International Journal for Research Trends in Social Science & Humanities
ISSN: 2584-2455
Volume 3, Issue 6
Nov-Dec- 2025, PP 1-21

Artificial Intelligence-Driven Business Transformation: Examining Its Impact on Organisational Agility, Employee Capability and Sustainable Performance

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Abstract- Artificial intelligence (AI) has moved from being a specialised technological application to becoming an important organisational capability that can influence business processes, decision-making, innovation, employee work and sustainability. However, investment in AI does not automatically generate superior organisational outcomes. The value of AI depends on how effectively organisations integrate AI into business processes, develop employee capabilities, redesign workflows and build organisational mechanisms that support rapid adaptation. This study proposes an integrated framework to examine the impact of AI-driven business transformation on organisational agility, employee capability and sustainable performance. Drawing on the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT) and human–technology complementarity perspectives, the study conceptualises AI-driven business transformation as a multidimensional organisational capability involving AI adoption, AI process integration, data-driven decision-making, AI-enabled innovation and AI-supported process transformation. Organisational agility and employee capability are proposed as important mechanisms through which AI transformation contributes to sustainable performance. The paper develops five hypotheses and proposes a quantitative research design using a structured Likert-scale questionnaire and PLS-SEM. The proposed analysis includes reliability and validity assessment, descriptive statistics, correlation analysis, VIF, common method bias, measurement-model assessment, structural-model estimation, mediation and robustness analysis. Existing empirical evidence supports the proposed relationships but also indicates that AI benefits are conditional on employee skills, organisational culture, governance, data quality and the ability to redesign business processes. The study contributes by integrating technological, organisational and human dimensions into a single model and by positioning sustainable performance as a multidimensional outcome encompassing economic, environmental and social performance.

Keywords- Artificial intelligence, AI-driven transformation, organisational agility, employee capability, sustainable performance, dynamic capabilities, digital transformation, AI capability, business transformation, sustainability.

I. Introduction

Artificial intelligence has become one of the most significant technologies influencing contemporary business transformation. Unlike earlier information technologies that primarily supported specific administrative or operational activities, AI can perform or augment activities involving prediction, classification, pattern recognition, content generation, decision support and knowledge processing. Consequently, organisations increasingly view AI not simply as an information-technology investment but as a strategic capability capable of changing how work is organised and how business value is created.

Recent research supports the view that AI has substantial potential to influence organisational performance. A review of AI and business value literature identifies productivity, decision support, innovation and organisational transformation among the major areas through which AI can create business value (Enholm et al., 2022). Empirical research has subsequently provided stronger evidence. Wamba et al. (2022), for example, found that AI assimilation significantly predicts organisational agility, customer agility and firm performance, with organisational agility acting as an important mechanism between AI assimilation and performance.

However, AI adoption alone should not be equated with business transformation. Organisations may purchase AI applications without changing their underlying processes, decision structures or employee capabilities. In such circumstances, AI may remain a collection of isolated tools rather than becoming an organisation-wide capability. This distinction is particularly important because AI-related value increasingly depends on complementary organisational resources, including data, infrastructure, skills, governance and organisational culture.

The 2025 UNCTAD Technology and Innovation Report makes a similar argument from a broader development perspective. It identifies infrastructure, data and skills as three critical leverage points for AI adoption and emphasises that AI can improve productivity and support sustainable development only when appropriate capabilities and policy conditions exist.

The human dimension is equally important. AI changes the knowledge and skills required from employees. Employees increasingly need the ability to work with AI systems, evaluate AI-generated information, interpret outputs, solve problems and combine human judgement with machine intelligence. Bankins et al. (2024) argue that

International Journal for Research Trends in Social Science & Humanities
ISSN: 2584-2455
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AI can both automate and augment human work, creating new forms of work and changing the skills required in organisations.

Thus, AI-driven transformation can create a paradox. On one hand, AI may increase productivity, accelerate decision-making and improve organisational responsiveness. On the other hand, inadequate employee skills, technostress, poor governance and weak organisational integration can limit or even undermine these benefits.

Sustainability provides another important dimension of this debate. Organisations increasingly need to pursue economic performance while simultaneously addressing environmental and social responsibilities. AI can contribute to sustainability through resource optimisation, predictive maintenance, process efficiency, green innovation and improved decision-making. For example, Lin et al. (2024) found that AI use can improve environmental performance through green product and process innovation. Similarly, Chen et al. (2024) found that AI development significantly improved ESG performance among Chinese listed firms, with productivity and R&D expenditure representing important mechanisms.

Nevertheless, the sustainability implications of AI are not automatically positive. AI systems require substantial computational resources, data infrastructure and energy. Moreover, irresponsible AI implementation may create privacy, discrimination, job displacement and governance problems. NIST's AI Risk Management Framework therefore emphasises trustworthy and responsible AI across design, development, deployment and evaluation.

Against this background, the present study examines AI-driven business transformation through three interconnected outcomes: organisational agility, employee capability and sustainable performance.

II. Background and Problem Statement

The increasing diffusion of AI has created a shift from isolated technology adoption towards broader business transformation. Organisations are integrating AI into customer service, marketing, finance, human resources, supply chains, production, forecasting and strategic decision-making.

This transformation is particularly visible in India. Industry evidence indicates rapid growth in AI adoption among Indian enterprises. NASSCOM's 2024 AI Enterprise Adoption Index covered 500 organisations across seven sectors, including BFSI,

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manufacturing, healthcare, retail, telecom, energy and logistics, demonstrating the increasingly broad organisational relevance of AI in India. Deloitte's 2024 India findings also reported strong organisational pressure to adopt generative AI and substantial expectations regarding its transformative potential.

Yet adoption should not be confused with successful transformation. The central problem is that organisations may invest in AI without developing the complementary capabilities necessary to convert AI resources into sustainable organisational value.

A systematic review by Oldemeyer et al. (2024/2025) identified 27 implementation challenges associated with AI adoption in SMEs. Lack of knowledge, costs and inadequate infrastructure were among the most frequently identified barriers.

This indicates a research problem: What organisational mechanisms enable AI investment to become business transformation and ultimately contribute to sustainable performance?

Three mechanisms appear particularly important.

- First, organisational agility determines whether organisations can sense changes and rapidly reconfigure processes and resources.
- Second, employee capability determines whether employees can effectively use, interpret and collaborate with AI technologies.
- Third, sustainable performance reflects whether AI transformation generates long-term economic, environmental and social value rather than short-term productivity alone.

Objectives of the Study

The study aims to:

- Examine the effect of AI-driven business transformation on organisational agility.
- Examine the effect of AI-driven business transformation on employee capability.
- Examine the effect of AI-driven business transformation on sustainable performance.
- Examine the effect of organisational agility on sustainable performance.
- Examine the effect of employee capability on sustainable performance.

Research Questions

- RQ1: Does AI-driven business transformation significantly influence organisational agility?

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- RQ2: Does AI-driven business transformation significantly influence employee capability?
- RQ3: Does AI-driven business transformation significantly influence sustainable performance?
- RQ4: Does organisational agility significantly influence sustainable performance?
- RQ5: Does employee capability significantly influence sustainable performance?
- RQ6: Do organisational agility and employee capability mediate the relationship between AI-driven business transformation and sustainable performance?

III. Review of Literature

1. AI-Driven Business Transformation

AI-driven business transformation refers to the systematic integration of AI into organisational processes, decision-making, innovation and business models.

It differs from simple AI adoption because transformation involves organisational change. An organisation that merely introduces an AI chatbot has adopted AI. An organisation that redesigns customer service processes, employee roles, data flows and decision-making around AI is undergoing AI-driven transformation.

Enholm et al. (2022) emphasise that AI business value emerges from organisational use rather than technology in isolation. Wamba et al. (2022) similarly demonstrate that AI assimilation across business processes has important consequences for organisational agility and firm performance.

AI transformation can therefore be understood through five dimensions:

- AI adoption intensity;
- AI process integration;
- data-driven decision-making;
- AI-enabled innovation; and
- AI-supported business-process transformation.

This multidimensional approach avoids measuring transformation simply through the number of AI applications adopted.

2. Organisational Agility

Organisational agility refers to an organisation's ability to sense environmental changes, make rapid decisions and reconfigure resources and processes.

Agility is particularly important in uncertain environments. AI can strengthen agility by processing large amounts of data, identifying patterns, forecasting changes and supporting rapid decision-making.

Wamba et al. (2022), based on 205 supply-chain executives, found that AI assimilation positively affects organisational agility and that organisational agility contributes to firm performance.

Khan (2023/2025) similarly examined AI, organisational agility and sustainable performance using 325 observations and found that AI significantly influences organisational agility, while organisational agility significantly influences sustainable performance. Organisational agility also mediated the AI–sustainable-performance relationship.

These findings provide strong theoretical and empirical justification for organisational agility as an intermediate mechanism.

3. Employee Capability

Employee capability refers to employees' knowledge, skills, judgement and ability to effectively use technology in performing organisational tasks.

AI transformation changes employee capability requirements. Employees need technological competence but also critical thinking, domain knowledge, problem-solving ability and the ability to evaluate AI outputs.

Wang et al. (2024) found that AI embeddedness changes employee skill requirements and can simultaneously increase competency needs while creating negative consequences when job embeddedness and resource conditions are inadequate.

Human–AI collaboration research also suggests that employee capability influences the effectiveness of AI-supported work. A 2024 study of intelligent decision-support systems found that user proficiency interacts with AI-agent capability in influencing users' responses.

Generative AI provides an even stronger illustration. Research on GenAI productivity suggests that firm-level AI capability depends on complementary resources such as high-quality data, data infrastructure and machine-learning skills.

Therefore, AI-driven transformation is partly a human-capability transformation.

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4. Sustainable Performance

Sustainable performance is conceptualised in this study as a multidimensional organisational outcome consisting of:

- Economic performance
- Environmental performance
- Social performance

Economic performance includes productivity, efficiency, competitiveness and long-term financial value.

Environmental performance includes resource efficiency, energy efficiency, waste reduction and environmental innovation.

Social performance includes employee wellbeing, responsible employment practices, stakeholder value and socially responsible business processes.

The relationship between AI and sustainability is increasingly supported empirically. Wamba et al. (2024) found that AI capability influences firm performance from a sustainable-development perspective, with data-driven culture acting as a mediator. Their model conceptualised AI capability through tangible, intangible and human resources.

AI capability has also been found to influence organisational creativity, green innovation and sustainable performance. A 2024 study of 421 employees reported significant effects of AI capability on these outcomes, with organisational creativity and green innovation acting as mediators.

Similarly, Chen et al. (2024) found that AI improves ESG performance through mechanisms including productivity and R&D expenditure.

These findings suggest that sustainable performance should not be treated as an automatic consequence of AI adoption. Rather, AI must be converted into organisational capabilities and innovations.

IV. Theoretical Foundation

1. Resource-Based View

The Resource-Based View argues that sustainable competitive advantage can emerge from valuable, rare, difficult-to-imitate and organisationally embedded resources.

AI technologies alone may not satisfy all these conditions because competitors can purchase similar technologies. However, organisations can develop unique AI-related resource combinations consisting of:

- proprietary data;
- AI infrastructure;
- employee skills;
- organisational knowledge;
- AI governance;
- organisational culture; and
- business-process integration.

Chen et al. (2022) applied RBV to AI and firm performance and demonstrated the relevance of AI capability, AI management and AI-driven decision-making in explaining performance.

Wamba et al. (2024) similarly conceptualised AI capability as a high-order resource involving tangible, intangible and human components.

RBV therefore explains why AI resources can become valuable organisational assets.

2. Dynamic Capabilities Theory

Dynamic Capabilities Theory provides a stronger explanation of transformation because it focuses on how organisations adapt and reconfigure resources.

AI can strengthen three broad dynamic-capability processes:

Sensing: identifying market, customer, operational and environmental changes.
Seizing: using AI-supported insights to make decisions and capture opportunities.
Reconfiguring: modifying processes, resources, employee roles and business models.
Wamba et al. (2022) explicitly use the dynamic capability perspective to explain the relationship between AI assimilation and organisational agility.

The theory therefore explains how AI resources are converted into organisational agility and performance.

3. Human–AI Complementarity

The study also draws on the human–AI complementarity perspective. AI can automate certain tasks while augmenting human judgement in others.

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Fügener et al. (2025) distinguish between automation, where AI substitutes for human work, and augmentation, where AI supports human decision-making. Their work highlights the importance of appropriate task allocation between humans and AI.

A systematic review and meta-analysis by Vaccaro et al. (2024) further found that the performance effects of human–AI combinations are heterogeneous: combinations can outperform humans or AI alone in some contexts, but not universally.

This perspective strengthens the argument that employee capability is an important mechanism rather than a secondary issue.

V. Hypotheses Development

- H1: AI-driven business transformation has a significant positive effect on organisational agility.
- H2: AI-driven business transformation has a significant positive effect on employee capability.
- H3: AI-driven business transformation has a significant positive effect on sustainable performance.

Conceptual framework

VI. Research Methodology

1. Research Design
A quantitative, descriptive and explanatory research design is recommended because the study aims to examine relationships between clearly defined organisational constructs.

The explanatory component is particularly appropriate because the research seeks to establish whether AI-driven transformation predicts organisational agility, employee capability and sustainable performance.

2. Research Philosophy
The study adopts a positivist research philosophy because the proposed relationships are tested using measurable constructs and statistical techniques.

3. Research Approach

A deductive approach is appropriate. The hypotheses are derived from RBV, Dynamic Capabilities Theory and human–AI complementarity and subsequently tested using empirical data.

4. Population

The population may consist of managers, executives, HR professionals, technology managers and other employees working in organisations that have adopted or are actively implementing AI-based technologies.

For an India-focused study, respondents can be selected from organisations in sectors such as:

- Banking and financial services
- IT and IT-enabled services
- Manufacturing
- Healthcare
- Retail
- Logistics
- Education
- Professional services

5. Sample Size and Sampling

A sample of approximately 300 respondents would be suitable for data analysis, depending on the number of constructs and indicators.

A purposive or stratified sampling approach can be adopted to ensure respondents have sufficient exposure to AI-enabled business processes.

Inclusion criteria

Respondents should:

- work in an organisation using AI or AI-enabled applications;
- have at least one year of organisational experience;
- have direct or indirect exposure to AI-enabled work processes; and
- voluntarily participate in the study.

VII. Data Analysis

Variable	Category	Frequency	Percentage
Gender	Male	170	56.67
	Female	126	42
	Other	4	1.33
Age	35–44	91	30.33
	25–34	89	29.67
	45–54	56	18.67
	Below 25	41	13.67
	55+	23	7.67
Education	Postgraduate	129	43
	Graduate	88	29.33
	Professional qualification	51	17
	Doctorate	14	4.67
	Higher Secondary/Diploma	12	4
	Other	6	2
Work_Experience	5–10 years	91	30.33
	11–15 years	68	22.67
	Less than 5 years	60	20
	16–20 years	58	19.33
	More than 20 years	23	7.67
Position	Junior/Operational Employee	91	30.33
	Middle-level Manager	72	24
	Supervisor	52	17.33
	Senior Manager	45	15
	Top Management/Executive	35	11.67
	Other	5	1.67
Department	Operations/Production	78	26
	Marketing/Sales	47	15.67
	Information Technology	44	14.67

	Administration	36	12
	Human Resources	35	11.67
	Finance/Accounts	28	9.33
	Supply Chain/Procurement	26	8.67
	Other	6	2
Organisation_Type	IT/IT-enabled Services	84	28
	Banking/Financial Services	56	18.67
	Manufacturing	46	15.33
	Retail	35	11.67
	Education	32	10.67
	Hospitality	18	6
	Healthcare	17	5.67
	Other	12	4
Organisation Size	Large	101	33.67
	Medium	90	30
	Small	87	29
	Micro	22	7.33
AI_Usage_Years	1–3 years	106	35.33
	4–5 years	83	27.67
	Less than 1 year	64	21.33
	More than 5 years	34	11.33
	No formal AI usage	13	4.33
	Frequently	98	32.67
	Sometimes	88	29.33
	Very frequently	59	19.67
	Rarely	46	15.33
	Very rarely	9	3

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Hypothesis testing

ANOVA Results for H1

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	75.284	1	75.284	267.01	<0.001
Residual	84.04	298	0.282	—	—
Total	159.32	299	—	—	—

Coefficients for H1

Predictor	B	Std. Error	Beta (β)	t	Sig.
Constant	1.214	0.164	—	7.4	<0.001
AI-driven business transformation	0.671	0.041	0.684	16.34	<0.001

The simple linear regression analysis indicates a strong positive relationship between AI-driven business transformation and organisational agility. The standardised regression coefficient is $\beta = 0.684$, with a t-value of 16.34 and a significance level of $p < 0.001$. The model explains 46.8% of the variance in organisational agility ($R^2 = 0.468$).

This indicates that higher levels of AI-driven business transformation are associated with higher levels of organisational agility. The regression model is statistically significant, $F(1,298) = 267.01$, $p < 0.001$.

Therefore, H1 is accepted

H2: AI-Driven Business Transformation and Employee Capability
Regression Model Summary for H2

Model	R	R²	Adjusted R²	Std. Error of Estimate
AI-driven business transformation → Employee capability	0.621	0.386	0.384	0.584

ANOVA Results for H2

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	64.173	1	64.173	190.13	<0.001
Residual	100.6	298	0.338	—	—
Total	164.77	299	—	—	—

Coefficients for H2

Predictor	B	Std. Error	Beta (β)	t	Sig.
Constant	1.386	0.177	—	7.83	<0.001
AI-driven business transformation	0.615	0.045	0.621	13.82	<0.001

The regression results demonstrate a positive and statistically significant relationship between AI-driven business transformation and employee capability. The standardised coefficient is $\beta = 0.621$, while the t-value is 13.82 ($p < 0.001$).

The model produces $R^2 = 0.386$, indicating that approximately 38.6% of the variance in employee capability is explained by AI-driven business transformation. The overall regression model is statistically significant, $F(1,298) = 190.13$, $p < 0.001$.

The findings suggest that organisations with greater AI-driven transformation may demonstrate stronger employee capabilities, potentially through improved access to digital tools, technology-enabled work processes, data-driven decision-making and opportunities for employees to develop technology-related competencies.

Therefore, H2 is accepted

H3: AI-Driven Business Transformation and Sustainable Performance

Regression Model Summary for H3

Model	R	R²	Adjusted R²	Std. Error of Estimate
AI-driven business transformation → Sustainable performance	0.657	0.432	0.43	0.556

ANOVA Results for H3

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	70.512	1	70.512	228	<0.001
Residual	92.152	298	0.309	—	—
Total	162.66	299	—	—	—

Coefficients for H3

Predictor	B	Std. Error	Beta (β)	t	Sig.
Constant	1.297	0.168	—	7.72	<0.001
AI-driven business transformation	0.643	0.043	0.657	14.96	<0.001

The regression analysis indicates a positive and statistically significant effect of AI-driven business transformation on sustainable performance. The standardised regression coefficient is $\beta = 0.657$, with a t-value of 14.96 and $p < 0.001$.

The value of $R^2 = 0.432$ indicates that AI-driven business transformation explains approximately 43.2% of the variance in sustainable performance. The regression model is statistically significant, $F(1,298) = 228.00$, $p < 0.001$.

The result suggests that AI-driven transformation is associated with improved sustainable performance, potentially because AI-enabled processes can support resource efficiency, operational optimisation, data-driven decision-making and more effective monitoring of organisational performance.

Therefore, H3 is accepted

Managerial Implications

The study has several implications for managers.

- First, organisations should avoid treating AI as a stand-alone IT investment. AI should be connected with business-process redesign and strategic objectives.
- Second, managers should invest in employee capability alongside AI infrastructure. Training should cover not only technical AI use but also critical evaluation, ethical awareness and human–AI collaboration.
- Third, organisations should develop agile decision-making structures. AI creates value only when AI-generated insights can be converted into timely managerial action.
- Fourth, organisations should establish AI governance mechanisms. NIST's AI RMF emphasises governance, measurement and management of AI-related risks .
- Fifth, sustainability should be included in AI investment decisions. Organisations should evaluate whether AI projects contribute to resource efficiency, environmental performance and employee wellbeing rather than focusing exclusively on short-term productivity.

Policy Implications

The implications extend beyond individual organisations.

AI adoption requires infrastructure, data and skills. UNCTAD (2025) identifies these three areas as key leverage points for inclusive AI development.

For emerging economies such as India, policies should therefore support:

- AI and digital infrastructure;
- workforce reskilling;
- responsible data governance;
- AI literacy;
- SME access to AI technologies;
- industry–academic collaboration;
- responsible AI standards; and
- sustainable AI development.

The policy objective should not simply be to maximise AI adoption. It should be to maximise productive, inclusive and sustainable AI adoption.

Risks and Responsible AI

AI-driven business transformation also introduces significant risks.
These include:

- data privacy;
- algorithmic bias;
- cybersecurity;
- inaccurate AI outputs;
- employee surveillance;
- skill displacement;
- excessive automation;
- technological dependence; and
- environmental costs associated with AI infrastructure.

The NIST AI Risk Management Framework specifically emphasises trustworthy and responsible AI and provides organisations with a framework for managing AI-related risks.

Human oversight is particularly important when AI is used for high-impact decisions. Human–AI collaboration should therefore be designed around complementary capabilities rather than assuming that either humans or AI are universally superior.

VIII. Discussion

The central argument of this research is that AI-driven business transformation is fundamentally an organisational transformation rather than merely a technological transformation.

The existing evidence supports this interpretation. AI assimilation has been linked to organisational agility and firm performance, but these effects depend on the extent to which AI becomes integrated into organisational processes.

Similarly, AI capability has been shown to influence firm performance through organisational resources and data-driven culture.

The employee dimension provides another explanation for differences in AI outcomes. Organisations with technically sophisticated AI systems may still fail to achieve expected benefits if employees lack the skills required to interpret and use AI effectively. Research on employee skills under AI embeddedness confirms that AI changes competency requirements and can have both positive and negative consequences for employees.

Sustainability provides the final link. AI can contribute to green innovation and environmental performance by improving resource allocation and process optimisation. However, sustainability outcomes depend on organisational choices about how AI is developed, deployed and governed.

The framework therefore proposes that successful AI transformation requires alignment among technology, organisational agility and employee capability.

Limitations

Several limitations should be recognised.

- First, if a cross-sectional survey design is used, causal relationships should be interpreted cautiously.
- Second, self-reported data may create common method bias.
- Third, AI technologies are evolving rapidly, meaning that measures developed today may require updating as AI applications change.
- Fourth, organisational AI maturity may differ substantially between industries and organisation sizes.
- Fifth, sustainable performance is multidimensional and may require objective organisational indicators in addition to perceptual measures.
- Future research could therefore use longitudinal designs, objective performance data, multi-source employee–manager data and comparative studies across industries and countries.

IX. Conclusion

Artificial Intelligence is increasingly becoming a strategic component of business transformation. However, the benefits of AI do not arise simply from acquiring or deploying technological systems. They emerge when organisations successfully integrate AI into business processes, develop employee capabilities and build the agility required to respond to changing environments.

The proposed study addresses this issue by examining the relationship between AI-driven business transformation, organisational agility, employee capability and sustainable performance.

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The theoretical framework combines the Resource-Based View and Dynamic Capabilities Theory with a human–AI complementarity perspective. The framework proposes that AI transformation creates valuable organisational resources, organisational agility converts those resources into adaptive action, and employee capability enables effective human–AI collaboration. Together, these mechanisms are expected to contribute to economic, environmental and social performance.

The available empirical literature provides encouraging evidence. AI assimilation has been linked with organisational agility and firm performance; AI capability has been associated with sustainable performance and data-driven culture; employee capabilities influence AI implementation; and AI has demonstrated potential to support green innovation and ESG performance.

Nevertheless, the literature also indicates that AI value is conditional. Organisations require appropriate infrastructure, quality data, employee skills, organisational culture, governance and process redesign. UNCTAD's 2025 assessment reinforces this broader perspective by identifying infrastructure, data and skills as fundamental conditions for inclusive AI development.

Accordingly, the key managerial lesson is straightforward: organisations should not ask only how much AI they have adopted; they should ask how effectively AI has transformed their capabilities, people, processes and sustainable value creation.

For a peer-reviewed empirical article, the next stage should be actual data collection and statistical testing of H1–H7. The paper should not report invented coefficients, p-values or hypothesis decisions without a respondent dataset.

References

1. Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. Sustainability, 16(5), 1864. (MDPI)
2. Bankins, S., Hu, X., & Yuan, Y. (2024). Artificial intelligence, workers, and future of work skills. Current Opinion in Psychology, 58, 101828. https://doi.org/10.1016/j.copsyc.2024.101828 (DOI)
3. Battistoni, E., Gitto, S., Murgia, G., & Campisi, D. (2023). Adoption paths of digital transformation in manufacturing SME. International Journal of Production Economics, 255, 108675. https://doi.org/10.1016/j.ijpe.2022.108675

4. Chen, D., Esperança, J. P., & Wang, S. (2022). The impact of artificial intelligence on firm performance: An application of the resource-based view to e-commerce firms. Frontiers in Psychology, 13, 884830. https://doi.org/10.3389/fpsyg.2022.884830 (Frontiers)
5. Chen, J., Wang, N., Lin, T., Liu, B., & Hu, J. (2024). Shock or empowerment? Artificial intelligence technology and corporate ESG performance. Economic Analysis and Policy, 83, 1080–1096. https://doi.org/10.1016/j.eap.2024.08.004 (ScienceDirect)
6. Deloitte. (2024). AI adoption in India driven by transformative potential balanced by cost sensitivity. Deloitte India. (Deloitte)
7. Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24, 1709–1734. https://doi.org/10.1007/s10796-021-10186-w (Springer Link)
8. Fosso Wamba, S., Queiroz, M. M., Pappas, I. O., & Sullivan, Y. (2024). Artificial intelligence capability and firm performance: A sustainable development perspective by the mediating role of data-driven culture. Information Systems Frontiers, 26(6), 2189–2203. https://doi.org/10.1007/s10796-023-10460-z (IDEAS/RePEc)
9. Fügener, A., Walzner, D. D., & Gupta, A. (2025). Roles of artificial intelligence in collaboration with humans: Automation, augmentation, and the future of work. Management Science. https://doi.org/10.1287/mnsc.2024.05684 (PubsOnline)
10. Ghobakhloo, M. (2021). Digital transformation success under Industry 4.0: A strategic guideline for manufacturing SMEs. Journal of Manufacturing Technology Management. https://doi.org/10.1108/JMTM-11-2020-0455
11. Khan, A. N. (2024/2025). Artificial intelligence and sustainable performance: Role of organisational agility and environmental dynamism. Technology Analysis & Strategic Management, 37(5), 568–583. https://doi.org/10.1080/09537325.2023.2290171 (Taylor & Francis Online)
12. Khunakornbodintr, S. (2024). Examining the impact of green technological specialization and the integration of AI technologies on green innovation performance: Evidence from China. Frontiers in Artificial Intelligence, 6. https://doi.org/10.3389/frai.2023.1237285 (Frontiers)
13. Lin, J., Zeng, Y., Wu, S., & Luo, X. R. (2024). How does artificial intelligence affect the environmental performance of organizations? The role of green innovation and green culture. Information & Management, 61(2), 103924. https://doi.org/10.1016/j.im.2024.103924 (ScienceDirect)
14. Oldemeyer, L., Jede, A., & Teuteberg, F. (2024/2025). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main

implementation challenges. Management Review Quarterly, 75, 1185–1227. https://doi.org/10.1007/s11301-024-00405-4 (Springer Link)

15. Roblek, V., Meško, M., Pušavec, F., & Likar, B. (2021). The role and meaning of the digital transformation as a disruptive innovation on small and medium manufacturing enterprises. Frontiers in Psychology, 12, 592528. https://doi.org/10.3389/fpsyg.2021.592528
16. Tabassi, E. (2023). Artificial Intelligence Risk Management Framework (AI RMF 1.0). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.100-1 (NIST)
17. UNCTAD. (2025). Technology and Innovation Report 2025: Inclusive artificial intelligence for development. United Nations Conference on Trade and Development. (UNCTAD)
18. Vaccaro, M., Almaatouq, A., & Malone, T. W. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. Nature Human Behaviour. (Nature)
19. Wahab, M. D. A., & Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises: A moderated multi-mediation model. Heliyon, 10(8), e29580. https://doi.org/10.1016/j.heliyon.2024.e29580 (ScienceDirect)
20. Wang, Q., Sun, T., & Li, R. (2025). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. Technology Analysis & Strategic Management. https://doi.org/10.1177/0958305X231220520 (Sage Journals)
21. Wamba, S. F., Queiroz, M. M., Trinchera, L., & others. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. International Journal of Information Management, 67, 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544 (ScienceDirect)
22. Wang, Y., et al. (2024). The effect of job skill demands under artificial intelligence embeddedness on employees' job performance: A moderated double-edged sword model. Behavioral Sciences, 14(10), 974. https://doi.org/10.3390/bs14100974 (MDPI)
23. Zheng, Q., Gou, J., Camarinha-Matos, L. M., Zhang, J. Z., & Zhang, X. (2024). Digital capability requirements and improvement strategies: Organizational socialization of AI teammates. Information Processing & Management. https://doi.org/10.1016/j.ipm.2023.103504 (ScienceDirect)