

BIG DATA AND ANALYTICS SOFTWARE APPLICATIONS IN MANUFACTURING IMPLEMENTATIONS: INDUSTRY 4.0

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ABSTRACT

Big Data Analytics (BDA) is a core enabler of Industry 4.0, transforming manufacturing business processes through real-time visibility, predictive capabilities, and intelligent automation. However, selecting the most suitable BDA tools remains a significant challenge for manufacturers due to the wide range of options and the need to align them with specific process requirements. This study systematically reviews BDA tools and applications in manufacturing from a Business Process Management (BPM) perspective. It develops and applies an Analytic Hierarchy Process (AHP) framework to support multi-criteria tool selection. Drawing on 45 core sources, the analysis identifies key trends, benefits, challenges, and high-impact applications. The AHP illustrative case demonstrates that Functionality and vendor support are the dominant criteria, with enterprise-grade solutions generally outperforming others for complex manufacturing processes. The framework contributes to both BPM theory and industrial practice by providing a structured approach to technology selection that integrates process governance, performance, and strategic alignment.

Keywords: (Analytic Hierarchy Process (AHP), Big Data Analytics (BDA), Business Process Management, Decision-making, Digital Transformation, Industry 4.0, Manufacturing, Tool Selection.)

1. INTRODUCTION

The Fourth Industrial Revolution has positioned Big Data Analytics (BDA) as a foundational pillar of Industry 4.0, enabling manufacturers to convert vast volumes of sensor, IoT, and operational data into actionable insights for process optimization, predictive maintenance, and competitive advantage [1], [2], [3]. The pillars of Industry 4.0 are illustrated in Figure 1, which clearly shows BDA as a core component of Industry 4.0 protocols.

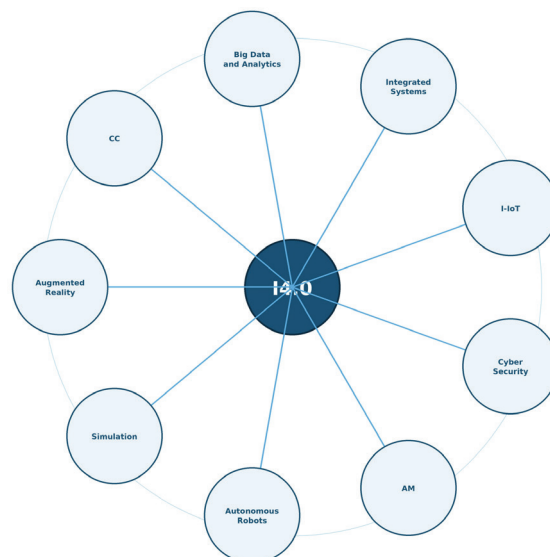


Figure 1: The pillars of Industry 4.0. adapted from [3]

While numerous studies have examined BDA technologies and isolated applications, three critical gaps persist in the literature. Firstly, most research remains descriptive or technology-focused, with limited integration of a Business Process Management (BPM) perspective [4], [5]. Secondly, there is a shortage of systematic, multi-criteria decision frameworks to guide tool selection in manufacturing contexts [6], [7]. Thirdly, few studies provide verifiable comparative analyses of tools linked to specific BPM outcomes such as process visibility, agility, and governance [8], [9]. This study addresses these gaps by:

- (i) Conducting a systematic review of BDA tools and applications through a BPM perspective.
- (ii) Proposing and illustrating an Analytic Hierarchy Process (AHP)-based decision framework for tool selection.
- (iii) Synthesizing empirical insights from real industrial cases.

The primary objective is to offer manufacturing organizations a rigorous, repeatable method for aligning BDA tools with strategic business processes while advancing theoretical understanding at the intersection of BDA, BPM, and Industry 4.0.

2. LITERATURE REVIEW

2.1 BDA WITHIN INDUSTRY 4.0 AND BPM

Industry 4.0 integrates cyber-physical systems, IoT, and advanced automation to create smart, interconnected manufacturing environments [10]. BDA functions as the cognitive backbone, supporting end-to-end process orchestration, real-time monitoring, and continuous improvement, core elements of contemporary BPM [11], [12], [13], [14]. BDA enables four levels of process analytics:

- (i) Descriptive (what happened).
- (ii) Diagnostic (why it happened).
- (iii) Predictive (what will happen).
- (iv) Prescriptive (what should be done).

These capabilities facilitate process redesign, exception handling, and the transition toward more autonomous and resilient business processes. Discussing the benefits, trends, challenges, and tool landscape of BDA. Key benefits include production optimization, predictive maintenance, quality improvement, energy efficiency, and enhanced supply chain visibility [15], [16], [17].

Emerging trends encompass real-time edge analytics, AI convergence, digital twins, sustainability applications, and low-code platforms. Major challenges involve data quality and interoperability, skills gaps, cybersecurity, and organizational resistance to process transformation [18], [19], [20]. A wide array of BDA tools exists, ranging from general-purpose platforms (Python, R, Power BI, Tableau) to specialized enterprise solutions (SAS, IBM Cognos, KNIME, MATLAB). However, systematic comparative evaluations grounded in BPM requirements remain scarce [8].

2.2 BDA WITHIN MANUFACTURING AND BPM

Big Data Analytics (BDA) transforms raw information from IoT sensors, equipment, and supply chain metrics into actionable intelligence [21], [22]. In manufacturing and Business Process Management (BPM), BDA enables real-time process monitoring, predictive maintenance, and bottleneck elimination, driving hyper-efficiency and data-driven agility. The primary difference between the paradigms of contemporary and conventional manufacturing is clearly shown in Figure 2. Evidently indicating BDA as a crucial subset of a sustainable or smart manufacturing system.

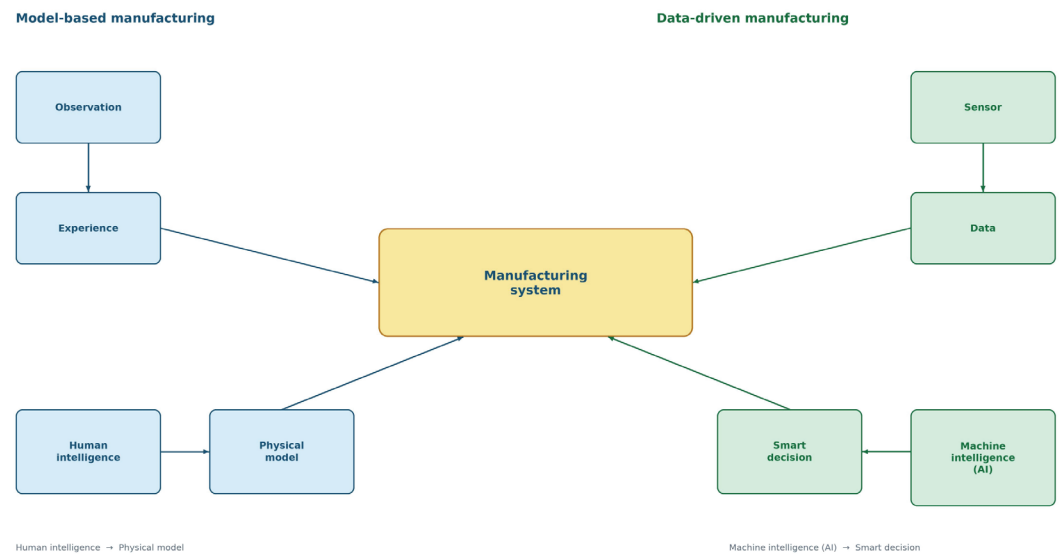


Figure 2: Model-based manufacturing and data-driven manufacturing

The most widely used BDA tools in a manufacturing context are Google Analytics, Microsoft Excel, Python, R-studio, Tableau, MySQL, SAS, Jupyter Notebook, Qlik, Sisense, Looker, Orange, Minitab, Power BI, Apache Spark, Domo, Alteryx, Google, KNIME, RapidMiner, IBM Cognos Analytics, MATLAB, JMP, SPSS, and Google Analytics [23], [24], [25], [26], [27].

3. METHODOLOGY

This study adopted a two-phase approach. Phase 1 involved a systematic literature review following established guidelines. Searches are conducted across Scopus, Web of Science, IEEE Xplore, and Google Scholar using combinations of keywords: "Big Data Analytics," "Industry 4.0," "Manufacturing," "Business Process Management," and individual tool names. Inclusion criteria focused on peer-reviewed articles (2017 - 2025) addressing tool applications, process impacts, or implementation outcomes in manufacturing. After screening, 45 high-relevance sources are synthesized.

Phase 2 applied the Analytic Hierarchy Process (AHP) [28], [29] as a structured multi-criteria decision-making method. AHP is chosen for its transparency, ability to handle qualitative and quantitative criteria, and widespread use in technology selection. An illustrative case for inventory management and demand forecasting processes is developed using four criteria that include cost, Functionality, technical requirements, and vendor support/maintenance.

4. RESULTS AND DISCUSSION

Successful BDA deployment requires adherence to principles of strategic alignment, data quality, reproducibility, security, scalability, and user-centric design. Recent trends highlight a shift toward real-time, AI-augmented, and sustainability-oriented analytics. Table 1 presents a synthesized overview of prominent BDA tools, their primary manufacturing applications, and BPM relevance.

Table 1: Selected Big Data Analytics Tools in Manufacturing: Applications and Business Process Management (BPM) Relevance

Tool	Key manufacturing applications	BPM relevance	Example company/ case	Source(s)
Power BI	Real-time dashboards, KPI monitoring, descriptive analytics	Process performance monitoring, real-time visibility, and exception management	Rheem Manufacturing	Original case data; Microsoft customer stories (2023–2025)
Tableau	Interactive visualization, self-service analytics	Descriptive & diagnostic process analysis, cross-functional insights	Bentley Motors	Tableau customer stories: original document
Python (with Pandas, Scikit-learn)	Predictive maintenance, quality control, automation scripting	Predictive & prescriptive process analytics, process automation	Philips	Original case: Philips digital transformation reports
Apache Spark	Large-scale data processing, real-time analytics	Scalable process data integration, batch & stream processing	Riot Games (adapted to manufacturing context)	Industry applications
SAS Viya	Advanced analytics, AI integration, predictive modeling	Enterprise process governance, compliance, and end-to-end analytics	Wienerberger	Original case; SAS customer stories
IBM Cognos Analytics	Financial & operational reporting, budgeting	Integrated performance management, cross-process reporting	ULMA Packaging	Original case; IBM customer success stories
KNIME	Workflow automation, data mining, predictive analytics	Process automation, reusable analytical workflows	Siemens	Original case: KNIME customer stories
RapidMiner	Predictive maintenance, root cause analysis	Diagnostic & predictive process improvement	Lufthansa Technik (aviation maintenance)	Original document; RapidMiner case studies
MATLAB / Simulink	Statistical analysis, simulation, predictive maintenance	Advanced process modeling, digital twins, quality control	Steel production plants	Original document; MathWorks industry cases
JMP	Statistical process control, design of experiments	Quality management, process validation & optimization	Thermo Fisher Scientific, GSK	Original document; JMP (SAS) case studies
Alteryx	Data preparation, advanced analytics workflows	Process data blending & automation	Anglo American (Mining)	Original document; Alteryx customer stories
Minitab	Statistical quality control, root cause analysis	Process capability analysis, Six Sigma initiatives	Canadian Solar	Original document; Minitab case studies

Table 1 synthesizes prominent BDA tools, their manufacturing applications, and relevance to BPM based on the systematic literature review and documented industrial cases. As shown in Table 1, tools such as SAS Viya and IBM Cognos Analytics offer stronger enterprise governance features, making these BDA tools particularly suitable for regulated manufacturing processes, while Python and Apache Spark excel in scalable predictive analytics. Power BI and Tableau, integrated with descriptive and diagnostic dashboards, offer strong capabilities for process monitoring, while KNIME and RapidMiner enable efficient workflow automation and predictive maintenance. MATLAB and JMP are mostly used for statistical process control and advanced analytics.

An illustrative Analytic Hierarchy Process (AHP) application is conducted for a typical manufacturing scenario (inventory management and demand forecasting). The AHP,

developed by [28], is a structured Multi-Criteria Decision-Making (MCDM) technique that assists decision-makers in evaluating and ranking alternatives based on multiple, often conflicting criteria. Below is a clear, step-by-step explanation of the AHP calculation process, selecting a Big Data Analytics (BDA) tool for inventory management and demand forecasting.

STEP 1: STRUCTURING THE HIERARCHY

Goal: Select the most suitable BDA tool for inventory management and demand forecasting processes based on the criteria and alternatives defined below.

Criteria: Cost, Functionality, Technical Requirements, Vendor Support/Maintenance.

Alternatives: Tool X, Tool Y, Tool Z.

STEP 2: PAIRWISE COMPARISON OF CRITERIA

Decision-makers compare each pair of criteria using Saaty's 1 - 9 scale, where 1 = equally important, 3 = moderately more important, 5 = strongly more important, 7 = very strongly more important, 9 = extremely more important, and 2, 4, 6, 8 are intermediate values. Table 2 shows the pairwise comparison of the defined criteria.

Table 2: Pairwise comparison of criteria

Criteria	Cost	Functionality	Technical Requirements	Support/Maintenance
Cost	1	1/3	4	2
Functionality	3	1	5	3
Technical Requirements	1/4	1/5	1	1/2
Support/Maintenance	1/2	1/3	2	1

The resulting criteria weights are Functionality (0.45), Support/Maintenance (0.31), Cost (0.18), and Technical Requirements (0.06).

STEP 3: CONSISTENCY CHECK FOR THE CRITERIA MATRIX

The mathematical formulas are highlighted below:

(i) Principal eigenvalue ($\lambda_{\max}$): This is a crucial step used to verify if the judgments are consistent. The first step is calculating the Priority Vector. Followed by normalizing the pairwise comparison matrix by dividing each entry by its column total, and then averaging the values in each row to get the priority weights. The original pairwise comparison matrix is then multiplied by the priority vector. This will result in a new vector where each element represents the sum of the products of each row. For each element in the resulting vector from the previous step, divide it by its corresponding priority weight. Finally, calculate the average of all the values generated. This average is the principal eigenvalue.

(ii) Consistency Index (CI): The principal eigenvalue is used to calculate the Consistency Index (CI) and the Consistency Ratio (CR) to ensure the judgments are logical and not entirely random. $CI = (\lambda_{\max} - n) / (n - 1)$.

(iii) Consistency Ratio (CR): $CR = CI / \text{Random Index (RI)}$. Random Index value corresponds to the matrix size. A CR of less than 0.10 generally means the pairwise comparisons are acceptably consistent ($CR \leq 0.10$ or 10%).

The following results are obtained. $\lambda_{\max} = 4.08$, $CI = 0.027$, and $CR = 0.03$ ($0.03 < 0.10 \rightarrow$ Acceptable). All consistency ratios followed similar mathematical formulas for the alternative matrices and are also below 0.10 (acceptable).

STEP 4: PAIRWISE COMPARISONS OF ALTERNATIVES UNDER EACH CRITERION

Tables 3, 4, 5, and 6 show the pairwise comparison for each of the criteria "cost, functionality, technical requirements, and support/maintenance".

Table 3: Pairwise comparison for cost criterion

Cost	X	Y	Z	Local Priority
X	1	1/2	1/4	0.09
Y	2	1	1/3	0.18
Z	4	3	1	0.73

Table 4: Pairwise comparison for functionality criterion

Functionality	X	Y	Z	Local Priority
X	1	1/3	1/5	0.10
Y	3	1	1/3	0.26
Z	5	3	1	0.64

Table 5: Pairwise comparison for technical requirements criterion

Technical Requirements	X	Y	Z	Local Priority
X	1	2	3	0.54
Y	1/2	1	2	0.30
Z	1/3	1/2	1	0.16

Table 6: Pairwise comparison for support/maintenance criterion

Support/Maintenance	X	Y	Z	Local Priority
X	1	1/2	1/4	0.14
Y	2	1	1/3	0.24
Z	4	3	1	0.62

STEP 5: SYNTHESIS OF GLOBAL PRIORITY SCORES

Multiply each alternative's local priority (under a criterion) by the criterion's weight. An example is shown with Tool X. " $0.09 \times 0.18 = 0.016$, $0.10 \times 0.45 = 0.045$, $0.54 \times 0.06 = 0.032$, $0.14 \times 0.31 = 0.043$. Then sum across all criteria to get the global priority score. This gives "0.136".

Table 7: Global priority calculation

Alternative	Cost (0.18)	Functionality (0.45)	Tech Req. (0.06)	Support (0.31)	Global Score	Rank
Tool X	0.016	0.045	0.032	0.043	0.136	3
Tool Y	0.032	0.117	0.018	0.074	0.241	2
Tool Z	0.131	0.288	0.010	0.192	0.621	1

The final ranking from Table 7 is shown in Table 8.

Table 8: Final ranking

Alternative	Global Priority Score	Rank
Tool X	0.18	3
Tool Y	0.22	2
Tool Z	0.61	1

The conclusion of AHP indicates Tool Z is the most suitable choice, with a global priority score of 0.621, demonstrating superior overall alignment with BPM requirements.

5. CONCLUSION AND IMPLICATIONS

This study contributes to the growing body of knowledge at the intersection of Big Data Analytics (BDA), Business Process Management (BPM), and Industry 4.0 by addressing critical gaps in technology selection and process-level digital transformation within manufacturing environments. Specifically, the study makes three main contributions. Firstly, it provides a systematic BPM-oriented review of BDA tools and applications in Industry 4.0 manufacturing. Unlike previous studies that adopted predominantly technology-centric or descriptive approaches, this review integrates a process management perspective, emphasizing how different tools support descriptive, diagnostic, predictive, and prescriptive process analytics. Secondly, the study develops and illustrates a practical Analytic Hierarchy Process (AHP) decision framework for BDA tool selection. By structuring the decision problem hierarchically and incorporating BPM-relevant criteria (cost, Functionality, technical requirements, and vendor support/maintenance), the framework offers manufacturing organizations a transparent, repeatable, and defensible method for technology evaluation and selection. Thirdly, the study synthesizes empirical insights linking BDA tool choices to process-level outcomes, demonstrating how appropriate tool selection can enhance process visibility, agility, governance, and overall performance in smart manufacturing contexts.

PRACTICAL IMPLICATIONS

For manufacturing practitioners and digital transformation leaders, the proposed AHP framework provides a valuable decision-support tool that can significantly reduce the risks associated with technology selection. By aligning BDA tools with specific business process requirements, organizations can accelerate value realization, minimize implementation failures, and achieve better integration between analytics initiatives and core operational processes. The framework is particularly useful for mid-to-large manufacturers undergoing Industry 4.0 transformation, where misalignment between tools and processes often results in fragmented adoption and sub-optimal returns on investment.

THEORETICAL IMPLICATIONS

Theoretically, this study strengthens the bridge between BDA, dynamic capabilities, and BPM literature. It reinforces the importance of viewing BDA not merely as a technical infrastructure but as a core enabler of process capabilities, including process monitoring, optimization, and intelligent automation. The integration of AHP as a decision mechanism also contributes to multi-criteria decision-making research in technology adoption and digital transformation contexts.

Despite the value addition of this study to BDA, BPM, and the manufacturing context, several limitations should be acknowledged. Firstly, the AHP application presented is illustrative rather than based on a specific real-time organizational decision process. Secondly, the case examples and tool evaluations rely partly on secondary data and publicly available company reports, which may introduce reporting bias. Thirdly, this study focuses primarily on the manufacturing sector, which may limit the generalizability of findings to other industries. Future studies can address these limitations through several promising avenues. Longitudinal empirical research employing robust quantitative methods such as Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM is recommended to validate the relationships between BDA tool selection, BPM capabilities, and organizational performance outcomes. Further investigation into the integration of agentic-AI and autonomous BPM systems within the proposed framework would be valuable. Comparative studies across different manufacturing sub-sectors such as automotive, aerospace, pharmaceuticals, and cross-industry applications would also enhance the framework's robustness. Finally, research examining governance, ethical considerations, and change management aspects of BDA-driven process transformation represents a rich area for future inquiry. Conclusively, as manufacturing continues its journey toward fully data-driven and intelligent operations, structured approaches to BDA tool selection, such as the one proposed in this study, will play an increasingly critical role in realizing the full potential of Industry 4.0.

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DATA AVAILABILITY STATEMENT

All the data from this study are available within the manuscript.

REFERENCES

- [1] J. B. Awotunde, K. Muduli, and B. Brahma, *Computational Intelligence for Analysis of Trends in Industry 4.0 And 5.0*. Boca Raton: Auerbach Publications, 2025. doi: 10.1201/9781003533023.
- [2] W. Babel, *Industry 4.0, China 2025, IoT*. Wiesbaden: Springer Fachmedien Wiesbaden, 2022. doi: 10.1007/978-3-658-37852-3.
- [3] D. G. S. Pivoto, L. F. F. de Almeida, R. da Rosa Righi, J. J. P. C. Rodrigues, A. B. Lugli, and A. M. Alberti, "Cyber-Physical Systems Architectures for Industrial Internet of Things Applications in Industry 4.0: A Literature Review," *Journal of Manufacturing Systems*, vol. 58, pp. 176–192, Jan. 2021, doi: 10.1016/j.jmsy.2020.11.017.
- [4] S.-L. Taguimdje, S. Wamba, J. R. Kamdjoug, and C. E. Wanko, "Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-based Transformation Projects," *Business Process Management Journal*, vol. 26, no. 7, pp. 1893–1924, May 2020, doi: 10.1108/BPMJ-10-2019-0411.
- [5] P. Mikalef, J. Krogstie, I. O. Pappas, and P. Pavlou, "Exploring the Relationship Between Big Data Analytics Capability and Competitive Performance: The Mediating Roles of Dynamic and Operational Capabilities," *Information & Management*, vol. 57, no. 2, p. 103169, May 2020, doi: <https://doi.org/10.1016/j.im.2019.05.004>.
- [6] D. Pamucar, V. Simic, Ö. F. Görçün, and H. Küçükönder, "Selection of the Best Big Data Platform Using COBRAC-ARTAS1 Methodology With Adaptive Standardized Intervals," *Expert Systems with Applications*, vol. 239, p. 122312, Apr. 2024, doi: 10.1016/j.eswa.2023.122312.
- [7] A. Sarkar and S. S. Goswami, "A Systematic Review of MCDM Techniques for Decision-Making in Smart Manufacturing Systems Under Industry 4.0," *Management Science Advances*, vol. 3, no. 1, pp. 290–306, Apr. 2026, doi: 10.31181/msa31202649.
- [8] W. Nyikana and T. Iyamu, "A Guide for Selecting Big Data Analytics Tools in an Organisation," *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2022, doi: 10.24251/hicss.2022.664.
- [9] S. Fosso Wamba and D. Mishra, "Big Data Integration With Business Processes: A Literature Review," *Business Process Management Journal*, vol. 23, no. 3, pp. 477–492, Jun. 2017, doi: 10.1108/bpmj-02-2017-0047.
- [10] Y. Lu, "The Current Status and Developing Trends of Industry 4.0: A Review," *Information Systems Frontiers*, vol. 27, no. 1, Nov. 2021, doi: 10.1007/s10796-021-10221-w.
- [11] V. P. Gupta, "Smart Sensors and Industrial IoT (IIoT): A Driver of the Growth of Industry 4.0," *Internet of Things*, pp. 37–49, 2021, doi: 10.1007/978-3-030-52624-5_3.

- [12] A. R. Santhi and P. Muthuswamy, "Industry 5.0 Or Industry 4.0S? Introduction to Industry 4.0 And a Peek Into the Prospective Industry 5.0 Technologies," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 17, no. 2, pp. 947-979, Feb. 2023, doi: 10.1007/s12008-023-01217-8.
- [13] M. Y. Santos *et al.*, "A Big Data Analytics Architecture for Industry 4.0," *Advances in Intelligent Systems and Computing*, pp. 175-184, 2017, doi: 10.1007/978-3-319-56538-5_19.
- [14] G. Sariyer, S. K. Mangla, Y. Kazancoglu, C. Ocal Tasar, and S. Luthra, "Data Analytics for Quality Management in Industry 4.0 From a MSME Perspective," *Annals of Operations Research*, vol. 350, no. 2, Aug. 2021, doi: 10.1007/s10479-021-04215-9.
- [15] H. Castro *et al.*, "Data Science for Industry 4.0 And Sustainability: A Survey and Analysis Based on Open Data," *Machines*, vol. 11, no. 4, p. 452, Apr. 2023, doi: 10.3390/machines11040452.
- [16] S. Jaskó and T. Ruppert, "The Future of Manufacturing and Industry 4.0," *Applied Sciences*, vol. 15, no. 9, pp. 4655-4655, Apr. 2025, doi: 10.3390/app15094655.
- [17] A. M. Ojeda, J. B. Valera, and O. Diaz, "Artificial Intelligence of Big Data for Analysis in Organizational Decision-Making," *Global Journal of Flexible Systems Management*, vol. 26, no. 3, Jul. 2025, doi: 10.1007/s40171-025-00450-2.
- [18] P. Tambare, C. Meshram, C.-C. Lee, R. J. Ramteke, and A. L. Imoize, "Performance Measurement System and Quality Management in Data-Driven Industry 4.0: A Review," *Sensors*, vol. 22, no. 1, p. 224, Dec. 2021.
- [19] W. Zhao, H. Chen, and A. Bulis, "How Are Industry 4.0 Technologies Transforming a Sustainable Society Across Industries?," *Digital Transformation and Society*, vol. 4, no. 3, May 2025, doi: 10.1108/dts-11-2024-0225.
- [20] Z. Zong and Y. Guan, "AI-Driven Intelligent Data Analytics and Predictive Analysis in Industry 4.0: Transforming Knowledge, Innovation, and Efficiency," *Journal of the knowledge economy*, vol. 16, no. 1, pp. 1-40, 2024, doi: 10.1007/s13132-024-02001-z.
- [21] M. Forozandeh and A. Mohammadnezhadiyan, "Industry 4.0 Technologies Transforming Operations in the Oil and Gas Industry: An Overview," *The IUP Journal of Operations Management*, vol. 24, no. 2, pp. 5-22, May 2025, doi: 10.71329/iupjom/2025.24.2.5-22.
- [22] S. Thangamani and R. Saranya, "Future Trends in Data Analytics," *Advances in systems analysis, software engineering, and high performance computing book series*, pp. 289-306, Jul. 2024, doi: 10.4018/979-8-3693-3609-0.ch013.
- [23] R. Lovelace, J. Nowosad, and J. Muenchow, *Geocomputation With R*. Boca Raton: Chapman and Hall/CRC, 2025. doi: 10.1201/9781003280569.
- [24] R. S. Mangrulkar and P. V. Chavan, "Introduction to Analytics," *Predictive Analytics with SAS and R*, pp. 1-30, 2025, doi: 10.1007/979-8-8688-0905-7_1.
- [25] D. Mortelmans, *Doing Qualitative Data Analysis With NVivo*. Cham: Springer Nature Switzerland, 2024. doi: 10.1007/978-3-031-66014-6.
- [26] J. Rogel-Salazar, *Data Science and Analytics With Python*. Boca Raton: Chapman and Hall/CRC, 2025. doi: 10.1201/9781003482062.
- [27] T. A. Runkler, *Data Analytics*. Wiesbaden: Springer Fachmedien Wiesbaden, 2024. doi: 10.1007/978-3-658-45951-2.
- [28] R. W. Saaty, "The Analytic Hierarchy Process—What It Is and How It Is Used," *Mathematical Modelling*, vol. 9, no. 3-5, pp. 161-176, 1987, doi: 10.1016/0270-0255(87)90473-8.
- [29] C. Medoh and A. Telukdarie, "Business Process Modelling Tool Selection: A Review," *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Dec. 2017, doi: 10.1109/ieem.2017.8289946.