and willingness to participate, surveys may have 210 respondents, while interviews may have 10–15 participants.

IX. Data Collection Methods

- **Primary Data:**
  - Surveys: A structured questionnaire with both close-ended and Likert scale questions.
  - Interviews: Semi-structured interviews with key HR and operational personnel.
  - Focus Groups: Sessions involving 5–8 participants to gather collective feedback.
- **Secondary Data:**
  - Company reports, industry white papers, government publications, and academic journals related to AI in HRM and smart manufacturing.

X. Data Analysis Techniques

- **Quantitative Data:**
  - Statistical analysis using software such as SPSS or Excel.
  - Techniques may include descriptive statistics, correlation analysis, regression analysis, and hypothesis testing (e.g., t-tests, ANOVA).
- **Qualitative Data:**
  - Thematic analysis to identify common themes, patterns, and sentiments from interview transcripts and focus group discussions.

XI. Ethical Considerations

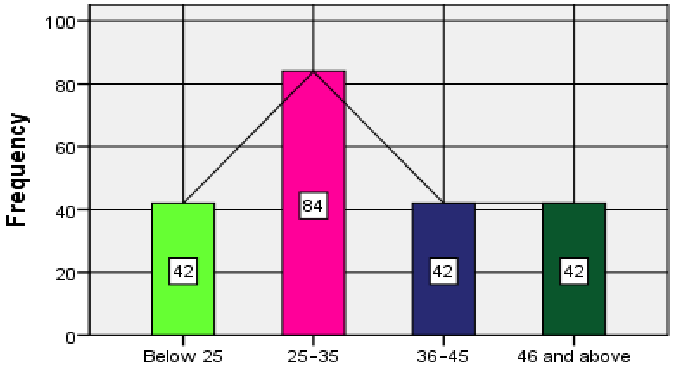
All participants will be asked for their informed consent and participant anonymity, and data confidentiality will be rigorously upheld. If necessary, ethical approval from the appropriate institutional review boards will be sought.

XII. Data Analysis and Discussion

Table No: 12.1 Age of the Respondents

Age of the Respondents					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 25	42	20.0	20.0	20.0
	25–35	84	40.0	40.0	60.0
	36–45	42	20.0	20.0	80.0
	46 and above	42	20.0	20.0	100.0
	Total	210	100.0	100.0	

Graph No: 12.1 Age of the Respondents

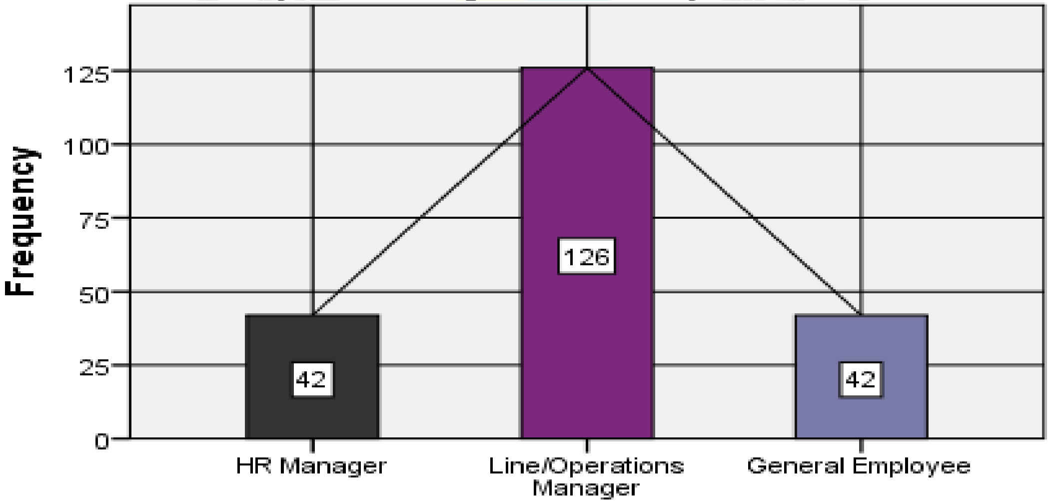


- The largest age group is 25–35 years, making up 40% of respondents.
- All other groups are equally represented at 20% each.
- This distribution suggests a relatively balanced sample, with a slightly younger population overall.
- The age spread also ensures diversity across different generational perspectives.

Table No: 12.2 Designation e of the Respondents

Designation of the Respondents					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	HR Manager	42	20.0	20.0	20.0
	Line/Operations Manager	126	60.0	60.0	80.0
	General Employee	42	20.0	20.0	100.0
	Total	210	100.0	100.0	

Graph No: 12.2 Designation e of the Respondents

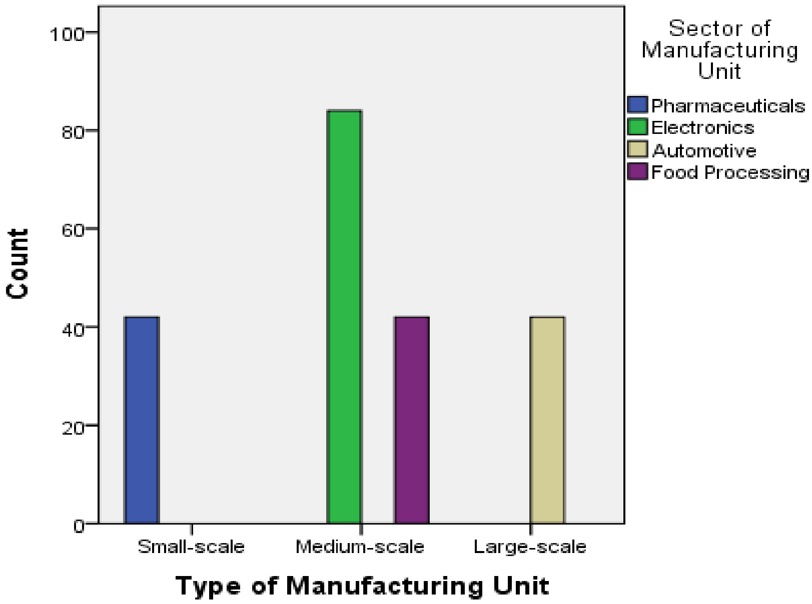


Line and operations managers make up the majority of responders (60%) while general employees and HR managers are equally represented (20%). The respondents in this distribution are primarily managers, which could have an impact on how performance tools or workplace technologies are viewed and used.

Table No: 12.3 Types and Sector of the Manufacturing Unit

Type of Manufacturing Unit * Sector of Manufacturing Unit Cross tabulation						
Count						
		Sector of Manufacturing Unit				Total
		Pharmaceuticals	Electronics	Automotive	Food Processing	
Type of Manufacturing Unit	Small-scale	42	0	0	0	42
	Medium-scale	0	84	0	42	126
	Large-scale	0	0	42	0	42
Total		42	84	42	42	210

Graph No: 12.3 Types and Sector of the Manufacturing Unit



Each type of manufacturing unit is exclusively associated with a single sector:

- Small-scale → Pharmaceuticals
- Medium-scale → Electronics and Food Processing
- Large-scale → Automotive

There is no overlap between sectors and unit types. This implies a perfectly structured, non-random relationship—each unit type only appears in specific sectors.

H₁: The adoption of AI in employee performance management significantly improves the accuracy and objectivity of performance evaluations in manufacturing units.

Table No: 12.4 Independent Sample T-Test

Group Statistics					
	Does your organization currently use AI tools in HR or performance management	N	Mean	Std. Deviation	Std. Error Mean
Performance Evaluation	Yes	168	4.3000	.41354	.03191
	No	42	5.0000	.00000	.00000

Table No: 12.5 Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Performance_ Evaluation	Equal variances assumed	107.284	.000	-10.950	208	.000	-.70000	.06393	-.82603	-.57397
	Equal variances not assumed			-21.940	167.000	.000	-.70000	.03191	-.76299	-.63701

F = 107.284, Sig. = 0.000

This determines whether the two groups' variances are equal. We reject the null hypothesis of equal variances because the p-value (Sig.) is less than 0.05. Utilize the row labeled "Equal variances not assumed." With a mean difference of -0.70, one group's Performance_ Evaluation score was 0.70 units lower than the others. This difference is statistically significant because the p-value is 0.000, which is less than 0.05. The significance is further confirmed by the 95% CI's exclusion of zero.

H₂: There is a positive correlation between the use of AI tools and overall employee productivity in Hyderabad-based manufacturing firms.

Table No: 12.6 Mann-Whitney Test

Ranks				
	Does your organization currently use AI tools in HR or performance management	N	Mean Rank	Sum of Ranks
Employee_ Productivity	No	42	105.50	4431.00
	Yes	168	105.50	17724.00
	Total	210		

Table No: 12.7 Test Statistics

	Employee_ Productivity
Mann-Whitney U	3528.000
Wilcoxon W	4431.000
Z	.000
Asymp. Sig. (2-tailed)	1.000
a. Grouping Variable: Does your organization currently use AI tools in HR or performance management	

This is the result of a non-parametric substitute for the independent samples t-test called the Mann-Whitney U test (also called the Wilcoxon rank-sum test). It is applied in situations where the equal variance or normality assumptions might not be true. **Test Information:**

Productivity of employees is the dependent variable. Grouping variable: Does your company currently use AI tools for performance management or human resources? There are two groups: Yes and No. Compared to 0.05, the Asymp. Sig. (2-tailed) = 1.000 is significantly larger. This indicates that the difference in employee productivity between companies that use AI tools for performance management and HR and those that don't is not statistically significant. The Z-score of 0.000 indicates that the two groups' score distributions are nearly identical.

Table No: 12.8 H3: AI-driven performance management systems are perceived more favourably by and there is an association between Performance Evaluation and Digital Infrastructure

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Performance_ Evaluation * Digital_ Infrastructure	210	100.0%	0	0.0%	210	100.0%

Table No: 12.9 Performance Evaluation * Digital Infrastructure

			Digital_ Infrastructure			Total
			4.00	4.25	5.00	
Performance_ Evaluation	4.00	Count	2	1	11	14
		Expected Count	.9	.3	12.7	14.0
	4.20	Count	4	0	3	7
		Expected Count	.5	.2	6.4	7.0
	5.00	Count	8	4	177	189
		Expected Count	12.6	4.5	171.9	189.0
Total		Count	14	5	191	210
		Expected Count	14.0	5.0	191.0	210.0

Table No: 12.10 Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	33.374[a]	4	.000
Likelihood Ratio	16.839	4	.002
Linear-by-Linear Association	15.110	1	.000
N of Valid Cases	210		
a. 5 cells (55.6%) have expected count less than 5. The minimum expected count is .17.			

The Pearson Chi-Square test is extremely significant (p =.000) in spite of the assumption problem. Additionally important are the Linear-by-Linear Association and the Likelihood Ratio test. This implies that the two categorical variables you're testing might have a strong correlation. The two categorical variables seem to be significantly correlated ($\chi^2 4$) = 33.374, $p < .001$). However, because more than 20% of expected counts are less than 5, the test's assumption is broken, casting doubt on the validity of this result.

XIII. Conclusion

With a focus on Hyderabad, a significant Indian industrial centre, this study sought to investigate how Artificial Intelligence (AI) might be incorporated into employee performance management systems in manufacturing facilities. This study has offered a thorough grasp of how AI is changing how manufacturing facilities oversee and evaluate worker performance through a mixed-methods approach that blended quantitative surveys and qualitative interviews.

XIV. Key Findings

- The results indicate that the use of AI in Hyderabad's manufacturing facilities is still in its infancy, with adoption rates differing significantly depending on the organization's size and industry. Larger companies have demonstrated a greater inclination to incorporate AI into their HR operations, including performance management, especially those in high-tech industries like electronics and pharmaceuticals.
- According to the majority of respondents, artificial intelligence (AI) tools like machine learning algorithms and predictive analytics have increased the impartiality and accuracy of performance reviews. This is in line with previous research that emphasizes how AI can help remove biases present in conventional performance management systems. Managers and staff observed a more data-driven approach to performance monitoring, which resulted in better-informed choices about training requirements, promotions, and pay increases.
- It was discovered that AI-powered systems improved worker productivity and engagement. AI systems free up managerial time for more strategic tasks by automating regular performance reviews and giving real-time feedback. Additionally, because workers feel more supported in their career advancement, AI's capacity to recognize customized development paths has been connected to increased employee motivation and satisfaction.
- Even with the encouraging outcomes, there are still a number of obstacles to overcome in the application of AI. The study identified several important obstacles, including a lack of technical know-how, employee opposition to AI-based assessments, and worries about data privacy. It was also challenging for manufacturing facilities, particularly smaller ones, to put in place the digital infrastructure required to properly support AI tools. The broad use of AI technologies in employee performance management has been slowed by these challenges.
- The study found that opinions on the fairness of AI-based performance management systems were divided. Employees voiced concerns regarding the transparency of AI decision-making processes, even though managers generally saw AI tools as more impartial and objective. There was a lack of trust because many people were unsure of how AI algorithms were being used to evaluate their performance.

XV. Implications of the study

The findings from this research have several important implications for both practitioners and policymakers in the manufacturing sector:

- Instead of viewing AI as a mere technical advancement, manufacturing companies should view it as a strategic tool for performance management. AI tools must be in line with corporate objectives and integrated with current HR procedures. In order to guarantee the efficient use of AI tools, companies should also concentrate on employee training.
- Proactively addressing ethical issues is necessary, especially those pertaining to transparency and data privacy. Manufacturing facilities ought to implement moral AI frameworks that guarantee accountability, transparency, and equity in decision-making. Building employee trust is essential to a successful AI integration.
- The significance of employee involvement in the AI adoption process is one of the study's main conclusions. One way to lessen resistance is to educate staff members about the advantages and operation of AI-based systems. The collaborative nature of AI tools should be emphasized by HR departments, emphasizing that these tools are meant to supplement rather than replace employees' professional development.
- According to the research, AI solutions ought to be customized to meet the unique requirements of each organization and the manufacturing sector. Customization will help guarantee that the AI tools are both scalable and flexible enough to be used in a variety of industry operational contexts.

XVI. Future Research Direction

Even though this study offers insightful information about AI's role in employee performance management, there are still a number of areas that warrant further investigation. Future research could broaden the focus by incorporating a greater number of participants from various geographical areas, which would enhance the results.

The long-term effects of AI adoption on employee career development and organizational performance could also be investigated through longitudinal studies. Future studies could also concentrate on the moral dilemmas raised by AI in performance management. Examining the wider societal effects of AI is essential given its growing use in employee evaluations, particularly with regard to algorithmic bias, job displacement, and privacy issues.

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