International Journal of Operations Research and Artificial Intelligence

www.ijorai.reapress.com

Int. J. Oper. Res. Artif. Intell. Vol. 2, No. 2 (2026) 67–79.

Paper Type: Original Article

Barriers to Artificial Intelligence Adoption in Manufacturing and Industrial Sectors: A Multi-Industry Synthesis and Prioritization Approach

Gholamreza Jamali[1,*], Abdullah Junbish[2]

[1] Department of Industrial Management, Faculty of Business and Economics, Persian Gulf University, Bushehr, Iran; gjamali@pgu.ac.ir; a.junbish@mehr.pgu.ac.ir.

Citation:

Received: 12 December 2025 *Revised: 14 Februray 2026* *Accepted: 18 April 2026*	Jamali, Gh., & Junbish, A. (2026). Barriers to artificial intelligence adoption in manufacturing and industrial sectors: A multi-industry synthesis and prioritization approach. *International Journal of Operations Research and Artificial Intelligence*, 2(2), 67-79.

Abstract

Artificial Intelligence (AI) is reshaping Industry 4.0, offering major opportunities to enhance productivity, improve product quality, and reduce manufacturing costs. Yet its adoption is hindered by technological, organizational, economic, and social/ethical barriers. This study applies a Systematic Literature Review (SLR) (2020–2025), the Technology–Organization–Environment (TOE) framework, and the Analytic Hierarchy Process (AHP) to identify, classify, and prioritize these obstacles. Extending TOE, the environmental dimension is divided into economic and social/ethical categories, yielding four groups. AHP-derived weights rank technological barriers highest (0.466), followed by organizational (0.277), economic (0.161), and social/ethical (0.096). The review screened 52 records (41 English and 11 Persian), with 24 studies meeting the inclusion criteria. From these, 16 sub-barriers were analyzed across the four categories. A TOE-based conceptual model connects each barrier group to targeted interventions and is reinforced by a practical roadmap with measurable KPIs, such as ≥ 95% data completeness, ≥ 12 training hours per employee, ROI payback ≤ 24 months, and 100% privacy compliance. The findings provide managers and policymakers with actionable guidance to focus resources on the most critical impediments and accelerate AI readiness in manufacturing industries.

Keywords: Artificial intelligence adoption, Manufacturing, TOE framework, AHP, Barrier prioritization, Digital transformation.

1 | Introduction

The rapid growth of digital technologies has reshaped manufacturing, with Artificial Intelligence (AI) emerging as a cornerstone of Industry 4.0 [1], [2]. AI enables predictive maintenance, automated quality

Corresponding Author: gjamali@pgu.ac.ir

https://doi.org/10.48314/ijorai.v2i2.90

control, process optimization, and supply chain management, offering gains in productivity, quality, and cost efficiency [3], [4].

Despite these benefits, adoption remains slow due to diverse barriers. Technological challenges include poor data quality, limited ICT infrastructure, and cybersecurity risks [5–7]. Organizational issues such as resistance to change, weak managerial support, and insufficient skills further impede integration [3], [8], [9]. Economic concerns (high capital costs, uncertain ROI, and limited incentives) add complexity [10–12]. Social and ethical issues, including job displacement, privacy, and fairness, affect stakeholder trust [13–15].

To address these challenges, this study applies the Technology–Organization–Environment (TOE) framework [16], extended by splitting the environmental dimension into economic and social/ethical categories. A Systematic Literature Review (SLR) (2020–2025) was conducted, and the Analytic Hierarchy Process (AHP) [17] was used to prioritize barriers.

The study contributes by: 1) extending TOE into four dimensions for finer classification; 2) integrating global and local perspectives on AI adoption challenges; and 3) proposing a conceptual model that links prioritized barriers to targeted managerial and policy interventions.

2 | Literature Review

2.1 | Technological Barriers

Technological barriers are among the most significant obstacles to AI adoption in manufacturing. These include insufficient ICT infrastructure, poor data quality and integration, algorithmic complexity, lack of interoperability, and cybersecurity vulnerabilities [5], [6], [18]. Poor data quality can hinder AI model training and deployment, while inadequate infrastructure limits computational capacity for real-time operations [4], [7]. In the Iranian context, limited technological readiness, outdated machinery, and weak integration of digital systems have been reported as major challenges [10], [19]. The absence of standardized data formats and inadequate IT support also impede AI-enabled predictive maintenance systems [20]. Recent studies further emphasize that insufficient ICT readiness, weak change management capabilities, and poor data governance can critically undermine AI adoption [8].

2.2 | Organizational Barriers

Organizational challenges include structural, managerial, and human resource factors influencing AI implementation. Commonly reported issues are resistance to change, lack of top management commitment, insufficient employee training, and weak change management strategies [3], [4], [9]. An organizational culture resistant to innovation can slow adoption even when technical resources are available [12]. In Iran, hierarchical decision-making structures, inadequate staff skill sets, and insufficient cross-departmental coordination have been identified as critical challenges [7]. Without targeted training programs, employees remain hesitant to engage with AI-driven changes [14]. In export-oriented SMEs, technological readiness and financial limitations are intertwined with insufficient managerial support and workforce shortages [9].

2.3 | Economic Barriers

Economic barriers mainly relate to the cost and financial justification of AI adoption. High initial investment, ongoing maintenance expenses, and uncertain ROI often deter organizations from committing to AI projects [6], [11], [12]. Limited access to funding and lack of government incentives exacerbate the problem, particularly for SMEs [1]. In Iran, financial constraints and prioritization of short-term profitability over long-term technological advancement delay AI integration [13]. Foreign exchange volatility and sanctions further increase acquisition and maintenance costs for advanced AI technologies [21]. Sustainable AI adoption also depends on long-term funding strategies, especially in resource-constrained SMEs [4].

2.4 | Social and Ethical Barriers

Social and ethical concerns involve workforce impacts, data privacy, algorithmic bias, and public trust in AI [15], [22]. In manufacturing, fears of job displacement and a lack of transparency in AI decision-making can lead to employee and community resistance [3], [21]. Ethical practices such as explainability and fairness are essential for building stakeholder trust [6]. In Iran, fear of job loss and limited public awareness of AI's benefits hinder adoption [20]. Weak data protection regulations create uncertainty and slow decision-making [5]. In sensitive sectors such as oil, privacy risks and ethical dilemmas in handling operational data further delay AI deployment [11].

2.5 | Summary

The reviewed studies indicate that AI adoption in manufacturing is constrained by a complex interplay of technological, organizational, economic, and social/ethical barriers. International research highlights scalability, interoperability, and governance as critical factors [4], [8], [18], while local studies emphasize structural inefficiencies, financial limitations, and socio-cultural resistance [7], [13], [20]. These combined insights justify the need for a structured prioritization approach, such as the AHP, to identify the most critical barriers and inform targeted strategies [17].

3 | Methodology

3.1 | Research Framework and Design

This research adopts a structured Multi-Criteria Decision-Making (MCDM) approach to analyze barriers to AI adoption in manufacturing industries. The Technology–Organization–Environment (TOE) framework [16] was employed as the classification scheme, with a methodological extension in which the environmental dimension was divided into two categories (economic and social/ethical), resulting in four overall groups. The hierarchical AHP model was structured in three levels: 1) Goal: Prioritization of AI adoption barriers, 2) four barrier categories, and 3) sixteen sub-barriers. Given the scope and page limits of this paper, DEMATEL or other causal mapping approaches were not implemented. Instead, robustness was ensured through sensitivity analysis, which is sufficient for validating prioritization results in this study.

3.2 | Systematic Literature Review

Barrier identification was conducted through an SLR covering January 2020–December 2025. Searches were performed in Scopus, Web of Science, IEEE Xplore, ScienceDirect, SID, and MagIran using combinations of: ("artificial intelligence" OR AI) AND (manufacturing OR "industrial sector") AND (barrier OR challenge* OR adoption) AND (AHP OR prioritiz*). The initial search retrieved 52 records (41 English and 11 Persian). After deduplication and eligibility screening, 24 studies met the inclusion criteria: peer-reviewed, focused on AI adoption barriers in manufacturing, and published in English or Persian. Exclusion criteria removed purely technical AI papers, duplicates, and non-manufacturing studies. A PRISMA-style flow diagram is reported in Appendix A.

3.3 | AHP Implementation and Analysis

Pairwise comparisons were derived from textual evidence in the reviewed studies using explicit coding rules aligned with Saaty's 1–9 scale [17]. Strong dominance (e.g., "barrier A is far more critical than barrier B") was coded as 7–9, moderate dominance as 3–5, and near equality as 1–2. When multiple studies reported the same comparison, the geometric mean of the coded intensities was used. Coding was performed by the authors; ambiguous cases were re-checked after a time gap to ensure reliability. Local weights were calculated by normalizing the pairwise matrices, and global weights were obtained by multiplying local weights by their parent category weight. Consistency Ratios (CR) were checked to remain ≤ 0.10. Analysis was performed using Microsoft Excel. All pairwise matrices, eigenvectors, local/global weights, and CR values are reported in Appendix B for transparency.

3.4 | Sensitivity Analysis

To examine the robustness of results, a sensitivity analysis was performed. The weights of each main barrier category were perturbed by ±10%, and the remaining categories were proportionally re-normalized. Additionally, two scenarios reflecting firm size were simulated: SMEs, characterized by higher cost sensitivity and lower ICT readiness, and large firms, characterized by stronger ICT infrastructure and lower relative cost constraints. The results confirmed that technological barriers consistently remained the top-ranked category under all perturbations. Minor rank swaps occurred between organizational and economic barriers under the SME scenario, while the overall order of priorities remained stable. Detailed results are reported in *Appendix D*.

4.5 | Data Sources and Analysis

Tools: The study relied exclusively on secondary data from both global and Persian literature. Persian sources were translated and incorporated where relevant. Pairwise comparison matrices and weight calculations were performed in Microsoft Excel, and visualizations (hierarchy diagrams and bar charts) were generated to support interpretation [1], [3], [7], [8].

4 | Findings

4.1 | AHP Results

The AHP was applied to determine the relative importance of the four main barrier categories (technological, organizational, economic, and social/ethical) and their associated sub-barriers. Pairwise comparison matrices were developed for both the main categories and the sub-barriers within each category.

The results in Table 1 show that technological barriers have the highest weight (0.466), followed by organizational (0.277), economic (0.161), and social/ethical barriers (0.096). All CR values are below the 0.1 threshold, indicating reliable judgments.

Table 1. Weights for main barrier categories.

Barrier Category	Weight
Technological	0.466
Organizational	0.277
Economic	0.161
Social/Ethical	0.096

The hierarchical structure used in this paper is illustrated in *Fig. 1*, showing the goal at Level 1, the four main barrier categories at Level 2, and their respective sub-barriers at Level 3.

4.2 | Global Ranking of Sub-Barriers

Table 2 presents the local weight of each sub-barrier within its category, the category's overall weight, and the resulting global weight. The top-ranked sub-barriers are data quality and integration (0.191) and lack of ICT infrastructure (0.163), both in the technological category, followed by lack of skilled workforce (0.116) and resistance to change (0.091) in the organizational category.

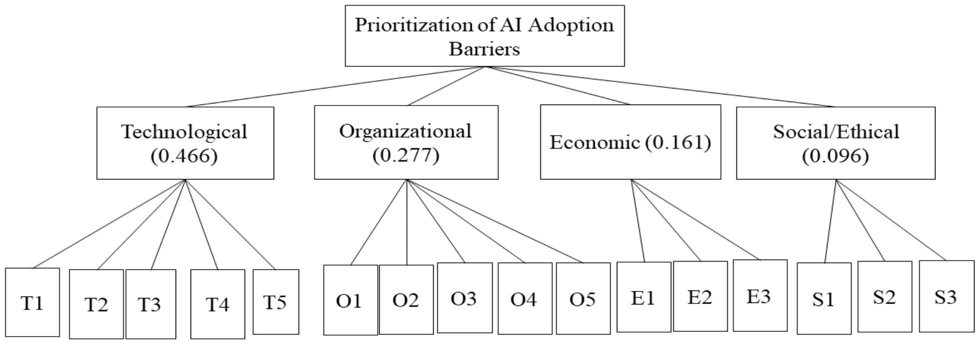

Fig. 1. Three-level AHP hierarchy for AI adoption barriers.

Table 2. Global weights of sub-barriers.

Rank	Category	Sub-Barrier (Code)	Local	Category	Global
1	Technological	Data quality & integration (T1)	0.410	0.466	0.191
2	Technological	Lack of ICT infrastructure (T2)	0.350	0.466	0.163
3	Organizational	Lack of skilled workforce (O1)	0.419	0.277	0.116
4	Organizational	Resistance to change (O2)	0.329	0.277	0.091
5	Economic	High CAPEX (E1)	0.500	0.161	0.081
6	Technological	Cybersecurity vulnerabilities (T3)	0.120	0.466	0.056
7	Economic	Uncertain ROI (E2)	0.300	0.161	0.048
8	Social/Ethical	Data privacy & protection (S1)	0.400	0.096	0.038
9	Social/Ethical	Job-displacement concerns (S2)	0.350	0.096	0.034
10	Organizational	Top management commitment (O3)	0.120	0.277	0.033
11	Technological	Interoperability & standards (T4)	0.070	0.466	0.033
12	Economic	Limited incentives/financing (E3)	0.200	0.161	0.032
13	Social/Ethical	Fairness & transparency (XAI) (S3)	0.250	0.096	0.024
14	Technological	Legacy system integration (T5)	0.050	0.466	0.023
15	Organizational	Organizational culture (O4)	0.080	0.277	0.022
16	Organizational	Cross-departmental coordination (O5)	0.053	0.277	0.015

The distribution of weights across main categories is shown in *Fig. 2*, highlighting the dominance of technological and organizational challenges over economic andsocial/ethical ones.

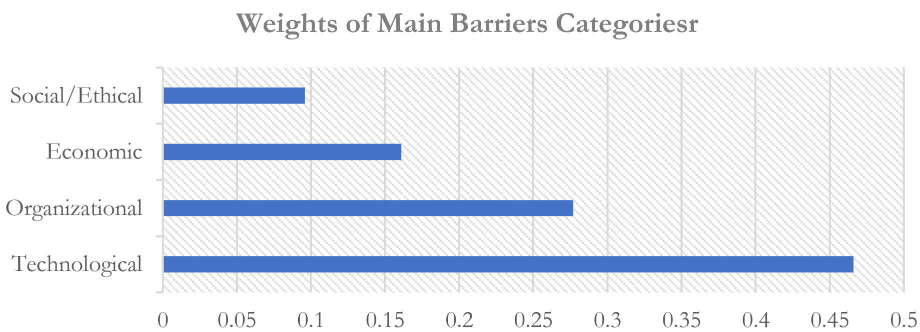

Fig. 2. Weights of main AI adoption barrier categories.

The global weights for all sub-barriers are illustrated in *Fig. 3*, where technological barriers are visibly more significant compared to others.

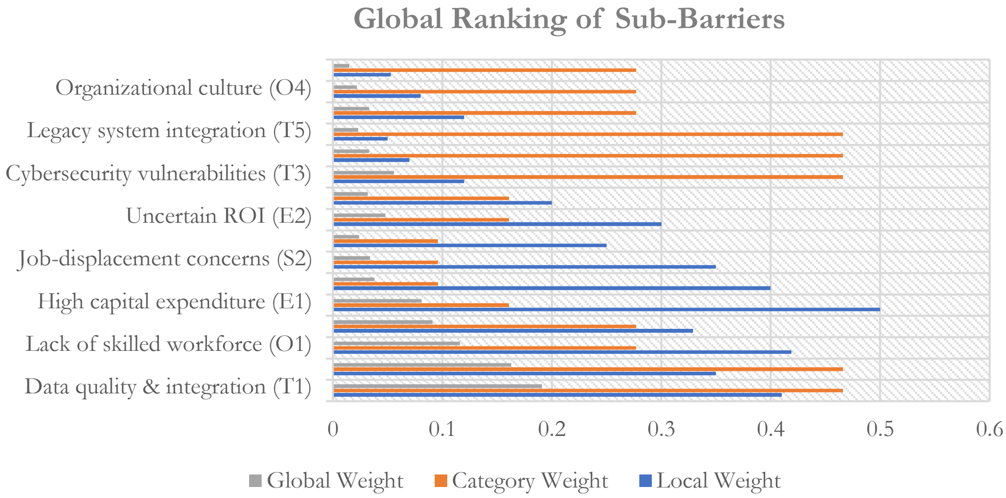

Fig.3. Global weights of sub-barriers.

3.4 | Conceptual Model

Based on the AHP results and guided by the extended TOE framework, a conceptual model was developed (see *Fig. 4*) linking each barrier category to targeted solutions. For example, technological barriers can be addressed through ICT infrastructure upgrades and improved data governance, while organizational barriers require structured change management and workforce training. Economic barriers may be mitigated through government incentives and phased investments, and social/ethical concerns can be alleviated via transparency, Explainable AI (XAI), and robust ethical governance policies.

To enhance practical applicability, the proposed TOE-based model is reinforced with measurable KPIs and a staged roadmap. Quick wins (short-term actions within 12 months) include data-quality audits and focused training modules. Structural initiatives (medium- to long-term) include ICT backbone upgrades, governance frameworks, and incentive schemes. KPIs such as data completeness (>95%), training hours per employee (>12 annually), ROI payback periods (<24 months), and privacy compliance rates (100%) are proposed to track progress. *Table 3* summarizes the mapping of barrier groups to interventions and KPIs.

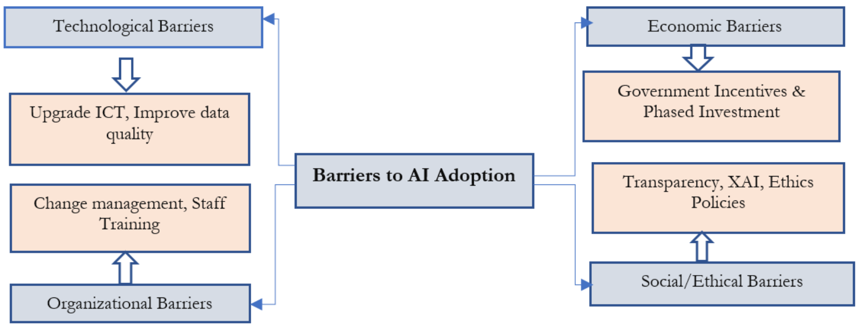

Fig. 4. TOE-based conceptual model linking barriers to targeted solutions.

Table 3. Mapping of priority barriers to interventions and KPIs.

Barrier Group	Intervention	Sample KPIs (12–24 Month Targets)
Technological	Data governance & ICT upgrade	≥95% data completeness; ≥30% MTBF increase
Organizational	Change management & AI training	≥12 training hours/employee; ≥20% readiness ↑
Economic	Phased CAPEX & financial incentives	ROI payback ≤24 months; budget adherence ≥90%
Social/Ethical	XAI & privacy safeguards	≥90% explain ability coverage; 100% privacy compliance

5 | Discussion and Conclusion

The results indicate that technological barriers are the most influential impediments to AI adoption in manufacturing, followed by organizational, economic, and social/ethical barriers. This ranking aligns with prior studies highlighting the central role of technical readiness, particularly data quality and ICT infrastructure, in enabling effective AI integration [4], [6], [18]. Poor infrastructure and fragmented data systems hinder real-time AI deployment, while low-quality or inconsistent data reduce the accuracy of AI-driven decisions.

Sensitivity analysis confirmed the stability of findings. Even when weights were varied by ±10% or adjusted to simulate SMEs versus large firms, technological barriers consistently held the highest priority. Minor shifts occurred between organizational and economic barriers, but managerial implications remained unchanged: ICT upgrades, workforce training, financial incentives, and ethical AI governance remain the most critical interventions.

The prominence of organizational barriers suggests that even with sufficient technical resources, resistance to change and insufficient workforce skills can delay adoption [3], [8], [9]. Economic constraints, while ranked third, remain decisive for SMEs facing high upfront costs and uncertain ROI [10], [12], [22]. Social and ethical concerns, including job displacement, data privacy, and fairness, may undermine stakeholder support [13], [15], [23].

By combining an SLR, the AHP method, and an extended TOE framework that separates economic and social/ethical dimensions, this study refines the classification of AI adoption barriers. To strengthen practical relevance, the conceptual model is complemented by a roadmap that links barriers to interventions and measurable KPIs. As summarized in *Table 3* (findings section), quick wins include data-quality audits and targeted training, while structural initiatives require ICT backbone upgrades, governance frameworks, and incentive schemes.

In conclusion, prioritizing resources toward ICT infrastructure, robust data governance, workforce development, change management, financial incentives, and ethical AI governance will accelerate AI readiness in manufacturing.

6 | Recommendations for Practice

Based on the prioritization results, several actionable strategies are recommended:

Technological: upgrade ICT infrastructure, establish data governance protocols, adopt standardized data formats, and implement cybersecurity measures [4], [6], [18].

Organizational: initiate structured change management, provide targeted AI training, and foster cross-departmental collaboration [3], [8], [9].

Economic: apply phased investments, secure subsidies, and create tax incentives [10], [12].

Social/ethical: implement transparency policies, adopt explainable AI frameworks, and establish ethical guidelines [13], [15], [23].

These recommendations should be tailored to each organization's maturity, culture, and resources.

7 | Limitations and Future Research

This study has several limitations. It relies exclusively on secondary data and literature-based pairwise comparisons, which may limit applicability in certain contexts. Inter-coder reliability was not assessed, as comparisons were coded by a single researcher. Moreover, causal mapping methods such as DEMATEL were not implemented due to space constraints; future work could integrate DEMATEL or fuzzy DEMATEL to capture interdependencies.

Future studies should validate these findings with primary data (surveys, interviews, Delphi) and extend the analysis across regions, sectors, and firm sizes. Longitudinal research may capture evolving trends as AI adoption matures. Complementary MCDM methods such as fuzzy AHP, DEMATEL, or SEM could also provide deeper insights into barrier interrelationships.

Acknowledgment

This article was prepared as part of a graduate course project in Advanced Production and Operations Management at Persian Gulf University. The authors confirm that no external funding was received. We acknowledge the use of AI-based tools (ChatGPT, OpenAI) for language editing and polishing; all content and analyses were conducted and verified by the authors.

References

[1] Sayem, A., Biswas, P. K., Khan, M. M., Romoli, L., & Dalle Mura, M. (2022). Critical barriers to industry 4.0 adoption in manufacturing organizations and their mitigation strategies. *Journal of Manufacturing and Materials Processing*, *6*(6), 136. https://doi.org/10.3390/jmmp6060136

[2] Sonntag, M., Mehmann, S., Mehmann, J., & Teuteberg, F. (2024). Development and evaluation of a maturity model for AI deployment capability of manufacturing companies. *Information Systems Management*, *42*(1), 37–67. https://doi.org/10.1080/10580530.2024.2319041

[3] Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes— an interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

[4] Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776. https://doi.org/10.1016/j.ijpe.2020.107776

[5] Farzin, O., & Samiei, R. (2023). Ethical and legal challenges of using artificial intelligence in digital businesses. *Journal of Technology in Entrepreneurship and Strategic Management*, *2*, 17–27. https://doi.org/10.61838/kman.jtesm.2.2.3

[6] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., …, Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

[7] Stornelli, A., Ozcan, S., & Simms, C. (2021). Advanced manufacturing technology adoption and innovation: A systematic literature review on barriers, enablers, and innovation types. *Research Policy*, *50*(6), 104229. https://doi.org/10.1016/j.respol.2021.104229

[8] Filho, M., Almeida, S., Junior, M., Osiro, L., Lima, B., & Callefi, M. H. (2025). A path to follow to overcome foundational barriers to the adoption of artificial intelligence within the manufacturing industry: A conceptual framework. *Enterprise Information Systems*, *19*(2025). https://doi.org/10.1080/17517575.2025.2458685

[9] Haq, F., Mohd Suki, N., Zaigham, H., Masood, A., & Rajput, A. (2025). Exploring AI adoption and SME performance in resource-constrained environments: A TOE–RBV perspective with mediation and moderation effects. *Journal of Digital Economy*, *5*. https://doi.org/10.1016/j.jdec.2025.07.002

[10] Sony, M., & Naik, S. (2019). Key ingredients for evaluating Industry 4.0 readiness for organizations: A literature review. *Benchmarking: An International Journal*, *27*(7), 2213–2232. https://doi.org/10.1108/BIJ-09-2018-0284

[11] Póvoas, M. D., Moreira, J. F., Neto, S. V, Carvalho, C. A., Cezario, B. S., Guedes, A. L., & Lima, G. B. (2025). Artificial intelligence in the oil and gas industry: Applications, challenges, and future directions. *Applied Sciences*, *15*(14), 7918. https://doi.org/10.3390/app15147918

[12] Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, *58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

[13] Nouri, M., Hosseini Shakib, M., & Khamseh, A. (2024). Unveiling financial barriers for SMEs in Iran: A fuzzy delphi approach to enhancing production financing. *Fuzzy Optimization and Modeling Journal (FOMJ)*, *5*(3), 1–21. https://doi.org/10.71808/fomj.2024.1127708

[14] Kamble, S., Gunasekaran, A., & Gawankar, S. (2018). Sustainable industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*. https://doi.org/10.1016/j.psep.2018.05.009

[15] Avoumatsodo, K. (2025). *Financial constraints, technology adoption, and convergence* [Thesis]. https://avoumatsodo.github.io/files/financial_development_technology_adoption_sectoral_productivity_convergence.pdf

[16] Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington Books. https://books.google.com/books?id=QWiwAAAAIAAJ

[17] Saaty, T. L. (1980). The analytic hierarchy process. *European Journal of Operational Research*, *48*, 9–26. https://d1wqtxts1xzle7.cloudfront.net/51627807

[18] Kusiak, A. (2017). Smart manufacturing must embrace big data. *Nature*, *544*(7648), 23–25. https://doi.org/10.1038/544023a

[19] Madanchian, M., & Taherdoost, H. (2025). Barriers and enablers of AI adoption in human resource management: A critical analysis of organizational and technological factors. *Information*, *16*(1), 51. https://doi.org/10.3390/info16010051

[20] Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*, 120880. https://doi.org/10.1016/j.techfore.2021.120880

[21] Esmailzadeh, M., Noori, S., Nouralizadeh, H., & Bogers, M. L. A. M. (2020). Investigating macro factors affecting the technological innovation system (TIS): A case study of Iran's photovoltaic TIS. *Energy Strategy Reviews*, *32*, 100577. https://doi.org/10.1016/j.esr.2020.100577

[22] Dignum, V. (2018). Ethics in artificial intelligence: Introduction to the special issue. *Ethics and Information Technology*, *20*(1), 1–3. https://doi.org/10.1007/s10676-018-9450-z

[23] Vacek, D. (2026). Responsible artificial intelligence? *AI & Society*, *41*(2), 843–855. https://doi.org/10.1007/s00146-025-02604-3

Appendix A

Systematic review protocol search strategy: A SLR was conducted to identify barriers to AI adoption in manufacturing. Searches were performed in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Persian databases (SID and MagIran) covering the period January 2020–December 2025. The following keywords and Boolean operators were applied: ("artificial intelligence" OR AI) AND (manufacturing OR "industrial sector") AND (barrier OR challenge* OR adoption) AND (AHP OR prioritize*).

Inclusion criteria:

I. Peer-reviewed journal or conference articles.

II. Explicit discussion of AI adoption barriers in manufacturing or industrial sectors.

III. Published in English or Persian.

IV. Full text available.

Exclusion criteria:

I. Purely technical AI studies without adoption issues.

II. Non-manufacturing domains (e.g., healthcare, agriculture).

III. Duplicates, abstracts without full text, or editorials.

Screening results: The search initially retrieved 52 records (41 English, 11 Persian). After removing duplicates, 45 de-duplicated records remained; title and abstract screening excluded 21 irrelevant items. Following full-text review, 24 studies satisfied all criteria and were included in the final synthesis.

Screening process: The process followed three stages: 1) title/abstract screening, 2) full-text eligibility check, and 3) snowballing from backward/forward references.

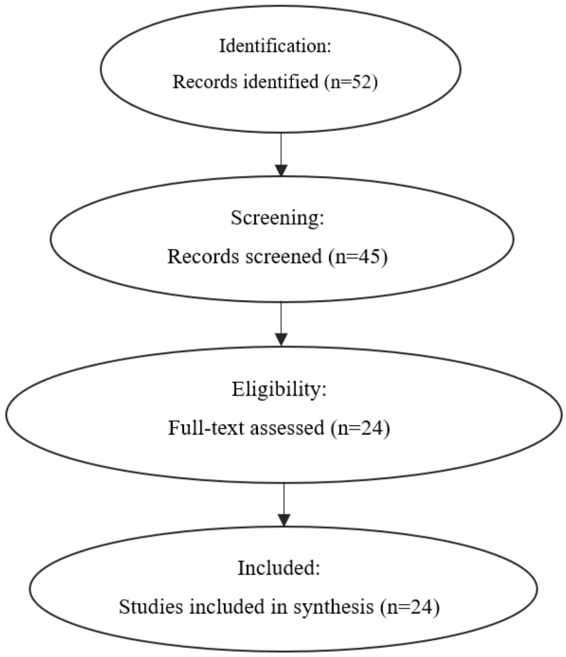

Fig. A1. PRISMA flow diagram of the screening process.

Appendix B

B1. Main barriers:

I. 4×4 matrix (Tech, Org, Econ, Soc/Eth).

II. Local weights, CR.

Table B1. Pairwise comparison of main barrier categories (CR = 0.06).

Barriers	Tech	Org	Econ	Soc/Eth	Weights
Tech	1	2	3	5	0.466
Org	1/2	1	2	3	0.277
Econ	1/3	1/2	1	2	0.161
Soc/Eth	1/5	1/3	1/2	1	0.096

B2. Technological sub-barriers:

I. T1: Data quality & integration.

II. T2: Lack of ICT infrastructure.

III. T3: Cybersecurity vulnerabilities.

IV. T4: Interoperability & standards.

V. T5: Legacy system integration.

VI. 5×5 matrix (T1–T5).

VII. Local weights (sum = 1.000).

VIII. Global weights = Local × 0.466.

Table B2. Pairwise comparison of technological sub-barriers (CR = 0.03).

	T1	T2	T3	T4	T5	Local w	Global W
T1	1	2	5	7	9	0.41	0.191
T2	1/2	1	4	6	8	0.35	0.163
T3	1/5	1/4	1	3	5	0.12	0.056
T4	1/7	1/6	1/3	1	3	0.07	0.033
T5	1/9	1/8	1/5	1/3	1	0.05	0.023

B3. Organizational sub-barriers:

I. O1: Lack of skilled workforce.

II. O2: Resistance to change.

III. O3: Top management commitment.

IV. O4: Organizational culture.

V. O5: Cross-departmental coordination.

VI. 5×5 matrix (O1–O5).

VII. Local weights (sum = 1.000).

VIII. Global weights = Local × 0.277.

Table B3. Pairwise comparison of organizational sub-barriers (CR = 0.07).

	O1	O2	O3	O4	O5	Local w	Global W
O1	1	2	5	7	9	0.42	0.116
O2	1/2	1	4	6	8	0.33	0.091
O3	1/5	1/4	1	3	5	0.12	0.033
O4	1/7	1/6	1/3	1	3	0.08	0.022
O5	1/9	1/8	1/5	1/3	1	0.05	0.015

B4. Economic sub-barrier:

I. 3×3 matrix (E1–E3).

II. Local weights.

III. Global weights = Local × 0.161.

IV. E1: High CAPEX.

V. E2: Uncertain ROI.

VI. E3: Limited incentives/financing.

Table B4. Pairwise comparison of economic sub-barriers (CR = 0.001).

	E1	E2	E3	Local w	Global W
E1	1	3	4	0.53	0.085
E2	1/3	1	2	0.28	0.045
E3	1/4	1/2	1	0.19	0.031

B5. Social/ethical sub-barriers:

I. S1: Data privacy & protection.
II. S2: Job-displacement concerns.
III. S3: Fairness/transparency (XAI).
IV. 3×3 matrix (S1–S3).
V. Local weights.
VI. Global weights = Local × 0.096.

Table B5. Pairwise comparison of social/ethical sub-barriers (CR = 0.02).

	S 1	S 2	S 3	Local w	Global W
S1	1	2	3	0.50	0.048
S 2	1/2	1	2	0.30	0.029
S 3	1/3	1/2	1	0.20	0.019

Appendix C

Sub-barriers and local/global weights:

Table C1. Technological sub-barriers (Σ Local = 1.000).

Code	Sub-barrier	Local Weight	Global Weight (×0.466)
T1	Data quality & integration	0.410	0.191
T2	Lack of ICT infrastructure	0.350	0.163
T3	Cybersecurity vulnerabilities	0.120	0.056
T4	Interoperability & standards	0.070	0.033
T5	Legacy system integration	0.050	0.023

Table C2. Organizational Sub-barriers (Σ Local = 1.000).

Code	Sub-barrier	Local Weight	Global Weight (×0.277)
O1	Lack of skilled workforce	0.419	0.116
O2	Resistance to change	0.329	0.091
O3	Top management commitment	0.120	0.033
O4	Organizational culture	0.080	0.022
O5	Cross-departmental coordination	0.052	0.015

Table C3. Economic Sub-barriers (Σ Local = 1.000).

Code	Sub-barrier	Local Weight	Global Weight (×0.161)
E1	High capital expenditure	0.500	0.081
E2	Uncertain ROI	0.300	0.048
E3	Limited incentives/financing	0.200	0.032

Table C4. Social/Ethical Sub-barriers (Σ Local = 1.000).

Code	Sub-barrier	Local Weight	Global Weight (×0.096)
S1	Data privacy & protection	0.400	0.038
S2	Job-displacement concerns	0.350	0.034
S3	Fairness & transparency (XAI)	0.250	0.024

Sub-barrier weights:

Tables C1–C4 present the complete list of sub-barriers within each category. Local weights in each category were normalized to sum to 1.000. Global weights were obtained by multiplying each local weight by the corresponding category weight (technological = 0.466, organizational = 0.277, economic = 0.161, social/ethical = 0.096). The weighting procedure ensures internal consistency across the hierarchy and provides transparency for prioritization results.

Appendix D

D1. ±10% perturbation of category weights table:

Table D1. Sensitivity of barrier rankings under ±10% perturbations.

Scenario	Technological	Organizational	Economic	Social/Ethical	Ranking Outcome
Base case (AHP results)	0.466	0.277	0.161	0.096	T > O > E > S
Tech +10%	0.513	0.251	0.146	0.090	T > O > E > S
Tech –10%	0.419	0.305	0.178	0.098	T > O > E > S
Org +10%	0.447	0.305	0.158	0.090	T > O > E > S
Org –10%	0.483	0.249	0.172	0.096	T > O > E > S
Econ +10%	0.455	0.271	0.177	0.097	T > O > E > S
Econ –10%	0.474	0.286	0.145	0.095	T > O > E > S
Soc/Eth +10%	0.458	0.272	0.158	0.112	T > O > E > S
Soc/Eth –10%	0.471	0.280	0.163	0.086	T > O > E > S

D2. SME vs. large firm scenarios:

Table D2. Scenario-based sensitivity analysis.

Scenario	Technological	Organizational	Economic	Social/Ethical	Ranking Outcome
SMEs	0.440	0.290	0.180	0.090	T > O > E > S
Large firms	0.490	0.270	0.150	0.090	T > O > E > S

Sensitivity analysis results:

Tables D1 and *D2* present the results of sensitivity analyses. Under ±10% perturbations of category weights, technological barriers consistently remained the top-ranked group. Only minor variations were observed in the relative positions of organizational and economic barriers. Scenario testing between SMEs and large firms confirmed the robustness of the prioritization: While SMEs place slightly more emphasis on economic constraints and large firms emphasize technological readiness, the overall ranking (technological > organizational > economic > social/ethical) remains stable. These results demonstrate that the proposed prioritization framework is robust to moderate changes in assumptions.