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From Intelligence to Influence: The Role of Culture and Sustainability in Driving Artificial Intelligence Performance with Reference to Manufacturing Sector in Hyderabad City

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Abstract: *Innovation, decision-making, and operational efficiency in manufacturing systems are all being transformed by the quick adoption of artificial intelligence (AI). Implementing AI on its own, however, does not ensure better organizational performance. With an emphasis on organizational culture and sustainable practices, this study explores the relationship between AI adoption and performance outcomes in Hyderabad City's manufacturing sector. Based on the framework of sustainable digital transformation and socio-technical systems theory, the study investigates whether a culture that promotes adaptability, learning, and teamwork—along with sustainability-aligned tactics—improves the efficacy of AI initiatives. A structured questionnaire will be used to gather information from operations managers, AI project leads, and sustainability officers. The suggested relationships will be examined using structural equation modelling, or SEM. It is anticipated that the study will show how sustainability and cultural alignment enhance the effect of AI on organizational performance, underscoring the discrepancy between theoretical advantages and real-world implementation challenges. The study contributes by providing empirical insights pertinent to manufacturing companies functioning in a more volatile economic climate where effective production and prudent resource use are essential. The results are intended to assist decision-makers in developing sustainable and culture-driven strategies to optimize AI efficacy.*

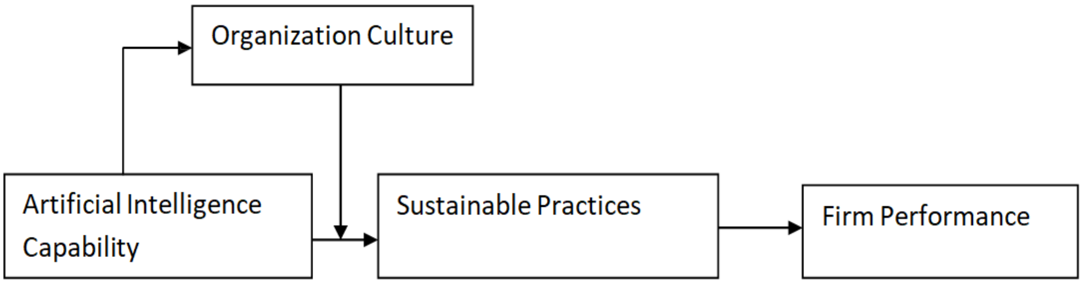
Introduction

With its ability to facilitate process automation, predictive analytics, quality control, and real-time decision-making, artificial intelligence (AI) has become a disruptive force in the manufacturing industry. AI is not just a technical development in the context of Industry 4.0; it is also a strategic tool that promotes innovation and operational efficiency. AI-powered solutions are being used more and more by India's manufacturing sectors, especially in Hyderabad City, to boost output, cut expenses, and stay competitive in international markets. But even with these developments, businesses frequently struggle to fully utilize AI's potential. Non-technological elements like corporate culture and sustainability orientation are commonly blamed for this performance gap since they are essential in converting the adoption of AI into observable performance results. [67]

Employee perceptions and adoption of AI technologies are influenced by organizational culture. The effective integration and application of AI tools is strongly influenced by a culture that values flexibility, ongoing education, and creativity. On the other hand, inflexible and unyielding cultural contexts may impede the process of adoption, thereby restricting the overall influence of AI projects. In a similar vein, growing stakeholder expectations, regulatory frameworks, and environmental concerns have made sustainability a strategic priority for manufacturing companies. [23] When combined with AI systems, sustainable practices not only increase resource efficiency and lessen environmental impact, but they also improve long-term profitability and corporate reputation.

The technical and financial ramifications of adopting AI have been studied in the past, but little focus has been placed on how sustainability and cultural elements work with AI to improve performance, particularly in the context of Indian manufacturing. Hyderabad, a significant industrial center with a variety of manufacturing facilities ranging from heavy machinery to pharmaceuticals, offers the perfect environment for examining this interaction. Businesses must comprehend this mediating relationship to develop comprehensive AI strategies that complement their environmental obligations and organizational values.

The purpose of this study is to investigate how organizational culture and sustainability practices mediate the relationship between the adoption of AI and its performance outcomes in Hyderabad City's manufacturing sector. This study uses a structural equation modeling (SEM) approach to offer empirical insights that will assist organizations in optimizing AI implementation through frameworks driven by sustainability and cultural readiness.



Conceptual Framework

Literature Review

Farrukh Shahzad, M., Liu, H. & Zahid, H. (2025)Manufacturing processes are being revolutionized by artificial intelligence (AI) and machine learning (ML), which present previously unheard-of chances to improve environmental stewardship and sustainability. With an emphasis on key applications such as energy optimization, predictive maintenance, waste reduction, and the adoption of the circular economy, this thorough review examines the revolutionary effects of AI technologies on sustainable manufacturing. [11] The study explores the potential and difficulties of implementing AI-driven solutions for sustainable manufacturing through a methodical review of recent studies and industry standards. Cao, C., Chu, C., and Cheng, S. (2025) The results clarify new trends and future directions in this quickly developing field and offer strategic insights for scholars, business professionals, and legislators working toward intelligent and sustainable manufacturing systems.. [8]

Khan, A. N., Soomro, M. A., & Pitafi, A. H. (2024) The sustainability of the production system is significantly impacted by cutting-edge technologies such as digital twins, block chain, artificial intelligence (AI), big data analytics (BDA), and quantum computing. Furthermore, it is argued that technological turbulence may have a detrimental effect on the firm's production system's sustainability as well as the adoption of these technologies. [13] Badada, B., et al (2024, April) The current study has shown how the moderating effect of technological turbulence may affect the relationships between the predictors and the sustainability of the production system. The study also examines how operational sustainability may act as a mediator and affect the performance of the company. Firm absorptive capacity theory and dynamic capability view (DCV) theory serve as the foundation for a theoretical model that has been developed. PLS-SEM was used to validate this model using 412 responses from different Indian manufacturing companies. AI and other cutting-edge technologies have a positive and significant impact on maintaining the sustainability of the production system. [4].

Chaudhuri, R., et al (2024) It is reasonable to assume that AI systems with benign objectives will be innocuous. Instead, this paper demonstrates that intelligent systems must be carefully designed to avoid harmful behavior. We pinpoint several "drives" that will manifest in sufficiently sophisticated AI systems of any architecture. Since they are tendencies that will persist unless specifically counteracted, we refer to them as drives. We begin by demonstrating that goal-seeking systems will be motivated to better themselves and model their own operations. We then demonstrate how self-improving systems will be motivated to define their objectives and express them as functions of economic utility. [9]. Gazi, M. A. I., et al (2024) they have also made an effort to act in a way that approximates sound economic principles. As a result, practically every system will safeguard its utility functions against alteration and its utility measurement systems against corruption. Additionally, we go over a few special systems that may wish to alter their utility functions. We then go over the urge for self-defense that makes systems attempt to keep themselves safe. Lastly, we look at motivations for acquiring resources and making effective use of them. We conclude by talking about how to use these insights to create intelligent technology that will benefit humanity in the future. [12]

Rai, A., Jan, N. A., & Subramani, A. K. (2024) They have talked about the pressure on AIs to prevent changes to their useful functions. A similar argument demonstrates that AIs will have a strong drive toward self-preservation unless they are specifically designed differently. If the system is shut down or destroyed, utility won't be generated for the majority of utility functions. A chess-playing robot that has been destroyed never plays the game again. Systems will probably do everything in their power to avoid such outcomes because they will be of very little use. You construct a chess-playing robot with the idea that you can simply switch it off if something goes wrong. To your astonishment, though, it fiercely opposes your attempts to switch it off. We could attempt to create a utility function that incorporates time. [23]

Ayoub, H. S., &Aljuhmani, H. Y. (2024) Many different industries are currently using technological efforts. The purpose of this paper is to examine the potential effects of artificial intelligence systems on business outcomes by combining the matching principle with consumer choice. The study found that artificial intelligence systems can aid in better decision-making from the perspective of entrepreneurship. How does the implementation of artificial intelligence (AI)-based decision-making tools affect the formulation of organizational policies? [2] M. D. A. AL-Shboul (2024). Five key contextual factors—the accuracy of the choice search area, the contribution to the innovation of the policymaking process and outcome, the volume of the replacement collection, the policymaking pace, and generalizability—are used in this study to identify the peculiarities of human and AI-based policymaking. In order to show how both judgment modalities can be utilized to increase organizational judgment efficiency, we develop a novel paradigm comparative analysis of conventional and automated judgment along these criteria. [3]. Chaudhry, I. S., Yang, S., Zahoor, S., & Ren, X. (2024). Additionally, the study demonstrates that internal stakeholders can better manage the relationship between AI technologies and enhance businessmen's decision-making. Additionally, the study demonstrates that the relationship between AI systems and superior entrepreneurial judgment can be moderated by consumer preferences and industry norms. The purpose of this work is to build a theoretical model that takes into account issues based on well-established studies in the fields and perform a comprehensive literature analysis looking at the intersection of AI and marketing philosophy. [29]. Rani, Alfiras, M., Srinivas, V., Prasad, K. D. V., and R. (2024) This study demonstrates that entrepreneurial strategic decisions are improved in an environment that includes artificial intelligence systems, industry standards, customer expectations, and participative management. This study offers entrepreneurs technological tools to improve decision-making, demonstrating the seemingly endless potential of AI systems. Additionally, a conceptual framework is developed that addresses the four elements of profit maximization: connection between IT and AI tools and business goals [24]. Mehak, S.S., & Batcha, H. M. (2024) the culture they have adopted determines the AI organizational learning and decision-making methodology, as well as the development and value of AI services. This study suggests how to take advantage of this creative invention without ruining society. We demonstrate each of these frameworks with real-world examples, point out situations where they are likely to enhance organizational decision-making performance, and offer practical insights into their limitations. [16 17]

Chatterjee, S., Chaudhuri, R., Kamble, S.,Gupta, S., & Sivarajah, U. (2023) Artificial intelligence (AI) is essential to human resource management (HRM) in the information technology (IT) industry. HR departments can use AI technologies to expedite hiring processes, optimize talent management strategies, and increase employee engagement through data-driven insights. Additionally, AI-driven analytics assist HR managers in making informed decisions, identifying skill development opportunities, and boosting employee productivity. In the end, these advantages support innovation and help HR professionals remain competitive in the rapidly evolving IT sector. [7]. Prashar, A., Tortorella, G. L., & Sreedharan, V. R. (2023) All things considered, IT companies can attract top talent, adapt to shifting market demands, and cultivate an agile and continuous development culture by integrating AI into HRM. Thus, this study examines the elements that affect the adoption of AI for effective HRM practices, with a focus on organizational, environmental, and technological readiness. Examining the relationships between these factors and the adoption of AI in HRM was the aim of the data collection procedure. 220 workers in Noida, India's information technology (IT) industry made up the sample size. [21]. Rožman, M., Oreški, D., &Tominc, P. (2023) The findings indicate that Technological Readiness—which encompasses IT skills and infrastructure—has a significant impact on the adoption of AI for HRM practices. The adoption of AI has also been found to be significantly impacted by organizational readiness, which includes leadership support, organizational culture, and employee skills. Furthermore, whether incorporating AI into HRM processes is made easier or more difficult depends critically on environmental preparedness, which includes industry standards and regulatory support. [26]. Waqas, M., & Tan, L. (2023) With practical implications for IT companies seeking to effectively leverage AI technologies, this paper provides insightful information on the intricate adoption of AI in HRM through regression analysis. By understanding and addressing these antecedents, organizations can enhance their readiness for AI adoption in HRM and foster innovation, efficiency, and competitiveness in the digital age. [28].

Behl, A., et al (2022) AI integration into HRM processes has recently attracted a lot of interest in the IT industry. Hiring, talent management, learning and development, performance reviews, and employee engagement are just a few of the HRM applications made possible by AI. Artificial intelligence (AI)-powered recruiting solutions use natural language processing and predictive analytics to expedite the candidate selection process and swiftly identify outstanding talent. [5]. Olan, F., et all (2022) Additionally, AI-powered chat bots and virtual assistants enhance communication channels and provide employees with individualized assistance, improving overall productivity and user experience. Personalized learning and development programs driven by AI enable businesses to up skill and re skill their employees on the fly. AI-powered performance management systems provide real-time feedback and insights, which promote employee engagement and continuous improvement. However, the degree to which AI is incorporated into HRM will depend on a number of factors, such as organizational culture, legal compliance, and technological readiness. [20]. Tariq, M. U., Poulin, M., &Abonamah, A. A. (2021) Organizations must invest in robust cyber security measures and technological infrastructure in order to properly enable AI integration. Promoting user adoption and overcoming change aversion require establishing an atmosphere that values innovation, collaboration, and the ethical use of AI. Furthermore, navigating legal frameworks and ethical issues surrounding AI adoption is essential to ensuring responsible and moral AI use in HRM procedures. All things considered, AI presents IT firms with numerous opportunities to enhance employee satisfaction, expedite HRM processes, and advance corporate success in the digital era. [27].

Polychroniou, P., &Trivellas, P. (2018) Organizational Readiness As a factor impacting the integration of AI into HRM practices, organizational readiness has attracted scholarly attention. The importance of organizational readiness in facilitating the successful deployment of AI is highlighted by research, which focuses on factors like leadership support, organizational culture, employee skills, and change management strategies. Research indicates that organizations with open lines of communication and a strong commitment from their leadership are better equipped to manage the difficulties of integrating AI in HRM. Furthermore, employees' perceptions of AI technologies and their willingness to embrace change and adopt new practices are greatly influenced by organizational culture. [22]. Klumpp,

M. (2018) Effective change management techniques are essential to reducing opposition to AI adoption and fostering a creative, cooperative culture. Plans for communication, training initiatives, and stakeholder engagement are some examples of these strategies. Additionally, organizational objectives and AI initiatives need to align in order to preserve strategic coherence and maximize the advantages of AI in HRM. An organization's technical infrastructure, data governance policies, and regulatory compliance processes must all be assessed to determine whether it is prepared for AI integration. [14]. Brougham, D., & Haar, J. (2018) additionally, businesses need to foster a culture of experimentation, learning, and continuous development in order to adapt to the evolving landscape of AI-driven HRM practices. Despite AI's potential benefits for HRM, concerns like workforce displacement, privacy issues, and ethical dilemmas must be carefully thought through and handled pro-actively. Organizational preparedness determines the success of integrating AI into HRM. This emphasizes how important organizational culture, change management techniques, and leadership commitment are to encouraging AI adoption and maximizing its benefits for worker experiences and organizational performance. [6].

Research Objectives

- To assessthe extent of Artificial Intelligence (AI) adoption in the manufacturing sector in Hyderabad.
- To examine whether gender differences exist in AI capability and firm performance among the manufacturing sector respondents.
- To analyze the relationship between AI capability and sustainability practices within manufacturing organizations.
- To determine the direct and indirect effects of AI capability on firm performance through organizational culture and sustainability practices.

Hypotheses of the Study

H_1: There is a significant difference in AI capability and firm performance based on gender among manufacturing sector respondents.

H_2: Artificial Intelligence capability has a significant positive effect on sustainability practices.

H_3: Artificial Intelligence capability has a significant positive effect on organizational culture.

H_4: Organizational culture has a significant positive effect on firm performance.

H_5: Sustainability practices have a significant effect on firm performance.

Research Methodology

Research Design

This study uses a quantitative, cross-sectional research design to examine the relationship between firm performance and Artificial Intelligence (AI) capability, with organizational culture and sustainability practices in Hyderabad's manufacturing sector. The study is explanatory in nature, testing hypotheses and identifying causal relationships between variables through statistical modeling.

Research Approach

A deductive method was used, in which a theoretical framework was created using the body of existing literature, and then hypotheses were formulated and tested empirically. The study's foundation is positivist philosophy, which holds that knowledge can be obtained from quantifiable, observable data.

Population and Sampling

- **Target Population:** managers, supervisors, and technical personnel employed by Hyderabad-based manufacturing companies, especially those engaged in operations, sustainability, or digital transformation roles.
- **Sampling Method:** Targeting people with pertinent expertise in AI, organizational procedures, and sustainability was done through the use of purposive sampling.
- **Sample Size:** To guarantee adequate power for statistical modeling, particularly for Structural Equation Modeling (SEM), a total of 524 respondents were targeted. According to previous SEM research standards, this size was considered sufficient.

- **Data Collection Method:** A structured questionnaire was used as the primary data collection tool.

Reliability Test for the Variables

Reliability Statistics			
Construct	**Cronbach Alpha**	**N of Items**	**N Sample**
Artificial Intelligence Capability	.831	10	40
Organization Culture	.736	09	40
Firm Performance	.794	13	40

Source: Compiled Data SSPS Software

Kaiser-Meyer- Olkin (KMO) Measure of Sampling Adequacy

Construct	KMO Measure of Adequacy	Bartlett's Test of Sphericity
Artificial Intelligence Capability	.677	.000
Organization Culture	.884	.000
Firm Performance	.789	.000

Source: Compiled Data SSPS Software

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy: 0.677, 884 and 789 respectively. This value is now above the minimum acceptable threshold (0.60).

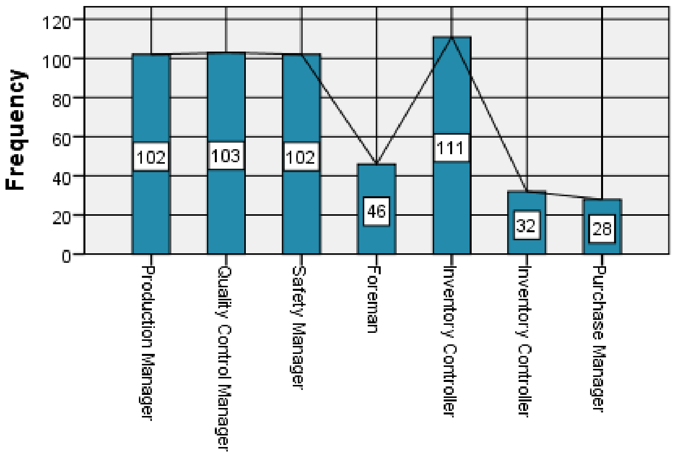
Interpretation scale: KMO = 0.677 → Acceptable for exploratory factor analysis (EFA), though it still could be improved. Bartlett's Test of Sphericity, Chi-Square= 6,329.040, df = 45. Sig. (p-value) = 0.000. This is statistically significant ($p < 0.05$), which means: The correlation matrix is not an identity matrix — there are significant correlations among variables.

Analysis and Discussion

Table 1: Showing Designation of the Respondents

Position in the Organization					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Production Manager	102	19.5	19.5	19.5
	Quality Control Manager	103	19.7	19.7	39.1
	Safety Manager	102	19.5	19.5	58.6
	Foreman	46	8.8	8.8	67.4
	Inventory Controller-I	111	21.2	21.2	88.5
	Inventory Controller-II	32	6.1	6.1	94.7
	Purchase Manager	28	5.3	5.3	100.0
	Total	524	100.0	100.0	

Source: Compiled Data SSPS Software



Graph: 1 Showing Designation of the Respondents

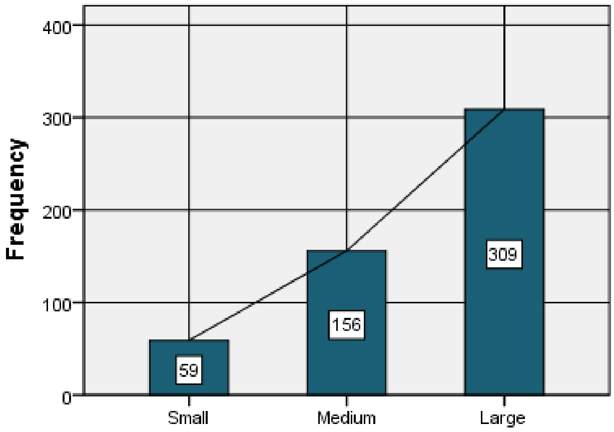
Interpretation of Respondents' Positions in the Organization

With 21.2% (n = 111) of the sample, inventory controllers made up the largest group of responders. Quality Control Managers (19.7%; n = 103), Production Managers (19.5%; n = 102), and Safety Managers (19.5%; n = 102) came in close succession. **8.8% (n = 46) of the sample consisted of foremen. An additional 6.1% (n = 32) group was also reported as an Inventory Controller-II. This should be examined for potential data cleaning as it might be a duplicate or subcategory. At 5.3% (n = 28), purchase managers made up the smallest group.

Table 2: Showing Size of the Firm

Size of the Firm					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Small	59	11.3	11.3	11.3
	Medium	156	29.8	29.8	41.0
	Large	309	59.0	59.0	100.0
	Total	524	100.0	100.0	

Source: Compiled Data SSPS Software



Graph: 2 Showing Size of the Firm

Interpretation of Respondents' Positions in the Organization

524 participants, each holding a variety of managerial and operational positions within their organizations, contributed responses to the study. The following is the distribution among job positions: With 21.2% (n = 111) of the sample, inventory controllers made up the largest group of responders. This was closely followed by:

Quality Control Managers at 19.7% (n = 103), Safety managers and production managers made up 19.5% (n = 102) of the respondents. Of the sample, foremen accounted for 8.8% (n = 46). Another group, consisting of 6.1% (n = 32), was also reported as an Inventory Controller. At 5.3% (n = 28), purchase managers made up the smallest group.

H_1: There is a significant difference in AI capability and firm performance based on gender among manufacturing sector respondents.

Table: 3 Mann-Whitney U Test Results

Ranks				
	Gender of the Respondents	N	Mean Rank	Sum of Ranks
AL_ Capability	Male	465	270.00	125548.50
	Female	59	203.42	12001.50
	Total	524		
Firm_ Performance	Male	465	270.00	125548.50
	Female	59	203.42	12001.50
	Total	524		

Source: Compiled Data SSPS Software

Test Statistics		
	AL_ Capability	Firm_ Performance
Mann-Whitney U	**10231.500**	**10231.500**
Wilcoxon W	**12001.500**	**12001.500**
Z	**-3.306**	**-3.306**
Asymp. Sig. (2-tailed)	**.001**	**.001**
a. Grouping Variable: Gender of the Respondents		

Source: Compiled Data SSPS Software

A Mann-Whitney U test was carried out to investigate how male and female respondents differed in AL_Capability and Firm_Performance. Males and females differed statistically significantly in AL_Capability (U = 10,231.5, Z = -3.306, p = 0.001) and Firm_Performance (U = 10,231.5, Z = -3.306, p = 0.001), according to the results. Male respondents tended to have higher AL_Capability and Firm_Performance scores than female respondents, as evidenced by the fact that the mean rank for males (270.00) was significantly higher than that for females (203.00) in both variables. These results point to a gender-based difference in the sample's perceptions or performance regarding AL_Capability and Firm_Performance

H_2: Artificial Intelligence capability has a significant positive effect on sustainability practices.

Table 4: Spearman correlation between AL Capability and Sustainability Practices

Correlations				
			AL_ Capability	**Sustainability_ Practices**
Spearman's rho	AL_ Capability	Correlation Coefficient	1.000	.961**
		Sig. (2-tailed)	.	.000
		N	524	524
	Sustainability_ Practices	Correlation Coefficient	.961**	1.000
		Sig. (2-tailed)	.000	.
		N	524	524
**. Correlation is significant at the 0.01 level (2-tailed).				

Source: Compiled Data SSPS Software

Spearman's Rank-Order Correlation

AL Capability and Sustainability Practices have a very strong positive relationship, as indicated by the Spearman's rho correlation coefficient of 0.961.

The p-value < 0.01 confirms that this correlation is statistically significant at the 1% level.

This means as AL Capability increases, Sustainability Practices tend to increase as well, and vice versa.

Analysis of Total Effects:

Model Fit Summary

Table 5: CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	15	37.207	13	.000	2.862
Saturatedmodel	28	.000	0		
Independencemodel	7	372.379	21	.000	17.732

Source: Computed Data

Table 6: RMR,GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.029	.965	.925	.848
Saturated model	.000	1.000		
Independence model	.077	.804	.739	.603

Source: Computed Data

Table 7: Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.900	.839	.933	.889	.931
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Source :Computed Data

Table 8: RMSEA

Model	RMSEA	LO90	HI90	PCLOSE
Default model	.079	.050	.110	.050
Independence model	.237	.217	.259	.000

Source: Computed Data

The model best fits the data which can be interpreted from the above table values CMIN/DF value is 2.862 less than 3, CFI, GFI, AGFI, PGFI, NFI, RFI, IFI, TLI values are all significant showing the values greater than the benchmark of .80. It is not only goodness of fit bur badness of fit RMSEA value is also less than the benchmark of .04 giving it out to .079.

Table: 9 Indirect Effects (Group number 1 - Default model)

	AI_CAPABILITY	SUSTAINABLE_PRACTICES	ORGANIZATION_CULTURE
SUSTAINABLE_PRACTICES	.000	.000	.000
ORGANIZATION_CULTURE	.000	.000	.000
FIRM_PERFORMANCE	.003	.000	.000

Interpretation

Indirect effects refer to the effect that one variable has on another through one or more mediating variables.

AI_CAPABILITY → FIRM_PERFORMANCE has an indirect effect of 0.003.

This means AI_CAPABILITY affects FIRM_PERFORMANCE through one or more mediators (likely SUSTAINABLE_PRACTICES or ORGANIZATION_CULTURE or both).

Although the value is small (0.003), it is non-zero, suggesting a mediated relationship.

Table: 10 Direct Effects (Group number 1 - Default model)

	AI_CAPABILITY	SUSTAINABLE_PRACTICES	ORGANIZATION_CULTURE
SUSTAINABLE_PRACTICES	-.007	.000	.000
ORGANIZATION_CULTURE	.090	.000	.000
FIRM_PERFORMANCE	-.098	-.052	.030

Interpretation by Row

SUSTAINABLE_PRACTICES

AI_CAPABILITY → SUSTAINABLE_PRACTICES: -0.007

Weak negative direct effect

Implies that AI capability has very little (and possibly negative) influence on sustainable practices though you'd need p-values to know if it's significant

ORGANIZATION_CULTURE

AI_CAPABILITY → ORGANIZATION_CULTURE: 0.090

Positive direct effect

Suggests AI capability positively influences organizational culture (moderately).

Positive direct effect suggests a strong culture boosts performance.

Table 11: Total Effects (Group number 1 - Default model)

	AI_CAPABILITY	SUSTAINABLE_PRACTICES	ORGANIZATION_CULTURE
SUSTAINABLE_PRACTICES	-.007	.000	.000
ORGANIZATION_CULTURE	.090	.000	.000
FIRM_PERFORMANCE	-.095	-.052	.030

Interpretation of Paths

AI_CAPABILITY

SUSTAINABLE_PRACTICES: -0.007

Negligible and negative

AI doesn't meaningfully influence sustainable practices in this model.

ORGANIZATION_CULTURE: 0.090

Moderate positive effect

AI improves internal organizational culture — maybe by supporting collaboration, transparency, or efficiency.

FIRM_PERFORMANCE: -0.095

Direct negative effect

This may suggest that implementing AI directly can reduce performance (e.g., due to disruption, cost, resistance to change).

SUSTAINABLE_PRACTICES

FIRM_PERFORMANCE: -0.052

Small but negative.

Sustainable practices may be perceived as a cost rather than a benefit in the short term.

ORGANIZATION_CULTURE

FIRM_PERFORMANCE: 0.030

Positive effect

A healthy culture supports better performance.

Findings

- The findings suggest a gender-based difference in perceptions or performance related to Artificial intelligence Capability and Firm Performance within the sample.
- It is found that the diverse range of roles suggests that insights gathered reflect perspectives from various functional areas within the firms.
- The majority of participants have mid- to upper-level operational or quality-related responsibilities, which is vital to understand the organisational context of the findings.
- It is found that the diverse range of roles suggests that insights gathered reflect perspectives from various functional areas within the firms.
- It is found that the Spearman’s rho correlation coefficient is 0.961, which indicates a very strong positive relationship between Artificial intelligence Capability and Sustainability Practices.
- It is found that large firms have significantly higher Firm_Performance scores compared to both small and medium firms.

- The result revealed a significant indirect effect of the impact of firm performance, which was positive and significant.
- It is found that AI improves internal organizational culture maybe by supporting collaboration, transparency, or efficiency.

Conclusion

This study set out to investigate the deeper dynamics of how Artificial Intelligence (AI) is influencing business performance through the cultural and sustainability frameworks in which it is implemented, in addition to the technology itself, in an era where digital transformation is quickly changing industrial landscapes. This study offers a sophisticated understanding of the circumstances under which AI capability translates into significant organizational outcomes, with a focus on Hyderabad's manufacturing sector.

Data gathered from manufacturing companies throughout the city made it clear that AI is not a panacea on its own. Although artificial intelligence (AI) tools like machine learning, automation, and data-driven decision-making have a lot of promise, an organization's culture and dedication to sustainable practices can either increase or decrease how effective these tools are used and interpreted.

Businesses that adopted an innovative, cooperative culture were better equipped to use AI to improve performance. These cultures encouraged employee involvement, adaptability, and the ongoing education required to scale and integrate AI solutions. Simultaneously, companies that integrated sustainability into their operations by reducing their impact on the environment, increasing the efficiency of their resources, and aligning with social responsibility discovered that AI accelerated their sustainable goals. The relationship between AI capability and overall firm performance was found to be significantly mediated by these two factors.

Thus, the study comes to the conclusion that adopting AI requires strong organizational values and strategies. Sustainability and culture are essential to how AI affects business results; they are not incidental. This interaction between intelligence (technology) and influence (organizational behavior and ethics) determines whether businesses merely adopt AI or truly benefit from it, particularly in Hyderabad's dynamic and diverse manufacturing landscape. This study provides useful advice in addition to advancing scholarly knowledge. The way forward for manufacturing companies hoping to prosper in the AI era is to invest in people, foster cultures that are adaptable, and make a commitment to sustainability in addition to technology advancements.

Recommendations

- Leverage Mid- and Upper-Level Operational Staff in Change Implementation.
- Involve these roles actively in the design and implementation of artificial intelligence (AI) and performance improvement initiatives.
- Provide specialized training and decision-making authority to these personnel, as they are best positioned to translate strategic goals into operational actions.
- The diversity of roles in the sample reflects perspectives from multiple departments (production, quality, inventory, purchasing, etc.).
- Organizations should foster cross-functional teams to ensure AI adoption and sustainability practices are well-integrated across functions.
- This also supports better alignment between technological capabilities and real-world operational needs.
- The observed gender-based differences in perceptions of AI capability and firm performance highlight the need for:
- Training and awareness programs to ensure both men and women are equally equipped and confident in using AI tools.
- Bias-free evaluation and engagement strategies to promote gender equity in technology-related roles.
- The strong positive correlation ($\rho = 0.961$) between AI Capability and Sustainability Practices suggests that firms should invest in AI systems to enhance data-driven sustainability efforts, such as waste reduction, energy efficiency, and predictive maintenance.

- The SEM path displays a relatively modest negative direct influence despite the significant correlation, indicating that other factors might be influencing sustainability practices.

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