

Managerial Drivers and Performance Outcomes of AI Adoption in Automotive Manufacturing

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Abstract—This article examines how artificial intelligence and machine learning reshape automotive manufacturing within Industry 4.0. Reported impacts include up to a 200 percent reduction in costs and a 400 percent gain in production efficiency, with controlled studies showing about a 15 percent improvement from process optimization. The largest early wins appear in quality management through computer vision and continuous inspection, followed by predictive maintenance that cuts unplanned downtime and stabilizes throughput. Supply chain and planning benefit from demand forecasting and inventory optimization that reduce bullwhip and working capital. Adoption barriers remain meaningful, including high initial investment, integration complexity, skills gaps, and trust and explainability requirements in regulated contexts. Effective programs use a common data and MLOps backbone, prioritize short cycle use cases, link model outputs to machine and recipe actions, and track value through OEE, ppm, MTBF, lead time, and service level. The discussion outlines practical steps to scale while noting evidence limitations and the need for standardized reporting on cost of ownership and time to value.

Keywords—Industry 4.0; automotive manufacturing; artificial intelligence; machine learning; quality 4.0; predictive maintenance

I. INTRODUCTION

Automotive manufacturing faces rising pressure on cost, quality, and lead time. Regulations tighten. Model variety grows. Launch cycles compress. Legacy methods struggle to keep pace. Industry 4.0 expands what you can do. Connected machines and sensors stream data across every station. Cloud and edge computing turn that stream into usable signals in real time. Cyber-physical systems coordinate actions on the line. Your factory becomes observable and controllable minute by minute. AI and machine learning convert raw signals into decisions. Computer vision detects defects as they appear. Predictive models surface failure risks before they stop the line. Optimization engines balance constraints and stabilize flow. Planning and supply chain systems gain accuracy through better forecasts and synchronized replenishment. Evidence shows material upside. Reported programs reach up to 200 percent cost reduction and up to 400 percent gains in production efficiency. Controlled studies show about 15 percent higher efficiency from process optimization. Plants also report higher first pass yield, fewer escapes, and shorter lead time. These results depend on scope and baseline, yet the direction is consistent. Quality management concentrates early value. Vision systems and anomaly models move inspection from sampling to continuous control. You cut rework and scrap.

You tighten process windows. You trace defects to machines, recipes, and suppliers. Asset reliability follows. Predictive maintenance brings failures forward. You reduce unplanned downtime. You lift mean time between failures. You coordinate maintenance with scheduling and spares to protect service while lowering buffers. Throughput improves when you close the loop. Models recommend setpoints at constrained steps. Changeovers shorten with recipe guidance. Schedulers use health and quality signals to sequence orders. Flow stabilizes without adding capacity. Supply chain performance rises with the same data backbone. Demand forecasting aligns with production plans. Inventory policies reduce stockouts and excess. Working capital falls while service level rises. Logistics costs drop through better routing and load building. Adoption still requires foundations. You need trustworthy data with clear ownership and lineage. You integrate AI with MES, ERP, and PLM. You run an MLOps backbone that versions models, monitors drift, and supports retraining and rollback. You upskill operators, technicians, and planners. You address explainability wherever safety and compliance demand it.

This article targets practical outcomes for you. It synthesizes impacts documented in automotive plants operating within Industry 4.0 settings. It focuses on use cases that deliver measurable value in quality, maintenance, throughput, and supply chain. It connects model outputs to machine actions and work standards. It defines a metric set to prove value each month.

You will see a structured path from pilot to scale. Start with contained use cases that pay back fast. Reuse one data and MLOps stack across lines and sites. Publish baselines and targets for OEE, defects per million, mean time between failures, unplanned downtime, lead time, and service level. Fund scale only when results persist over time.

This work positions the research in a clear scope. Automotive manufacturing within an Industry 4.0 environment. Production systems that mix legacy assets and new equipment. Teams that must deliver gains without compromising safety or regulatory commitments. Three questions guide the study. Where do you capture the fastest value across quality, availability, or flow. Which data gaps block defect detection or failure prediction on your lines. How will you prove monthly gains on OEE, defects per million, mean time between failures, lead time, and service level while sustaining trust with teams and regulators. The article follow use the IMRAD structure. Methods explain how evidence and cases were selected and analyzed. Results present quantitative effects and operational changes. Discussion interprets drivers, limits, and actions you can take now.

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II. RELATED WORK

The automotive industry faces growing pressure to improve efficiency, reduce costs, and enhance product quality while meeting increasing consumer demands and regulatory requirements. Traditional manufacturing approaches are being transformed through the integration of artificial intelligence, machine learning, and deep learning technologies that promise to revolutionize how vehicles are designed, produced, and delivered to market. This technological evolution represents a fundamental shift from conventional manufacturing paradigms toward smart, data-driven production systems that can adapt and optimize in real-time.

The convergence of AI technologies with automotive manufacturing aligns with the broader Industry 4.0 movement, which emphasizes digital transformation, connectivity, and intelligent automation across industrial processes. Car manufacturers are increasingly recognizing that successful adoption of these technologies requires not only technical implementation but also significant organizational changes, workforce development, and strategic management approaches. The potential benefits include substantial improvements in productivity, quality control, cost reduction, and lead time optimization, making AI adoption a critical competitive factor in the modern automotive landscape.

A. AI and Machine Learning Application in Automotive Industry

The automotive industry has become one of the largest adopters of AI technologies, with transportation and automotive applications projected to hold the largest market share in the AI application segment [1]. Computer vision technologies are being widely used in vehicles to avoid collisions and enable lane-keeping assistance, making driving safer [2]. Beyond vehicle features, AI is helping automotive companies increase productivity, sustainability, reliability, and safety across their operations, with particular success in areas like understanding vehicle activity profiles to meet fuel consumption and emission standards [3].

Quality management has seen some of the most significant AI applications in automotive manufacturing. AI tools such as artificial neural networks (ANN), deep learning (DL), and principal component analysis (PCA) have greatly improved prediction and problem identification capabilities with high precision [4]. Machine learning approaches now enable real-time part inspection, reducing dependence on manual inspections and improving early defect detection in highly automated manufacturing lines [4]. These systems use computer vision with convolutional neural networks (CNN) to inspect automotive components with great precision, while also providing predictive maintenance by forecasting equipment shutdown before it happens [4].

The technology applications extend to supply chain and production optimization, where AI has improved inventory management efficiency and spare parts demand projection [4]. Generative models are being used for problem prediction and correction before manufacturing begins, which reduces both costs and lead time [4]. These advances have not only improved operational efficiency but also enhanced the industry's

sustainability by reducing material waste and environmental impact [4] (Fig. 1).

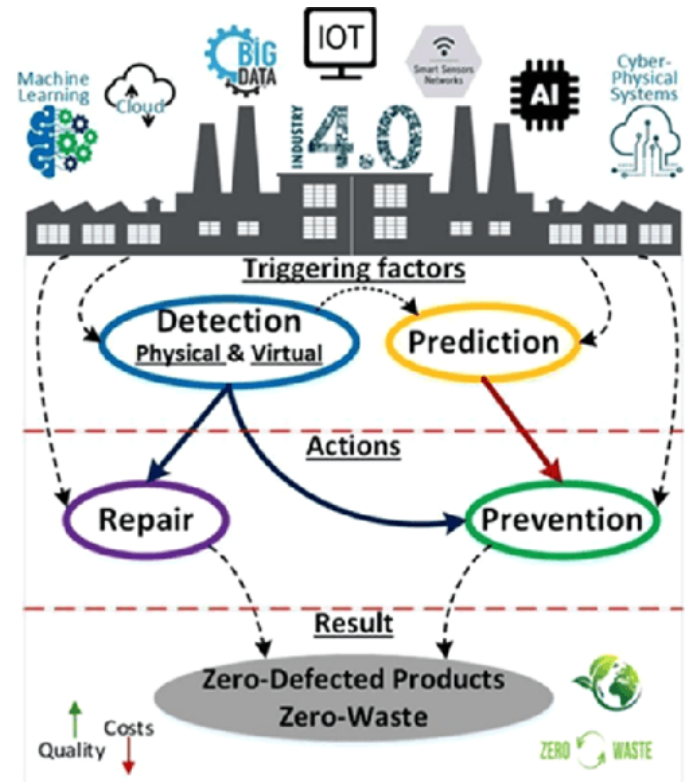


Fig. 1. Framework for ZDM.

III. METHODOLOGY

A. Study Design

This study applies a systematic literature review with a bibliometric layer. I fixed the protocol before data collection and followed a PRISMA workflow from identification to inclusion. The goal is to synthesize evidence on artificial intelligence and machine learning in automotive manufacturing under Industry 4.0 and to quantify the structure of the field.

B. Data Sources and Scope

I queried three scholarly databases Scopus, Web of Science, and OpenAlex. I scoped the search over 2010–2024 to capture field growth and then restricted the review core to English documents published during 2020–2024. I included peer-reviewed journal articles, conference papers, and book chapters. I excluded theses, editorials, and non-scholarly items.

C. Search Strategy

I used a single Boolean query harmonized across the three databases (“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning”) AND (“automotive industry” OR “car manufacturing” OR “automobile sector”) AND (“industrial performance” OR “productivity” OR “quality” OR “cost reduction” OR “lead time”) AND (“industry 4.0” OR “digital transformation”) AND (“adoption” OR “implementation” OR “management” OR “organizational factors” OR “technology acceptance”). I exported full metadata for all hits.

D. Screening and Eligibility

Identification returned 110, 200 records across sources. After database filters I screened titles and abstracts for 73, 457 records. I assessed **15,380** records for eligibility on the basis of title, abstract, and keywords. I removed duplicates and off-scope items. The final dataset included 13, 080 records for analysis Fig. 2.

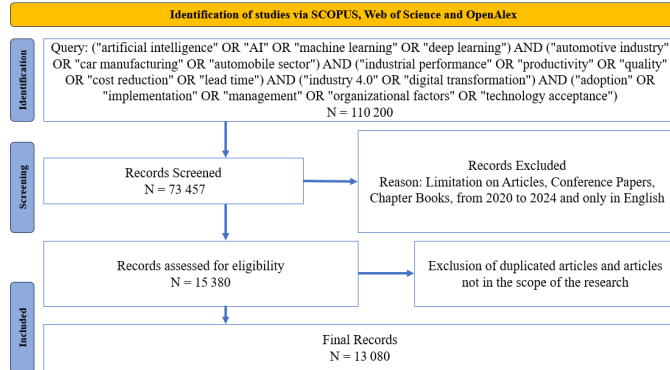


Fig. 2. Prisma.

E. Inclusion and Exclusion Criteria

I included studies that analysed automotive manufacturing or adjacent vehicle production value chains and that applied AI or ML methods. Each included study reported at least one relevant outcome such as productivity, quality, cost, lead time, maintenance, throughput, supply chain performance, or adoption and management factors. I excluded papers focused only on in-vehicle functions when no manufacturing link was present. I removed non-English items in the 2020–2024 core.

F. Data Extraction

For every included study I extracted bibliographic fields authors, year, venue, country, collaboration, citations, and author keywords. I coded AI methods computer vision, deep learning, time-series modelling, anomaly detection, optimization, and explainable AI. I coded use cases quality inspection, predictive maintenance, process optimization, scheduling, and supply chain planning. I captured metrics overall equipment effectiveness, first-pass yield, defects per million, mean time between failures, unplanned downtime, lead time, throughput, and unit cost. When effect sizes were reported I expressed them as relative change from baseline to support comparison.

G. Bibliometric Profile of the Corpus

The consolidated dataset shows a fast-growing and collaborative field. It spans 2010–2024 and covers **4,937** sources and **13,042** documents. The annual growth rate reaches **47.87%**. There are **38,035** authors, including **3,274** single-authored contributors. International co-authorship accounts for **17.87%**. The mean number of co-authors per document is **3.22**. Author keywords total **4,038**. The references cited across the corpus sum to **229,261**. The average document age is **2.88** years and the average citations per document are **12.37** (Fig. 3).



Fig. 3. Bibliometric profile of the corpus.

H. Synthesis and Analysis

I combined descriptive bibliometrics with qualitative synthesis. The bibliometric layer mapped volume, growth, collaboration, and citation impact. The synthesis layer grouped findings by use case quality, availability, and flow and by adoption enablers data governance, systems integration with MES–ERP–PLM, workforce skills, and explainability. I reported outcomes using a stable metric set overall equipment effectiveness, defects per million, mean time between failures, lead time, and service level.

IV. RESULTS

A. Industrial Performance Impact

The integration of AI and machine learning technologies in manufacturing has generated substantial measurable improvements across key performance indicators. Industry 4.0's data-driven approach has enabled smart exploitation of data that provides competitive advantages impacting productivity, quality, and efficiency KPIs [5]. Recent analysis shows that AI integration in Industry 4.0 has resulted in a notable 200% cost reduction and a cumulative 400% boost in production efficiency [6]. Experimental studies have demonstrated that machine learning algorithms for process optimization can achieve significant increases in production efficiency by 15% while improving product quality [7] (Fig. 4).



Fig. 4. Analysis the case study for AI is transforming the manufacturing industry.

AI technologies are transforming manufacturing operations through multiple pathways to performance improvement. AI reduces the chances of machine failure, improves product quality control, increases productivity in industries, and enables substantial cost reduction of products [8]. The major benefits of using ML and AI approaches result in error reduction, cost reduction and revenue growth in manufacturing industries [9]. Machine learning algorithms have been extensively used to

optimize production processes, resulting in reduced downtime, improved quality control, and increased throughput [10] (Fig. 5).

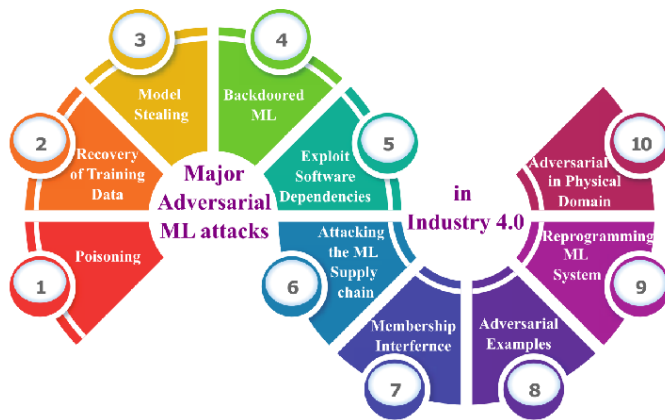


Fig. 5. Adversarial ML attacks affecting industrial organizations.

Quality control has emerged as one of the most impactful areas for AI implementation in manufacturing. AI algorithms can analyze data from sensors, cameras, and other sources to detect defects or anomalies in the production process, with machine vision systems equipped with AI able to identify and reject faulty products, ensuring consistent quality throughout the production line [11]. Automated quality inspection systems powered by AI technology can replace manual inspections, enabling manufacturers to satisfy growing demand for higher-quality products efficiently while directly impacting firm productivity through time and cost savings [12][13] (Fig. 6).

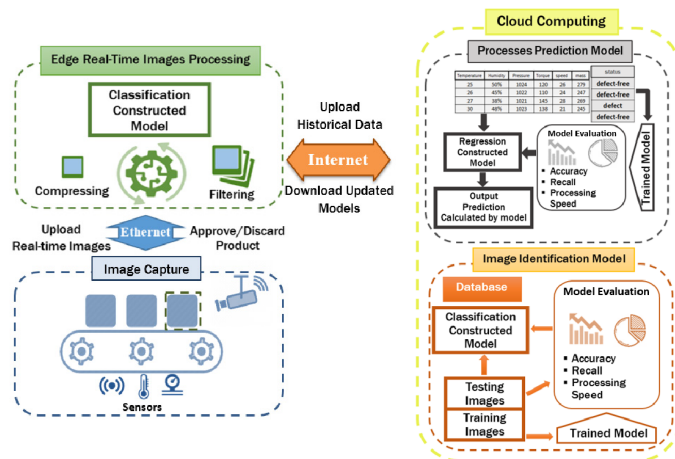


Fig. 6. Intelligent machine vision model for defective product inspection and for defective product inspection.

Predictive maintenance and supply chain optimization represent additional major sources of performance gains. Predictive maintenance powered by AI has demonstrated its ability to identify equipment failures before they occur, leading to substantial cost savings and minimizing unplanned downtime [10]. AI-driven supply chain management systems enable efficient inventory management, demand forecasting, and logistics optimization, leading to cost reduction and improved customer

satisfaction [7]. AI algorithms can optimize the allocation of resources such as raw materials, energy, and labor by analyzing production data to identify inefficiencies and bottlenecks, enabling enterprises to streamline operations, minimize waste, and reduce costs [11].

B. Industry 4.0 and Digital Transformation

Industry 4.0 has emerged as the perfect scenario for boosting the application of artificial intelligence and machine learning solutions to industrial process monitoring and optimization, with this paradigm being fundamentally data-driven where smart exploitation of data provides competitive advantages impacting productivity, quality, and efficiency key performance indicators [5]. The technological foundation of Industry 4.0 relies heavily on advanced AI capabilities, with Internet of Things (IoT), cloud computing, artificial intelligence, augmented reality, cyber-physical systems (CPS), and cognitive computing serving as the backbone of Industry 4.0 concepts [14]. After the Internet and mobile Internet sparked the 3rd Industrial Revolution, AI technologies, fueled by data, are now creating an atmosphere of Industry 4.0, with the digital revolution beginning with data collection, followed by artificial intelligence to interpret the data [2] (Fig. 7).

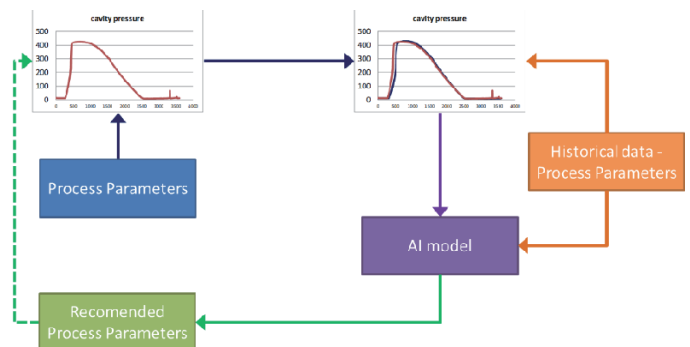


Fig. 7. Iterative comparison to optimized production setup comparing known optimal process parameters versus new acquired ones.

The manufacturing industry has recognized the transformative potential of machine learning technologies within the Industry 4.0 framework, utilizing various I4.0 technologies in applications such as smart manufacturing, fault diagnosis and prediction, robotic assembly, quality monitoring, and job shop scheduling [15][16] (Fig. 8). Industry 4.0 radically alters manufacturing organization and management by fostering collection and analysis of increasing amounts of data, with advanced data analytics such as machine learning being essential for implementing Industry 4.0 and obtaining insights regarding production, better decision support, and enhanced manufacturing quality and sustainability [17][18].

The advancement of AI and widespread use of machine learning and deep learning techniques are paving the way for these technologies to play a central role in implementing Industry 4.0, with AI-based approaches enabling intelligent devices to conduct functions such as self-monitoring, interpretation, diagnosis, and analysis autonomously [19][20][21] (Fig. 9).

Modern manufacturing systems leverage AI to facilitate seamless communication, coordination, and collaboration between different parts of the manufacturing process, with AI

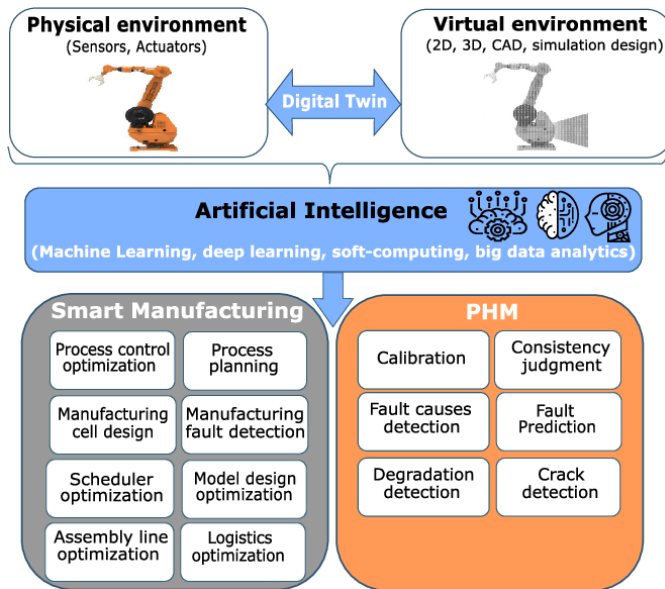


Fig. 8. DT-based smart manufacturing using big data analytics and AI-ML.

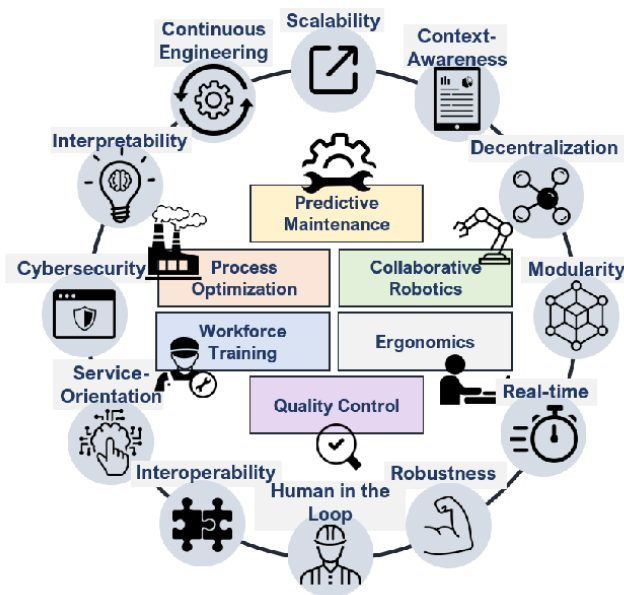


Fig. 9. The main design principles acting as pillars of Industrial AI in the context of its application areas.

algorithms processing vast amounts of data generated by sensors and machines to extract valuable insights for optimizing operations [22][23].

The digital transformation enabled by Industry 4.0 technologies extends beyond basic automation to create intelligent, adaptive manufacturing systems. Machine learning and AI approaches contribute to revolutionary changes in industry by allowing the creation of smart factories and process automation, with IoT, artificial intelligence, cyber-physical systems working together to enable intelligent manufacturing [24][25]. Deep learning technology enables intelligent decision-making, resource optimization, and waste reduction through real-time

monitoring and analysis of production line data, empowering production systems with autonomous learning and adaptability that fosters progression toward intelligent manufacturing [26][27][28][29].

However, the adoption of AI technologies for Industry 4.0 varies considerably across industrial sectors, and the transition requires addressing challenges related to explainability and trust in AI systems [30][31]. The deep integration of machine learning with technologies such as augmented reality, data mining, IoT, and cyber-physical systems continues to drive digital transformation, with industrial artificial intelligence becoming the brain of future smart factories for intelligent decision-making and deployment [32]. This technological evolution enables enterprises to better adapt to market demands through AI-optimized mechanical design, improved manufacturing efficiency, and intelligent monitoring and maintenance capabilities [33][34][35].

C. Adoption Challenges and Organizational Factors

Despite the proven benefits of AI and machine learning technologies, automotive manufacturers encounter substantial barriers to successful adoption that extend beyond technical considerations. The manufacturing industry faces challenges related to high initial investments, integration complexities, and resistance to change, which can create cultural barriers to AI adoption within organizations [10]. Small and medium-sized enterprises (SMEs) may particularly struggle with the financial burden of AI implementation, although long-term benefits often justify the initial expenditure [36]. The uneven development between industries has seriously hindered the process of intelligent manufacturing across society, with AI enterprises attracting capital and labor inflows while gradually occupying leading positions in their industries [11].

Workforce adaptation and organizational transformation represent critical success factors for AI adoption in automotive manufacturing. Successfully integrating AI into the manufacturing sector necessitates a proficient workforce and cultural transformation that embraces data-driven decision-making and fosters harmonious collaboration between human expertise and machine capabilities [10]. The need for skilled personnel to manage AI-driven systems presents another challenge, necessitating investments in workforce training and upskilling [36]. Upgrading production activities with AI requires important investment and adaptation in training and infrastructure [4].

Technical complexity and explainability issues create additional adoption hurdles that manufacturers must address. Using AI brings challenges such as transparency, explainability, system integration, and ethical issues, leading to the development of explainable artificial intelligence (XAI) approaches [37]. The increasing complexity and limited explainability of complex machine learning models makes it increasingly difficult to address fairness, accountability, and transparency principles, thus hindering applications in industrial and mission-critical scenarios [17]. Implementing AI solutions in manufacturing processes still presents challenges in many aspects, particularly in handling irregular datasets influenced by diverse manufacturing settings [38].

Integration complexities extend to both technical and organizational dimensions of digital transformation. The imple-

mentation process involves navigating complexities such as data security, workforce adaptation, and ethical considerations when implementing AI-driven automation in manufacturing processes [39]. Financial, regulatory, and organizational management constraints remain significant challenges in effectively integrating intelligent technologies, despite the expected benefits of increased production speed and energy efficiency [38]. The adoption of XAI methodologies can help humans make trustworthy decisions for critical applications, but requires careful implementation without compromising the efficiency of models developed using deep learning algorithms [31].

V. DISCUSSION

AI and machine learning now shape how you design, build, and scale automotive production. The evidence shows large performance gains. Reported effects include a 200 percent cost reduction and a 400 percent boost in production efficiency, alongside a 15 percent lift from process optimization experiments. These numbers point to strong upside and also to context dependence. You capture value when data, process discipline, and change management align.

Quality management concentrates much of the early value. Vision models and defect analytics raise first pass yield and cut rework. Plants that move from sample checks to continuous inspection report fewer escapes and tighter process windows. You can link model outputs to corrective actions at the machine and recipe level. This closes the loop and sustains gains.

Maintenance and throughput follow next. Predictive models pull failures forward. You reduce unplanned downtime and stabilize takt. When planners integrate health predictions with scheduling and inventory, you shrink buffers without risking stockouts. The result is faster flow and lower working capital.

Supply chain and planning benefit from the same data backbone. Demand signals, spare parts forecasts, and replenishment models reduce bullwhip. The payoff shows up in service level and logistics cost. Generative approaches add a design lever by simulating issues before tooling. You avoid late changes and compress lead time.

Adoption still hinges on people and systems. High upfront spend, integration work, and resistance to change slow programs down. SMEs feel this most. You can offset the burden by sequencing small but material use cases and recycling the same data and MLOps stack across lines. Explainability matters as models move into safety and compliance boundaries. XAI techniques improve trust, but they add design trade offs that you should make explicit.

Data quality remains the rate limiter. Irregular datasets from varied settings and machine vintages create drift and blind spots. You need governance that names owners, defines gold metrics, and enforces traceability from raw data to decisions. Without this, models decay and perceived value erodes.

Managerial implications are direct. Tie each model to a cost line or a revenue driver. Publish baseline and target for OEE, ppm, MTBF, lead time, and service level. Hold monthly value reviews with operations and finance. Fund scale ups only after pilots hit agreed thresholds. Limitations of current evidence deserve attention. Reported 200 percent cost cuts and 400 percent efficiency gains likely reflect specific scopes

and baselines. Few studies disclose full cost of ownership. Replication across plants and suppliers is sparse. Future work should standardize metrics, disclose denominators, and report time to value and sustainability impact.

A. Benefits and Performance Outcomes

The comprehensive benefits of AI adoption in automotive manufacturing extend across all operational dimensions, creating measurable value that justifies implementation investments. AI technology reduces the chances of machine failure, improves product quality control, increases productivity in industries, and enables substantial cost reduction of products, with quality prediction of products at different stages of the life-cycle and real-time monitoring helping to ensure improved production yield, better quality management, and improved customer value [8]. The major benefits of using ML and AI approaches result in error reduction, cost reduction and revenue growth in manufacturing industries [9]. These quantifiable improvements demonstrate that AI integration has resulted in a notable 200% cost reduction and a cumulative 400% boost in production efficiency [6].

Specific performance improvements have been documented across multiple manufacturing applications. Experimental studies show that machine learning algorithms for process optimization can achieve a significant increase in production efficiency by 15% and improved product quality through the utilization of AI methods, with AI methods showing substantial benefits in quality control through real-time defect detection, reduced rework, and improved product consistency [7]. Machine learning algorithms have been extensively used to optimize production processes, resulting in reduced downtime, improved quality control, and increased throughput [10].

The automotive industry has realized particularly significant gains in quality management and operational efficiency through AI implementation. AI tools such as artificial neural networks (ANN), deep learning (DL), and principal component analysis (PCA) have importantly upgraded prediction and issue-identification capabilities with high precision, with machine-learning-based approaches enabling on-time part inspection, decreasing dependence on manual inspections, and improving early defect detection in highly automated manufacturing lines [4]. The usage of generative models for issue estimation and correction before manufacturing decreases costs and lead time, while AI has launched fundamental innovations such as enhancement of preventive maintenance by forecasting equipment shutdown before it happens and quality control procedures using computer vision with convolutional neural networks (CNN) to inspect automotive components with great precision [4].

AI-driven systems enable manufacturers to achieve unprecedented levels of operational flexibility and customization. The progressive adoption of artificial intelligence and machine learning techniques improves the flow of resources through the manufacturing process, with AI assisting in predicting maintenance, generative designing, manufacturing, delivering quality, human-robot collaboration, supply-chain management, waste reduction, and production optimization [40]. AI-driven predictive maintenance algorithms can forecast equipment failures before they occur, reducing downtime and maintenance costs, while ML models can optimize supply chains

by predicting demand fluctuations, ensuring that resources are allocated efficiently [41][42]. The adoption of AI and ML in Industry 4.0 is facilitating a shift towards customization and flexibility in manufacturing, allowing manufacturers to offer highly personalized products without compromising efficiency or increasing costs significantly [41].

The creation of smart factories represents the culmination of AI benefits in automotive manufacturing. AI is facilitating the creation of smart factories where networked systems, IoT devices, and AI algorithms combine to provide a highly automated and intelligent manufacturing environment, with the incorporation of AI into these smart factories paving the way for improved productivity, real-time monitoring of manufacturing processes, and data-driven decision-making [10][19][43]. These systems enable cyber-physical systems to communicate and cooperate with humans in real-time, significantly improving manufacturing processes and outcomes, while AI revolutionizes operations by employing advanced algorithms for deep learning and machine learning to improve and expedite procedures, resulting in enhanced efficiency through AI-powered systems that can analyze extensive information to identify patterns, make informed decisions, and adapt to evolving production circumstances [41][44].

VI. CONCLUSION

AI and machine learning deliver consistent gains in automotive manufacturing. Programs report up to 200 percent cost reduction and up to 400 percent efficiency gains. Controlled studies show about 15 percent improvement from process optimization. Quality inspection with computer vision and predictive maintenance produce the most reliable early wins.

Results depend on foundations you control. You need clean, traceable data with clear ownership. You need tight integration with MES, ERP, and PLM. You need an MLOps backbone that versions models, monitors drift, and supports retraining and rollback.

Focus turns pilots into scale. Start with one inspection flow and one critical failure mode. Link model outputs to machine settings and standard work. Publish baselines and monthly targets for OEE, defects per million, mean time between failures, unplanned downtime, lead time, and service level. Scale only after three consecutive months above target.

The path is repeatable when people, data, and process move together. Invest in skills and explainability where safety and compliance apply. Reuse one data and MLOps stack across lines and sites to cut unit cost and time to value. What line gives you the fastest measurable ROI next quarter. Which data gaps still block defect detection or failure prediction. How will you sustain these models across shifts and plants without losing trust.

REFERENCES

- [1] L. Belova, "Experience of Artificial Intelligence Implementation in Japan," *E3S Web of Conferences*, 2020.
- [2] I. H. Sarker, "AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems," *SN Computer Science*, 2022.
- [3] S. Katreddi, S. Kasani, A. Thiruvengadam, "A Review of Applications of Artificial Intelligence in Heavy Duty Trucks," *Energies*, 2022.
- [4] O. M. Matamoros, J. G. T. Nava, J. J. M. Escobar, B. A. C. Chávez, "Artificial Intelligence for Quality Defects in the Automotive Industry: A Systemic Review," *Italian National Conference on Sensors*, 2025.
- [5] F. Bonada, L. Echeverria, X. Domingo, G. Anzaldi, "AI for Improving the Overall Equipment Efficiency in Manufacturing Industry," *New Trends in the Use of Artificial Intelligence for the Industry 4.0*, 2020.
- [6] E. Dmitrieva, V. Balmiki, S. Lakhanpal, G. Lavanya, P. Bhandari, "AI Evolution in Industry 4.0 and Industry 5.0: An Experimental Comparative Assessment," *BIO Web of Conferences*, 2024.
- [7] D. Verma, "Analysis of Smart Manufacturing Technologies for Industry Using AI Methods," *Turkish Journal of Computer and Mathematics Education*, 2018.
- [8] S. Jagatheesaperumal, M. Rahouti, K. Ahmad, A. I. Al-Fuqaha, M. Guizani, "The Duo of Artificial Intelligence and Big Data for Industry 4.0: Review of Applications, Techniques, Challenges, and Future Research Directions," *arXiv.org*, 2021.
- [9] A. Jamwal, R. Agrawal, M. Sharma, A. Giallanza, "Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions," *Applied Sciences*, 2021.
- [10] R. M. Rakholia, A. L. Suárez-Cetrulo, M. Singh, R. S. Carbajo, "Advancing Manufacturing Through Artificial Intelligence: Current Landscape, Perspectives, Best Practices, Challenges, and Future Direction," *IEEE Access*, 2024.
- [11] X. Huang, "Dynamics of labor and capital in AI vs. non-AI industries: A two-industry model analysis," *PLOS ONE*, 2024.
- [12] S. Shaikh, D. P. Hujare, S. K. Yadav, "Surface Defect Detection using Convolutional Neural Network Model Architecture," *Journal of Engineering Research and Sciences*, 2022.
- [13] T. Benbarrad, M. Salhaoui, S. B. Kenitar, M. Arioua, "Intelligent Machine Vision Model for Defective Product Inspection Based on Machine Learning," *J. Sens. Actuator Networks*, 2021.
- [14] S. K. Kaya, E. Ayçin, "An integrated interval type 2 fuzzy AHP and COPRAS-G methodologies for supplier selection in the era of Industry 4.0," *Neural Computing & Applications (Print)*, 2021.
- [15] A. Marosi, M. Emodi, Á. Hajnal, R. Lovas, T. Kiss, V. Poser *et al.*, "Interoperable Data Analytics Reference Architectures Empowering Digital-Twin-Aided Manufacturing," *Future Internet*, 2022.
- [16] M. M. Rathore, S. A. Shah, D. Shukla, E. Bentafat, S. Bakiras, "The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities," *IEEE Access*, 2021.
- [17] M. Vukovic, S. Thalmann, "Causal Discovery in Manufacturing: A Structured Literature Review," *Journal of Manufacturing and Materials Processing*, 2022.
- [18] J. Berlak, S. Hafner, V. Kuppelwieser, "Digitalization's impacts on productivity: a model-based approach and evaluation in Germany's building construction industry," 2020.
- [19] M. Ryalat, H. Elmoaqet, M. Alfaouri, "Design of a Smart Factory Based on Cyber-Physical Systems and Internet of Things towards Industry 4.0," *Applied Sciences*, 2023.
- [20] R. S. Peres, X. Jia, J. Lee, K. Sun, A. Colombo, J. Barata, "Industrial Artificial Intelligence in Industry 4.0 – Systematic Review, Challenges and Outlook," *IEEE Access*, 2020.
- [21] I. Ahmed, G. Jeon, F. Piccialli, "From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where," *IEEE Transactions on Industrial Informatics*, 2022.
- [22] U. Othman, E. Yang, "Human-Robot Collaborations in Smart Manufacturing Environments: Review and Outlook," *Italian National Conference on Sensors*, 2023.
- [23] J. Wan, X. Li, H. Dai, A. Kusiak, M. Martínez-García, D. Li, "Artificial-Intelligence-Driven Customized Manufacturing Factory: Key Technologies, Applications, and Challenges," *Proceedings of the IEEE*, 2020.
- [24] N. Kashpruk, C. Piskor-Ignatowicz, J. Baranowski, "Time Series Prediction in Industry 4.0: A Comprehensive Review and Prospects for Future Advancements," *Applied Sciences*, 2023.
- [25] B. E., L. R. Flaih, Y. Dursaimy, S. K., A. Jayanthiladevi, T. Kumar, "Use Case of Artificial Intelligence in Machine Learning Manufacturing 4.0," *2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 2019.

- [26] X. Wang, H. Hu, Y. Wang, Z. Wang, "IoT Real-Time Production Monitoring and Automated Process Transformation in Smart Manufacturing," *Journal of Organizational and End User Computing*, 2024.
- [27] C. Favoretto, G. H. Mendes, M. G. Filho, M. Oliveira, G. Ganga, "Digital transformation of business model in manufacturing companies: challenges and research agenda," *The Journal of Business & Industrial Marketing*, 2021.
- [28] L. Zhou, Z. Jiang, N. Geng, Y. Niu, F. Cui, K. Liu *et al.*, "Production and operations management for intelligent manufacturing: a systematic literature review," *International Journal of Production Research*, 2021.
- [29] H. Tercan, T. Meisen, "Machine learning and deep learning based predictive quality in manufacturing: a systematic review," *Journal of Intelligent Manufacturing*, 2022.
- [30] F. Ababsa, "Advanced Deep Learning Techniques for Industry 4.0: Application to Mechanical Design and Structural Health Monitoring," *International Conference on Agents and Artificial Intelligence*, 2024.
- [31] T. Gadekallu, P. K. R. Maddikunta, P. Boopathy, N. Deepa, R. Chengoden, N. Victor *et al.*, "XAI for Industry 5.0—Concepts, Opportunities, Challenges, and Future Directions," *IEEE Open Journal of the Communications Society*, 2025.
- [32] J. Yang, Y. Liu, P. Morgan, "Human-machine interaction towards Industry 5.0: Human-centric smart manufacturing," *Digital Engineering*, 2024.
- [33] S. Wang, "Deep Integration of AI Technology for Intelligent Transformation in Mechanical Engineering," *Academic Journal of Engineering and Technology Science*, 2025.
- [34] J. Qiu, "The deep separable convolution with DSC NCF model and optimization mechanism of digital economy for intelligent manufacturing under sales order recommendation algorithm," *Scientific Reports*, 2025.
- [35] H. Malik, G. Chaudhary, S. Srivastava, "Digital transformation through advances in artificial intelligence and machine learning," *Journal of Intelligent & Fuzzy Systems*, 2021.
- [36] K. R. Kotte, "Smart Factories, Smarter Finances: AI's Role in Cost Efficiency & Profitability," *International Journal for Sciences and Technology*, 2024.
- [37] A. Ucar, M. Karakose, N. Kırımca, "Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends," *Applied Sciences*, 2024.
- [38] J. Lee, J. Jang, Q. Tang, H. Jung, "Recipe Based Anomaly Detection with Adaptable Learning: Implications on Sustainable Smart Manufacturing," *Italian National Conference on Sensors*, 2025.
- [39] P. Dupare, S. Sangole, "AI-Powered Revolution: Transforming Industrial Production through Automation," *International Journal of Advanced Research in Science, Communication and Technology*, 2024.
- [40] B. Mareschal, M. Kaur, V. Kharat, S. S. Sakhare, "Convergence of Smart Technologies for Digital Transformation," *Tehnički glasnik*, 2021.
- [41] M. A. Bappy, "Exploring the Integration of Informed Machine Learning in Engineering Applications: A Comprehensive Review," *American Journal of Science and Learning for Development*, 2024.
- [42] Z. Costello, H. Martín, "A machine learning approach to predict metabolic pathway dynamics from time-series multiomics data," *npj Systems Biology and Applications*, 2018.
- [43] R. Rai, M. Tiwari, D. Ivanov, A. Dolgui, "Machine learning in manufacturing and industry 4.0 applications," *International Journal of Production Research*, 2021.
- [44] T. A. Khan, S. M. Ali, K. M. Ali, A. Aziz, S. Ahmad, A. Anwar *et al.*, "Harnessing Artificial Intelligence for Optimum Performance in Industrial Automation," *1st International Conference on Industrial, Manufacturing, and Process Engineering (ICIMP-2024)*, 2025.