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Review

# Automation and Industry 4.0 in Production Engineering: A Comprehensive Review

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**Abstract**

The comprehensive review investigates how automation has developed within production engineering and showcases different methodologies and applications from various historical stages. The paper discusses industrial challenges while proposing future research pathways and practical applications. The study demonstrates how automation tools such as robotics, artificial intelligence (AI), and Internet of Things (IoT) revolutionize production efficiency and resource management. The paper examines how cyber-physical systems (CPS) function within automated systems with a focus on security measures essential for Industry 4.0 environments. Researchers, practitioners, and industry professionals can leverage these findings to explore automation impacts and drive field innovation. This review integrates both historical research findings and modern advancements to enhance comprehension of how automation boosts productivity and sustainability within manufacturing systems.

**Keywords:** automation, digitalization, Robotic Process Automation (RPA), Industry 4.0, cyber-physical systems

## Abbreviations

| | |
|---|---|
| ADI | Austempered Ductile Iron |
| AGVs | Automated Guided Vehicles |
| AI | Artificial Intelligence |
| AIVs | Autonomous Intelligent Vehicles |
| AOI | Automatic Optical Inspection |
| aPS | Automated Production Systems |
| BCI | Brain-Computer Interface |
| CAD | Computer-Aided Design |
| CAE | Computer-Aided Engineering |
| CAM | Computer-Aided Manufacturing |
| CAPP | Computer-Aided Process Planning |
| CNC | Computer Numerical Control |
| CP | Constraint Programming |
| CPPS | Cyber-Physical Production Systems |
| CPS | Cyber-Physical Systems |
| DCS | Distributed Control Systems |
| DL | Deep Learning |
| DOF | Degrees Of Freedom |
| DRL | Deep Reinforcement Learning |
| DT | Digital Twin |
| EEG | Electroencephalogram |
| EMOEA | Effective Multiobjective Evolutionary Algorithm |
| ERP | Enterprise Resource Planning |
| FMS | Flexible Manufacturing Systems |
| GHG | Greenhouse Gas |
| GSM | Green Smart Production |
| HSE | Health, Safety, and Environment |
| HTO | Human, Technology, and Organisation |
| IoT | Internet of Things |
| IPA | Intelligent Process Automation |
| IPS | Integrated Production Systems |
| IRL | Inverse Reinforcement Learning |
| IT | Information Technology |
| JSPMR | Job Shop scheduling Problem with Mobile Robots |
| KPIs | Key Performance Indicators |
| LCA | Life Cycle Assessment |

| | | | |
|---|---|---|---|
| LEMA | Linear Electromechanical Actuators | RL | Reinforcement Learning |
| MAS | Multi-Agent System | RPA | Robotic Process Automation |
| MES | Manufacturing Execution Systems | RRUM | Robotic Rotary Ultrasonic Milling |
| MILP | Mixed-Integer Linear Programming | SAALBP | Semi-Automated Assembly Line Balancing Problem |
| ML | Machine Learning | SIS | Safety Instrumented Systems |
| NC | Numerical Control | SMEs | Small And Medium-Sized Enterprises |
| NDE | Non-Destructive Evaluation | SMTs | Serial Machine Tools |
| NLP | Natural Language Processing | SPA | Subassembly Process Automation |
| OCR | Optical Character Recognition | SPS | Smart Production Systems |
| OPA | Open Process Automation | SSFDANet | Steel Surface Faulty Detection Attention Net |
| PLC | Programmable Logic Controller | TCPs | Tool Center Points |
| PMR | Parallel Machining Robot | VBA | Visual Basic for Applications |
| PnP | Perspective-N-Point | VR | Virtual Reality |
| PSO | Particle Swarm Optimization | | |
| RAMI 4.0 | Reference Architecture Model Industry 4.0 | | |

## 1. Introduction

Production engineering automation plays a vital role in increasing productivity while reducing labor expenses and enhancing product quality (Orynbet & Razakova, 2024). The field uses automated equipment to control electrical systems remotely or in real-time, which enables significant development opportunities and optimization of production methods (Nazami & Yan, 2021). Modern manufacturing requires automation due to increasing global competition and the growing diversity of customer demands (Sari et al., 2023).

The engineering industry, along with automobile manufacturing, plays a major role in national economic growth and industrial progress. The engineering sector advances production development while accelerating scientific progress and technical innovation, which leads to higher labor productivity and strengthens national security while enhancing general quality of life. Industries need to integrate sophisticated robotic technologies within their local production systems to enhance production quality and boost both efficiency and productivity to stay competitive. Industry experts predict the industrial robot market value to hit $30.8 billion in 2027 with a consistent 14.3% yearly growth rate (Orynbet & Razakova, 2024).

Multiple reviews highlight how automation functions within particular industry sectors. An analysis of Malaysian pineapple production reveals significant dependence on manual workforces while advocating Industry 4.0 technology implementation to enhance production efficiency and lower operational expenses. Authors propose CPS as an effective solution for overcoming challenges in planting and crop management along with harvesting processes (Bakar et al., 2021). Recent research examines canned food sterilization improvements that focus on using automated computing processes to enhance economic efficiency while ensuring product safety and quality (Stolyanov et al., 2020).

The combination of RPA with AI presents significant opportunities for businesses to automate processes and improve productivity. RPA transforms into Intelligent Process Automation (IPA) through the integration of advanced technologies such as Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL) (Siderska et al., 2023). Research investigates how companies implement RPA so workers can take on more complex responsibilities while robots handle routine activities. Through this approach, companies learn about effective methods in RPA (Da Silva Costa et al., 2022).

This extensive review delivers essential insights into the dynamic field of production engineering automation through an in-depth analysis of methodologies and applications across different historical phases. This paper addresses the challenges and future directions so it becomes an essential resource for researchers, practitioners, and industry professionals who need to comprehend automation's transformative impact and guide future field innovations.

## 2. Review Methodology

The paper uses a systematic approach to examine the existing literature about automation in production engineering. The following section describes the primary elements of the review methodology used in this research:

- Literature Selection: The review examines a broad selection of articles published between 2019 and 2024 that highlight major advancements in automation within production engineering. The paper selected articles from leading academic databases, including Google Scholar, Science Direct, IEEE Xplore, and SpringerLink. The analysis covered 109 papers to discover significant trends and technological progress in the field.
- Categorization of Research: To examine the evolution of automation technologies, researchers divided selected papers into three separate phases:
  - During the initial phase from 2019 to 2020, research concentrated on developing automated manufacturing processes that were sustainable,
  - During the Second Phase (2021-2022), research demonstrated how digitalization technologies were integrated with automation systems,
  - The most recent phase from 2023 to 2024 studied the advancements made in industrial automation and control systems.
- Comparative Analysis: The paper features comparative tables that systematically evaluate automation trends by organizing research papers based on specific criteria:
  - Authorship,
  - Publication date,
  - Study focus,
  - Application methodology,
  - Datasets used,
  - Key findings,
  - Identified research gaps.

The structured framework enables clear insight into how automation technologies have developed and their resulting effects.

- Focus on Methodologies and Applications: The review analyzes how automation technologies evolved through various historical periods and demonstrates their transformative effects on production systems. The discussion examines ongoing challenges and potential future developments within this area of study.
- Data Visualization: The paper uses visual data presentations through figures and tables to improve clarity for readers. The visual aids demonstrate how publication trends evolve while measuring research impact and tracking technological developments throughout history.
- Integration of Case Studies: The review connects theoretical concepts with practical application through case studies that demonstrate how automation technologies function in real-world scenarios. Examples include:
  - Digital twins (DTs) enable real-time optimization of processes,
  - The use of AutomationML technology improves manufacturing process efficiency.

The comprehensive methodology enables the review to perform both a summary of past research and to identify research gaps while proposing future directions within the domain of automation in production engineering.

This review article delivers a unique and significant contribution to production engineering by systematically examining 109 peer-reviewed papers from 2019 to 2024 to showcase the latest advancements in automation technologies. The article analyzes existing research through a thorough literature review to highlight essential research gaps while offering future innovation pathways for industry advancement. The study follows strict methodological standards to achieve reliable outcomes, which establish a standard for subsequent reviews, and examines new technologies like AutomationML alongside interdisciplinary knowledge to better understand automation's changing function in production environments. The article establishes itself as an essential resource through its integration of technological methods and strategic approaches to help researchers and practitioners push forward automation practices while solving current production engineering challenges.

The subsequent flowchart demonstrates the systematic review methodology for automation in production engineering through its main phases, which consist of literature selection and categorization, followed by comparative analysis methodology, focused data visualization, and case study integration.

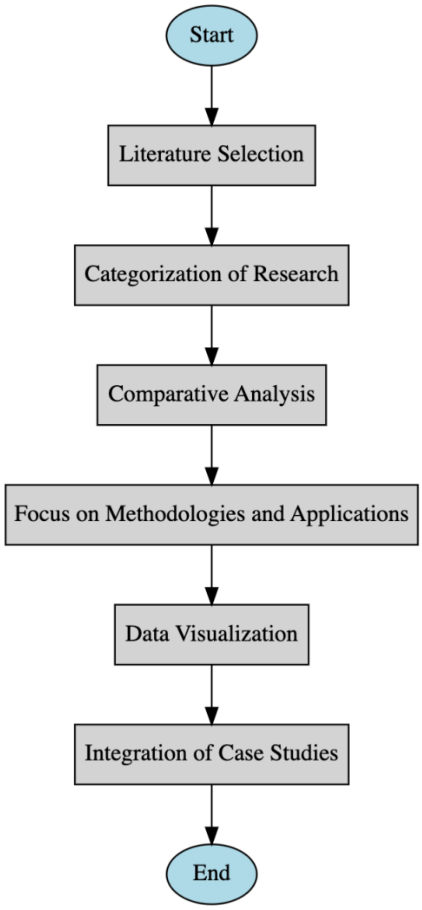


**Fig. 1.** Flowchart depicting the systematic review methodology for automation in production engineering.

## 3. Socio-Economic and Geopolitical Implications of Automation in Production Engineering

Automation technologies in modern production systems affect various sectors such as automotive, aerospace, electronics, horticulture, and supply chains, thereby transforming industrial practices and societal structures (Banur et al., 2024; C et al., 2024). Automation technologies have become widely adopted, resulting in significant changes to how work gets organized as well as the structure of national economies and global trade systems.

### 3.1. Effects on Employment Patterns and Workforce Skills

Production engineering automation brings significant changes to employment structures as well as job roles and workforce skill requirements (Adebayo et al., 2024; Kurian, 2025). The implementation of automation technologies improves operational efficiency and reduces production cycle times but leads to the elimination of many routine, manual, and low-skilled positions (Kurian, 2025; Madwe et al., 2025; Olaniyi et al., 2024). Employees who perform tasks that involve repetitive patterns and can be easily programmed face substantial risk because AI systems now have the ability to replace human work in these fields (Liang, 2024; Masriadi et al., 2023). Automation does not mean widespread unemployment, as research reveals job creation in technical and creative fields that require skills for managing intelligent systems (Adebayo et al., 2024; Gangoda et al., 2023; Kurian, 2025).
As manufacturing environments become automated, the need for employee upskilling and reskilling programs becomes more critical (Nedelkoska & Quintini, 2018; Olaniyi et al., 2024). To succeed in today's changing employment landscape, employees need to develop digital literacy together with systems thinking and advanced technical abilities (Gangoda et al., 2023; Shuangyin et al., 2024). The growing disparity between automated production needs and current workforce capabilities requires joint efforts from both industry leaders and government officials to address the skills gap (Liang, 2024; Olaniyi et al., 2024).

### 3.2. Impacts on Income Distribution and Social Equity

Automation plays a substantial role in shaping income distribution, which typically results in increased wage disparities and social inequalities (Madwe et al., 2025; Pal, 2024). While automation-complementary high-skill jobs result in increased wage premiums that benefit workers with advanced education and technical skills, automation simultaneously leads to wage stagnation or job displacement for workers in low-skill routine positions (Kurian, 2025; Madwe et al., 2025). Research from various areas shows that productivity increases resulting from automation create unequal wealth distribution, which leads to greater income disparities (Liang, 2024; Pal, 2024;).

Automation intensifies current disparities and threatens government income systems based on labor taxes in developing regions with poor digital frameworks and significant joblessness, such as parts of Africa (Madwe et al., 2025). The shift of economic power to capital owners due to declining labor demand from automation makes current tax systems outdated and leads to the consideration of new fiscal measures, including robot taxation, which can reallocate economic profits to support workforce training initiatives (Madwe et al., 2025).

### 3.3. Workforce Adaptation and Social Policy Responses

Effective adaptation to automation demands progressive changes in education systems alongside vocational development programs and innovative policy approaches (Madwe et al., 2025; Olaniyi et al., 2024). Both governments and industry sectors need to partner in determining future skill requirements, which should be incorporated into educational programs while supporting continuous learning opportunities (Gangoda et al., 2023; Shuangyin et al., 2024). Vocational education that matches mechanical manufacturing and automation needs helps improve job prospects and contributes to socio-economic progress (Shuangyin et al., 2024).

Policy solutions have featured training and educational subsidies directly and fiscal innovation incentives alongside proposals for technological innovation taxes that fund social security systems and workforce retraining programs (Chu et al., 2023; Madwe et al., 2025). Such strategies achieve effectiveness through their ability to adjust to local economic circumstances while emphasizing inclusive participation (Madwe et al., 2025). Balanced approaches that integrate technological development and social unity create essential pathways for spreading automation-generated prosperity among all societal groups (Madwe et al., 2025; Piontek, 2020).

### 3.4. Automation and Restructuring in Global Supply Chains

Automation technologies have transformed global supply chains by boosting efficiency and resilience with innovations such as machine-to-machine communication and smart warehouses (Banur et al., 2024; Govorkov et al., 2019; Mahmud et al., 2023). Automated systems enable real-time tracking alongside predictive maintenance and optimized routing with advanced data analytics, which supports manufacturers and logistics providers in managing disruptions and market changes with greater agility (Borisoglebskaya et al., 2020; Parshuramkar et al., 2024).

The ongoing digital transformation enables the development of globally distributed value chains, which strategically place production stages in areas with superior technological resources (Fontagné et al., 2023; Panwar et al., 2022). Automation drives advanced economies to adopt nearshoring and reshoring strategies, which transform international trade systems and shift production economic geography (Hazari et al., 2022; Meltzer, 2023). Global competitiveness shifts, while the industry location and employment prospects for both developed and developing markets present future uncertainties.

### 3.5. International Trade and Geopolitical Repercussions

Automation in production operations transforms international trade through changes in comparative advantages and factor intensities while promoting emerging trade models as described by Fontagné et al. (2023) and Hazari et al. (2022). Technologically advanced economies benefit from automation, which enables growth in high-skill, capital-intensive industries, thus overturning traditional trade theories and establishing new economic specialization patterns and functional divisions within global value chains (Fontagné et al., 2023; Klügl & Nordås, 2024). Developing nations need to modify their industrial approaches to stay competitive as automation and innovation drive today's economic landscape (Azmeh et al., 2022; Madwe et al., 2025).

The countries at the forefront of automation technology development enhance their international clout through increased national productivity, innovation advancements, and military strength

(Blokhin, 2020; Colther et al., 2025; Nedelcu, 2024). Technological capacity becomes essential for strategic power, which alters economic and political influence, while countries that do not advance technologically run the risk of being sidelined globally (Bánkuty-Balogh, 2024; Dahiya & Kumar, 2024). Technologically advanced nations use automation to serve national interests and industrial competitiveness, which generates competition and cooperation between states and establishes sector dominance (Bánkuty-Balogh, 2024; Blokhin, 2020). The struggle between the United States, Western countries, and China for control over AI and automation production approaches underscores the role of technological advancement in shaping global power relations (Blokhin, 2020; Schmidt, 2023).

### 3.6. National Competitiveness and Industrial Policy

Substantial investments in production automation by countries lead to enhanced national competitiveness, according to C et al. (2024), and Nedelcu (2024). Automation propels growth through process optimization, which enables better output quality and creates opportunities for product and process innovation (Matta, 2019; Shinkevich et al., 2020). The progress made in automation technologies improves a country's position within global supply networks and amplifies its power to direct international trade and investment movements (Klügl & Nordås, 2024; Panwar et al., 2022).

To maintain industrial competitiveness during rapid technological advancements, national policies must support automation adoption through direct subsidies, research and development incentives, workforce retraining, and innovation ecosystem development (Chu et al., 2023; Lei, 2021). Nations that postpone or poorly execute automation initiatives face economic decline and geopolitical setbacks while risking industrial disappearance and strategic independence loss (Azmeh et al., 2022; Blokhin, 2020).

### 3.7. Socio-Economic Transformation and Sustainability

The implementation of automation delivers significant economic and social advantages by enhancing productivity levels and product quality while promoting sustainable manufacturing through efficient resource use and reduced waste generation (Agarwal, 2023; Lei, 2021; Matta, 2019). Through automation smart factories achieve energy optimization and incorporate environmentally sustainable production techniques to support both sustainability and economic aims (Agarwal, 2023). Without intentional policy interventions, automation risks worsening social exclusion while also leading to job polarization and uneven regional development (Madwe et al., 2025; Piontek, 2020).

## 4. Steps to Implement Automation in Production Engineering

The implementation of automation technologies in production engineering requires a systematic strategy that aims to boost efficiency while cutting costs and elevating product quality (Kozlova et al., 2021; Nakamoto & Takasugi, 2023; Negi, 2024). The first essential move toward automated production quality control is the process of digitization (Toro et al., 2023). These steps guide the implementation of automation in production engineering processes.

- Identifying Repetitive and Time-Consuming Tasks: To begin automation implementation, it is necessary to find tasks that repeat frequently and require substantial time investment. The first step requires conducting a detailed analysis of current production processes to identify the areas which automation would benefit the most. The nature of process-oriented tasks within supply chains necessitates building these tasks with automation to achieve both error-free operations and high efficiency (Negi, 2024).
- Feasibility Study and Technology Assessment: A technical and economic feasibility study needs to be executed to evaluate automation potential (Brzezinski, 2022). Identifying the most appropriate automation technologies for specific production processes requires evaluation of robotics, AI, and ML solutions (Sajja & Addula, 2024). Current technological advances enable businesses to operate more efficiently while boosting productivity within competitive market environments (Negi, 2024).
- System Design and Planning: The automated system design process requires developing a comprehensive plan that details how various components will be integrated. The process requires choosing suitable hardware and software while designing the automated production line layout and planning data communication control systems (Aicher et al., 2014). The system's design allows for maximum flexibility and reconfigurability, which matches Industry 4.0 standards (Novák & Vyskočil, 2022).

- Integration of CPS: Modern production lines require integration of CPS to achieve effective monitoring and control capabilities (Ferrer & Lastra, 2017). The process requires building system-level models that reflect production system characteristics and requirements by depicting production and computational processes as infrastructure-delivered services (Lora et al., 2024). The incorporation of CPS provides essential control and monitoring capabilities for contemporary production lines (Ferrer & Lastra, 2017).
- Software and Hardware Implementation: Software engineers must execute programming automation tasks as well as simulation and system visualization for production operations. The definition of software and hardware communication interfaces becomes essential during both virtual and real commissioning processes. Through the adoption of a unified engineering information model, organizations achieve greater parameter data consistency, which leads to faster software development processes and better overall consistency (Aicher et al., 2014).
- Testing and Validation: Following implementation, comprehensive testing and validation processes must be executed to verify that the automated system operates properly and reaches required performance benchmarks (Meixner et al., 2019; Ulewicz & Vogel-Heuser, 2018). System regression tests are necessary to locate faults that appear in the automated production system after making changes (Ulewicz & Vogel-Heuser, 2018). Verification and validation activities during system evolution benefit from the use of models (Meixner et al., 2019).
- Training and Skill Transfer: Manufacturers have often encountered operational issues due to unexpected machine breakdowns and defective product shipments. AI techniques will provide operational efficiency improvements and facilitate new product development while allowing for product design customization and future financial planning (Nakamoto & Takasugi, 2023). Employees require training programs to operate and maintain the new automated systems effectively (Rakhmasari et al., 2025).
- Addressing Potential Barriers: The implementation of green smart production (GSM) requires dealing with multiple obstacles. A lack of financial resources, together with limited supplier availability and data security concerns, alongside insufficient knowledge about surrounding conditions, forms major barriers. The systematic resolution of barriers remains essential for deploying GSM systems successfully (Agarwal et al., 2024).
- Monitoring and Continuous Improvement: The automated system requires ongoing monitoring after activation to discover potential areas for enhancement. The process optimization requires tracking core metrics like production output, defect rates, and system downtime through key performance indicators (KPIs). AI-driven automated systems can analyze data to enhance their performance continuously, which results in sustained logical quality (Sajja & Addula, 2024).

## 5. Benefits and Applications of Automation in Production Engineering

Automation in production engineering has transformed manufacturing processes through improved efficiency and precision while enabling scalability. The following section highlights key benefits and applications that showcase its impact on different industries.

### 5.1. Benefits

Implementing automation in production engineering results in better efficiency alongside cost reductions while both product quality improves and scalability expands (C et al., 2024; Xie, 2020). Automation technology plays an essential part in advancing intelligent operations within human production activities and daily life (Zhang, 2024). The research highlights how ongoing investment in automation technologies remains crucial for stimulating innovation and productivity growth within mechanical engineering fields (C et al., 2024).

- Enhanced Efficiency and Productivity: Automation enables substantial gains in efficiency and productivity across multiple industries. In agriculture, automated technologies such as planting, seeding, irrigation, and harvesting result in enhanced efficiency (Phadnis, 2023). The oil and gas industry benefits from digitalization and automation through improved plant availability while offering real-time data to engineering and maintenance teams for early decision-making and operational excellence (Chettiar et al., 2020). Robot-operated production systems achieve a production growth of approximately 17% when compared to traditional manually operated machines (Barosz et al., 2018).

- Cost Reduction and Economic Benefits: Automation serves to lower both production expenses and operational system costs (Xie, 2020). The implementation of a custom automatic system with compact injection machines and automation in the automotive components industry achieved an energy consumption reduction of 80% while production rates increased by 12% (Penne et al., 2022). Automation achieves substantial cost savings by streamlining processes and eliminating human mistakes (Amaugo, 2024). The automation of measuring instruments' calibration processes provides economic advantages (Furkatovna et al., 2022).
- Improved Quality and Reduced Waste: Manufacturing equipment achieves high precision and consistency in workpieces through automation, which also delivers repeatability and accuracy (Jindal & Kaur, 2021). The fast food industry experiences significant product quality improvements through process automation (Sono et al., 2024). Industrial manufacturing benefits from Subassembly Process Automation (SPA) programs, which improve production accuracy and efficiency while diminishing scrap and maintaining strict quality standards (Dacian et al., 2024). Automation system design for processes like Tempura shrimp frying enables consistent quality output while minimizing waste production (Vo et al., 2021).
- Scalability and Flexibility: Automation capabilities allow production systems to achieve higher scalability and flexibility (C et al., 2024; Djalab et al., 2024). Flexible Manufacturing Systems (FMS) deliver advantages including shorter lead times and enhanced production flexibility while reducing operational expenses (Malik et al., 2024). The automotive industry demonstrates how automation creates quick operational responses to changing market demands (Amaugo, 2024). Industry 5.0 combines automation with human-centered approaches to fulfill expectations while maintaining workforce accountability (Górny, 2023).
- Reduced Human Effort and Improved Safety: Automation reduces human involvement in demanding physical tasks (Jindal & Kaur, 2021). Automation in the oil and gas sector enables a 'single window' operational structure to streamline plant management while it provides predictive/preventive maintenance support to maintain plant availability without production loss. Automation enforces absolute adherence to Health, Safety, and Environment (HSE) standards while reducing workforce exposure to hazardous conditions (Chettiar et al., 2020). Employees can concentrate on complex and essential tasks because automation assigns routine and rule-based duties to digital systems (Da Silva Costa et al., 2022).

### 5.2. Applications of Automation in Production Engineering

Automation technology in production engineering boosts operational efficiency while decreasing expenses and enhancing quality and scalability across multiple industrial sectors. The scope of this technology includes robotics systems as well as Computer numerical control (CNC) machine operation and IoT connectivity (C et al., 2024). This discussion examines how it facilitates process streamlining while improving quality control and resource optimization and advances technology integration.

- Streamlining Processes:
  - Software automation enhances repetitive task management by substituting manual operations with automated systems to speed up workflows and minimize human errors. The result is increased reliability and standardization in production line management and inventory control (Ajiga et al., 2024).
  - The automation of material delivery analysis reduces errors and report preparation time while providing significant advantages for small and medium enterprises. Companies can dramatically reduce the time spent on manual tasks by using Visual Basic for Applications (VBA) macros to automate these operations (Khan et al., 2021).
  - The SMART system represents a specific instance of how integrated automated construction systems apply automation technology to distinct construction processes. Automated construction systems illustrate how automation technology can increase operational efficiency and accuracy during construction projects (Yamazaki & Maeda, 1998).
- Enhancing Quality Control:
  - AI-driven systems such as steel surface faulty detection attention net (SSFDANet) enhance the accuracy and classification of defect detection during steel strip production. By implementing DL and attention mechanisms, these systems provide instantaneous defect identification, which leads to reduced inspection periods and better production line performance (Chen et al., 2023).

- Automated inspection systems utilize advanced sensors and imaging technologies to perform defect detection while ensuring product standards in real-time. The ability to take swift corrective measures leads to less waste and better product quality (Ajiga et al., 2024).
- SPA achieves higher production precision and efficiency by implementing systematic advancements together with detailed quality control strategies. The use of automation for complete process supervision enables SPA to minimize mistakes while maximizing resource efficiency and preserving manufacturing quality standards (Dacian et al., 2024).

- Optimizing Resource Management:
  - Automated inventory management systems enhance stock control by continuously monitoring inventory levels and modifying purchase orders accordingly. This process enables efficient resource allocation while minimizing surplus inventory (Ajiga et al., 2024).
  - Greenhouse technology boosts agricultural productivity by allowing continuous crop growth throughout the year while safeguarding against unfavorable environmental conditions. Hydroponics and aeroponics as advanced technologies achieve high resource efficiency while reducing environmental impact (Singh et al., 2024).
  - The SPA program utilizes automation in waste reduction processes to minimize scrap production while maintaining strict quality control standards. The enhancement of environmental sustainability through effective scrap management depends on improving production flow and minimizing waste creation (Dacian et al., 2024).
- Integrating Advanced Technologies:
  - The combination of AI and IoT technologies facilitates both predictive maintenance and process optimization within manufacturing sectors (C et al., 2024; Ajiga et al., 2024). AI algorithms use real-time data analysis to forecast equipment breakdowns, which reduces downtime, and IoT technology links physical equipment with virtual platforms for enhanced data gathering and examination (Ajiga et al., 2024; Karabegovic et al., 2019).
  - Industrial robots drive modernization and automation across automotive manufacturing industries, which leads to better energy usage and the adoption of novel materials. The implementation of IT technologies boosts robot utilization, which leads to better production process outcomes (Karabegović et al., 2015).
  - Digitalized automation engineering employs DTs to generate formal descriptions of production resources along with their operations. Working closely with DTs improves engineering tasks while optimizing production processes (Novák & Vyskočil, 2022).

## 6. Past Projects in Companies Implementing Automation in Production Engineering

Many leading companies have successfully implemented automation in production engineering to enhance efficiency, reduce costs, and improve overall manufacturing processes, as seen in the following projects.

- Siemens: Siemens had used its Tecnomatix suite of tools, Process Simulate, to drive productivity and project times reduction by 30% for SGAR, a Spanish engineering and industrial automation firm. SGAR programming and production line verification is a service we provide to automotive industries. Using Siemens' sophisticated simulation tools, SGAR became much more capable of evaluating mechanical processes and streamlining processes in challenging environments, which is a huge efficiency boost (Siemens, n.d.).
- Bosch Rexroth: Bosch Rexroth and DWFritz Automation set up a completely automated battery manufacturing line. The project answered the growing need for small, high-throughput manufacturing in the battery industry for real-time data collection and process optimization. Bringing together the most cutting-edge motion control technology with the highest tolerances in assembly, this partnership has made new manufacturing cycles and scaling of new processes faster (Bosch Rexroth Corporation, 2021).
- Mitsubishi Electric: Mitsubishi Electric Integrated Production Systems (IPS) implemented a single device, custom solution to replace older equipment for an anechoic foam manufacturer, with minimum maintenance and footprint. IPS' use of a high-end motion control system and Mitsubishi components enabled it to automate the once cumbersome dual-machine process to reduce labor and ensure better product quality (Mitsubishi Electric Automation Inc., 2023).

- Omron: Omron added new automation capabilities and solved manufacturing problems of customers using AI and IoT (Satoshi and Yasuyuki, 2024). By designing a technological sharing system, the firm has helped enable smaller improvements at all production sites, which is in turn resulting in higher productivity and quality products across multiple sectors, especially in the midst of labor shortages (Kohei et al., 2024).
- Rockwell Automation: Rockwell Automation, in collaboration with Schlumberger, has built Sensia, a complete oil and gas industry automation solution that places a focus on digital transformation in the workplace (Rockwell Automation, 2019a; Rockwell Automation, 2019b). Such cooperation will automate processes through high-speed data transmission and real-time tracking while improving production and safety standards across all industries, especially mining (Military & Aerospace Electronics, 2001).
- FANUC Robotics: FANUC Robotics has lately been involved in various projects that are supporting the automation of various manufacturing areas. Among others, they helped one automotive customer improve the overall performance of its existing robotic systems by reflashing the vision system for selecting torque converters to reduce downtime and improve operational efficiency by 74%. FANUC also took on a new assembly line project where they assisted the design of material handling equipment using both their robot and Siemens programmable logic controller (PLC), illustrating their capabilities in the integration of robots and other manufacturing technologies (Hitchcock, 2015).
- ABB Robotics: ABB's Project Genesis is an attempt to automate every stage of the semiconductor manufacturing process at its facility in Switzerland. The first of its kind, the project not only embeds more than 55 robots on the line but also uses cutting-edge automated guided vehicles (AGVs) to execute the intricate logistics of semiconductor manufacturing. The project will eliminate manual labor and the chances of errors and will increase the efficiency and high quality of manufacturing (Rayner, 2020).
- KUKA Robotics: KUKA Robotics released the PULSE carrier conveyor to improve auto production. This breakthrough technology took over the older assembly line technologies and permitted the movement of vehicle body sections with freedom through robot stations. The PULSE system has shown up to 99% faster system performance compared to previous systems, which reduces the production cost with no interruption of production (Rockwell Automation, 2017). This initiative is part of KUKA's drive to revolutionize the auto manufacturing process with new-generation automation technology.
- Yaskawa Motoman: Yaskawa Motoman has delivered a robot bandsaw for a wooden packaging products supplier with the six-axis handling robot. The technology is based on a high degree of consistency during the cutting and thus can yield higher capacities of production while keeping the safety and operational efficiency intact (Yaskawa America, Inc., n.d.). Because of this implementation, the overall productivity rate of the manufacturer has increased, which indicates that Yaskawa has successfully applied production engineering optimization across all sectors.
- Kawasaki Robotics: Kawasaki Robotics completed a job to replace a robotics paint system with older Kobelco robots with current Kawasaki models. This upgrade promised speed and precision, which are important in the high-quality automotive sector. Thanks to the modern vision systems and new robots, significant reduction in manpower and downtime was possible, and production was maximized (Patti Engineering, Inc., 2013). This is a project that shows Kawasaki's commitment to using technology to bring manufacturing improvement.

## 7. Overview of Past Research on Automation in Production Engineering

The past five years in production engineering automation reveal considerable progress that mirrors industrial trends toward better efficiency and sustainability alongside digital transformation. The study explores 109 significant papers from 2019 to 2024 to identify major trends and technological developments in the field. The publication rates depicted in Figure 1 showed variation across different years, yet research output reached a significant peak starting in 2022. The selected papers represent high-impact contributions to the field, categorized into three distinct phases: The initial period of sustainable and automated manufacturing development occurred during 2019–2020, while digitalization merged with automation in 2021–2022, followed by the latest industrial automation and control advancements from 2023–2024. The outlined phases demonstrate how automation technologies have evolved while expanding their influence on the transformation of current production systems.

The number of articles covered in this review on the Automation in Production Engineering are shown in Figure 2 from 2019 through 2024.

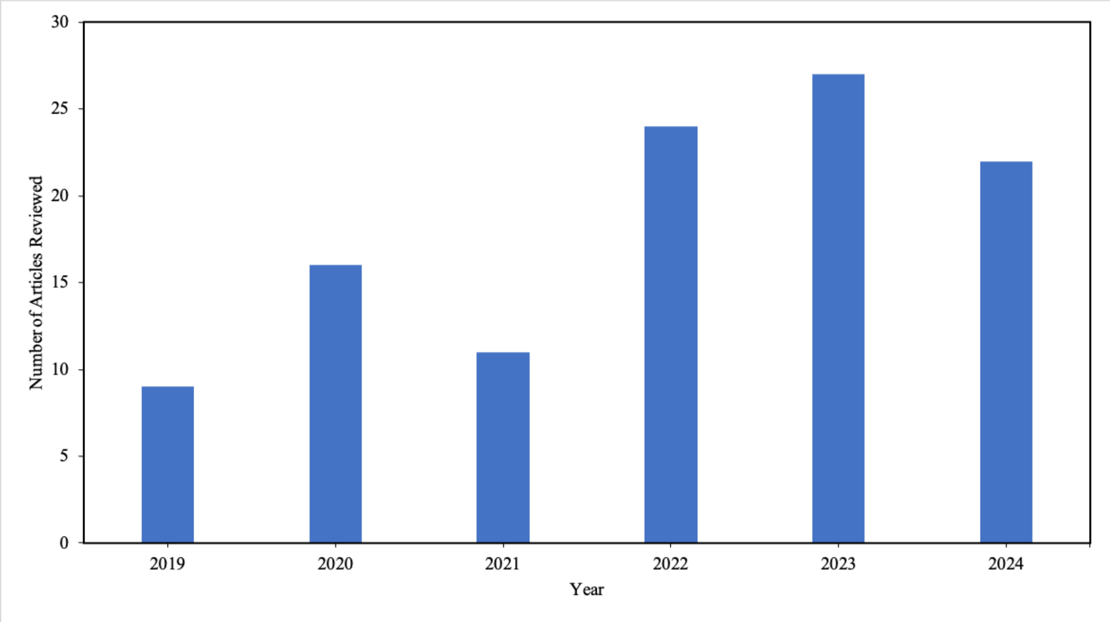


**Fig. 2.** Number of articles on Automation in Production Engineering vs. Year.

Table 1 below shows a quantitative distribution by publisher of the number of articles related to the applications of Automation in Production Engineering.

**Table 1.** Number of articles on the applications of Automation in Production Engineering by Publisher

| Publisher | Number of Articles Reviewed |
|---|---|
| Elsevier | 32 |
| Springer | 16 |
| IEEE | 14 |
| MDPI | 14 |
| IOP Publishing | 5 |
| Taylor & Francis | 4 |
| Wiley | 3 |
| DergiPark Akademik | 2 |
| EDP Sciences | 2 |
| ASME Digital Collection | 1 |
| Asosiasi Riset Ilmu Teknik Indonesia (ARITEKIN) | 1 |
| Belgorod State Technological University University named after V.G. Shukhova | 1 |
| elibrary.ru | 1 |
| EWA Publishing | 1 |
| Forum Komunikasi Dosen Peneliti (FKDP) | 1 |
| Frontiers | 1 |
| Global Journal For Research Analysis (GJRA) | 1 |
| IGI Global Scientific Publishing | 1 |
| Indospace Publications | 1 |
| Knowledge E | 1 |
| Open Transportation JournalOpen Transportation Journal | 1 |
| Publishing Center RIOR | 1 |
| Singidunum University | 1 |
| University North - University Center Varazdin | 1 |
| Voronezh State Forest Engineering University named after G.F. Morozov | 1 |
| Zeal Scientific Publication | 1 |
| **Total** | **109** |

### 7.1. Advancements in Sustainable and Automated Manufacturing (2019–2020)

Matta's research (Matta, 2019) explored sustainable production automation by focusing on energy efficiency and waste reduction throughout manufacturing operations. The study demonstrated advancements in algorithm design alongside models and smart manufacturing technologies, which serve to improve product lifecycle management while minimizing environmental effects. Industrial robots achieved up to 30% energy savings by optimizing movements and decreasing idle time, while future advancements will include the use of renewable energy sources alongside advanced smart technologies. Gonçalves et al. (2019) studied how AutomationML could bring together different engineering data elements to support sensor fusion in industrial environments. The authors created an ontology that improved AutomationML functionality through efficient real-time data management for sensor integration. The heating fluids case study showed that the developed ontology successfully handled sensor fusion, which resulted in enhanced operational efficiency. The ontology demonstrated its capacity for reuse in multiple systems, thereby achieving widespread use across different manufacturing environments. The research by Alavian et al. (2019) examined how Smart Production Systems (SPS) can automate decision-making processes within the manufacturing sector. SPS systems showed the ability to self-diagnose system health and create improvement projects, which enhanced productivity. These systems utilized sensors together with data analytics and ML algorithms to monitor performance and generate solutions independently of human input. The study findings demonstrated that SPS substantially boosted productivity through automated decision-making and rapid responses to operational issues.

Pilipenko et al. (2019) focused on warehouse automation for industrial environments using sensors, robots, and control algorithms for storage and transportation optimization to maximize efficiencies and financial returns. They developed a cyber-physical system with an algorithm to handle inventory and shift with production demands, handling issues around logistics and part preparation. Schlette et al. (2019) designed a robot assembly cell for improved production in high-mix, low-volume production conditions, presented at the World Robot Challenge 2018. Their system was based on two UR10e cobots with varying grippers and it did object picking, bin picking, and assembly, though there were some tasks that had to be tested more to make it better. Flexibility was further developed with modular programming and an open design that allowed for flexible production requirements. The study by Gadaleta et al. (2019) addressed industrial robot energy consumption through a new simulation tool that created energy-efficient motion parameters resulting in lower energy usage while maintaining productivity levels. The experimental validation executed with a KUKA Quantec industrial robot demonstrated their optimization approach's effectiveness to enhance sustainability.

Pogliani et al. (2019) examined security weaknesses in industrial robots operating in interconnected manufacturing systems and highlighted how cyber threats present growing risks in Industry 4.0. The research uncovered attack methods through programming language manipulation and control parameter tampering that result in serious cyberattack consequences, including both production downtime and safety risks. In contrast, the research conducted by Tan et al. (2019) optimized industrial robot assembly scheduling through multi-agent reinforcement learning (RL) models that enhanced process efficiency and adaptability in dynamic production settings. The simulation outcomes revealed improved real-time decision-making capabilities for managing variable product demand challenges. Fazlollahtabar (2019) developed a mathematical programming model to plan autonomous robot paths by reducing transportation costs and delays and avoiding collisions. Numerical analysis evaluations proved the model's capacity to assign robots to machining centers efficiently under varying operational constraints.

Cha et al. (2020) turned to model-based engineering of automated production systems (aPS) in Industry 4.0, where the lack of a metamodel at the heart is cited as one of the biggest barriers to consistency and cross-domain reuse. Their work compared different metamodels, and it found that a common metamodel is necessary for communication and for designing and running aPS efficiently. Meanwhile, Sorokin et al. (2020) specialized in new automation and digitalization for manufacturing lines for the production of organic raw materials. They devised a control algorithm to automate technological processes on production lines and a software system to control modular machinery to provide process control with assurance. They also mentioned choosing modular machines according to the customer requirements, and they gave a matrix to guide the automation. Vicentini (2020), on the other hand, presented an extensive survey of cooperative robotics, where we see the change of human-robot collaboration in public environments. Control performance, safety, and the integration of human factors into production efficiency were all part of the equation. It developed a design for collective robots from the perspective of industrial usability and safety. Rao et al. (2020) analyzed Manufacturing Execution Systems (MES) and Autonomous Intelligent Vehicles (AIVs) with a LabVIEW-based middleware. Their studies focused on automating processes through real-time data communication between MES and AIVs, thereby improving the delivery of products in Industry 4.0. The results showed the middleware's capability to handle inter-system communication, visibility into operations, and automated product movement following MES-driven production flows.

The study by Lipka et al. (2020) improved semi-automated manufacturing processes with a wireless tracking system that enhanced production stage monitoring in small series production. Wireless sensors and beam tracking enabled the system to achieve 3.18 cm tracking accuracy, which showed promising results. In contrast, Pittino et al. (2020) presented research on detecting anomalies in operating manufacturing equipment through the use of statistical learning techniques that enable constant and reliable real-time monitoring. The study found that automatic anomaly detection systems could function reliably without ongoing recalibration and achieved near-perfect recall on the dataset necessary to sustain system reliability. Gašpar et al. (2020) developed a reconfigurable robot workcell that automated previously labor-heavy low-volume production processes. Modular control software, together with easy-to-use programming methods, enabled the system to seamlessly adapt its configuration as production requirements changed. The workcell demonstrated adaptability and efficiency through successful testing across five different production processes in real-world applications.

Hagemann and Stark (2020) presented an optimal knowledge-based search algorithm aimed at creating robotic assembly systems specifically for automotive body-in-white production. The study confirmed that the algorithm effectively lowered system design time and complexity while demonstrating practical success through industrial-scale validations. Zhang et al. (2020) recommended combining DTs with AutomationML technology to improve intelligent manufacturing capabilities within cyber-physical production systems (CPPS). The research highlighted how DTs enable virtual models of physical manufacturing assets to support instant data exchange and better system connectivity. Their case studies on aircraft engine fault diagnosis and blisk machining proved that their method improved resource efficiency while enhancing collaboration among manufacturing units. In contrast, Meng et al. (2020) addressed collaborative automation within FMS through improved machine interoperability and reduction of human intervention. Through the integration of smart machines and information and communication technologies, they developed a collaborative network system for machines that was proven effective with the PickNPack food manufacturing line. Substantial production speed improvements and reduced human operator involvement led to enhanced overall production flexibility and efficiency, according to the results.

Sun et al. (2020) demonstrated that robotic rotary ultrasonic milling (RRUM) improves machining stability and reduces chatter because ultrasonic vibrations boosted stability by 133% when compared to traditional robotic milling. The research revealed that increased ultrasonic vibration frequencies and amplitudes led to better machining quality and process stability. Similarly, Ferreras-Higuero et al. (2020) developed a predictive model to enhance precision in robotic drilling within flexible manufacturing cells by considering cutting forces, joint stiffness, and robot configuration. The investigations showed process-induced deviations made up 40% of positional uncertainty while their model corrected systematic errors to increase machining precision. In contrast, Amersdorfer et al. (2020) developed a sensor-based geometric method for real-time freeform surface tracking in force-controlled robotic tooling applications that enabled autonomous adaptation to surface variations without computer-aided design (CAD) models. The experimental validation successfully achieved precise surface tracking and force control, which improved robotic polishing and grinding operations.

Engemann et al. (2020) created the autonomous mobile manipulator OMNIVIL to improve flexible production with holonomic kinematics integration alongside advanced sensor localization and a new workspace monitoring system for safe human-robot collaboration. Their study highlighted adaptive manipulation techniques and zonal navigation methods to boost productivity in ever-changing industrial environments. In contrast, Shahzad et al. (2020) developed vision-based path planning techniques for a 6-DOF robotic manipulator that combined stereo vision systems and neural networks to improve object tracking precision in bottling applications. The proposed method attained a path prediction accuracy score of 91.8% while simultaneously enhancing precision and real-time calibration capabilities in the management of fragile objects. Bänziger et al. (2020) created a simulation tool for human-robot task allocation, which was tested in Volkswagen's Wolfsburg plant and used genetic algorithms to enhance task sequencing. The implementation of intelligent task distribution resulted in a task completion time decrease from 57.5 seconds to 43.0 seconds, according to their findings.

The following table provides a side-by-side comparison of research papers about sustainable and automated manufacturing that appeared in the years 2019 and 2020. The table organizes research papers according to authorship and publication date followed by study focus and application methodology and datasets as well as key findings and metrics and discovered research gaps and unresolved issues.

**Table 2.** Comparison of Papers on Advancements in Sustainable and Automated Manufacturing (2019–2020).

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Matta (2019) | Sustainable Production Automation to enhance energy efficiency and reduce waste | Development of innovative algorithms, models, and hardware; focus on optimizing the product life cycle | Energy savings of up to 30% in robot operations; emphasis on smart battery manufacturing and remanufacturing challenges | Need for further integration of smart manufacturing and renewable energy sources; challenges in remanufacturing due to unpredictable supply and varying quality |
| Gonçalves et al. (2019) | Using AutomationML-based ontology for sensor fusion in industrial plants | Development of an ontology to enhance AutomationML; case study with heating fluid processes using various sensors | Ontology successfully identified sensor fusion and its location; improved AutomationML integration for real-time decision-making | Further integration with OPC server needed; enhancement of system capability for real-time data management |
| Alavian et al. (2019) | SPS for automating decision-making in manufacturing | Implementation of SPS for autonomous diagnosis and improvement projects; integration of sensors and ML | Enhanced productivity through autonomous system health diagnosis and continuous improvement project design | Need for more robust integration with existing manufacturing workflows; further validation in large-scale industries |
| Pilipenko et al. (2019) | Automation engineering in adaptive industrial warehouses | Development of a cyber-physical system for warehouse automation; use of sensors, robots, and control algorithms | Optimization of warehouse productivity; development of an algorithm for digital warehouse interaction | Challenges in real-time adaptation to production changes; need for improved inventory management strategies |
| Schlette et al. (2019) | Robotics in production engineering, focusing on enhancing reconfigurability and agility in high mix/low volume scenarios using methods like DTs and computer vision | Development of a robotic assembly cell, modular framework in Python, and utilization of two UR10e robots. Four tasks in WRC 2018 for validation | Winning score of 145 points at WRC 2018, excelled in Task 1. Challenges faced in Tasks 2 and 3 due to novel approaches. Future work aims to expand robotic cell design into a matrix structure for better workflows | Further testing required for Tasks 2 and 3; expand into matrix structure for higher production efficiency |
| Gadaleta et al. (2019) | Energy optimization of industrial robots, focusing on sustainability and reducing energy consumption during robot code generation | Development of a simulation tool for generating energy-optimal robot code. Validation on a KUKA Quantec KR210 R2700 robot | Successfully reduced energy consumption without compromising productivity. Introduced integration with offline programming tools for energy optimization | Integration with a broader range of robot models and offline programming tools needs further exploration |
| Pogliani et al. (2019) | Security of industrial robots in the connected factory, addressing cybersecurity in interlinked systems | Comprehensive analysis of attack surfaces, vulnerabilities, and case studies for ABB and Universal Robots. Discussion of cybersecurity concerns in IIoT contexts | Identified vulnerabilities in programming and control of robots, highlighting serious risks of cyberattacks. Proposed mitigation strategies include secure software practices, access controls, and robust programming languages | Need for further exploration into secure programming languages and deeper integration of cybersecurity into robot development. |
| Tan et al. (2019) | Modeling, planning, and scheduling of assembly processes with dynamic cyber-physical interactions in CPS-based smart industrial robot production | Multi-agent model for industrial robot assembly, intelligent planning with RL, real-time data fusion for dynamic scheduling | Simulation results showed improved efficiency and adaptability over traditional methods. Emphasized flexible, efficient assembly processes for Industry 4.0 | Simulation-based; real-world industrial application tests needed to validate scalability and effectiveness |
| Fazlollahtabar (2019) | Autonomous robot path planning for minimizing delays and transportation costs in production systems | Proposed a mathematical model for autonomous robot path planning. Numerical study with 8 machining centers and 3 robots for validation | Optimized robot assignment and path planning minimized delays and transportation costs. Results showed efficient path allocation with an objective function value of 72. | Considering uncertainties in movement times and robot capacities in future models would enhance flexibility |
| Cha et al. (2020) | Model-based engineering for aPS in Industry 4.0; need for a core metamodel to address inconsistencies | Analysis of existing metamodels; criteria-based evaluation for inconsistencies and gaps | Lack of a core metamodel hampers reuse and cross-disciplinary collaboration; need for a universal metamodel | Challenges in defining a universally accepted metamodel; practical implementation across industries |
| Sorokin et al. (2020) | Modern approaches to automation and digitalization of equipment in production lines for organic raw materials | Developed a software package for controlling modular equipment in production lines. Focus on control algorithms and modular equipment selection | Proposed an algorithm for automation control, matrix for equipment selection, and presented schematic diagrams. Supported the use of optimal market equipment for processing organic raw materials | Scientific novelty exists in the integration of software and information tools, but gaps remain in refining the algorithm and addressing real-time issues in large-scale implementations |

**Table 2.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Vicentini (2020) | Collaborative Robotics in industrial settings for safe human-robot interaction | Survey, historical context, focus on actuation, perception, safety, and resource optimization | Enhanced human-robot interaction, improved control systems, safety standards, organizational impact on productivity | Need for standardized design frameworks, further integration with human factors in industrial applications |
| Rao et al. (2020) | Integration of AIVs with MES to improve automation in Industry 4.0 | Developed a LabVIEW-based middleware scheduler for real-time communication between MES and AIVs. Tested using SAP MES and Robotnik 'RB-1' in a real factory | The scheduler enabled real-time tracking of AIVs, facilitating automated product delivery based on MES-defined sequences. Integration with low-cost ROS-built AIVs demonstrated versatility | Scalability and adaptability of the middleware for different MES and AIV configurations need further investigation. Potential latency issues in large-scale environments |
| Lipka et al. (2020) | Wireless tracking system for live data control in semi-automated manufacturing processes | Implementation of wireless sensors with localization and torque control; Kalman-filter-based beam tracking | Tracking accuracy of 3.18 cm with beam-tracking precision of 0.58° azimuth and 0.89° elevation | Need for further miniaturization and improved power efficiency of mobile units; real-world industrial validation required |
| Pittino et al. (2020) | Automatic anomaly detection in in-production manufacturing machines using statistical learning methods for enhanced reliability in Industry 4.0 | Statistical learning methods, control charts; considers operational conditions and wear states; dataset variability accounted for | High recall rate (~1) in detecting anomalies; robust automatic detection without continuous recalibration | Impact of extreme operational variations on detection accuracy; scalability for different manufacturing settings |
| Gašpar et al. (2020) | Reconfigurable robot workcell for automating low-volume production; integration of passive hardware elements and user-friendly programming | Developed a reconfigurable workcell with ROS-based modular control software; evaluated through five distinct production processes | Workcell successfully adapted to various tasks; intuitive programming enhances usability | Optimization of reconfiguration time; long-term impact on production efficiency |
| Hagemann and Stark (2020) | Knowledge-based search algorithm for optimal robotic assembly system design in automotive body-in-white production | Algorithm developed and tested through a software prototype; validated in large-scale industrial scenarios | Algorithm improves efficiency and reduces design complexity; enhances resource allocation | Applicability to other manufacturing domains; integration with existing assembly line frameworks |
| Zhang et al. (2020) | Integration of DTs and AutomationML in CPPS for enhanced manufacturing intelligence | Proposed a four-layer CPPS architecture; case studies on aircraft engine fault diagnosis and blisk machining | DTs improve resource interconnection and manufacturing service encapsulation; AutomationML facilitates integration | Standardization of DT applications across industries; security concerns in data sharing |
| Meng et al. (2020) | Architecting Ubiquitous Communication and Collaborative-Automation-Based Machine Network Systems for Flexible Manufacturing | The research integrates smarter machines with ICTs to enhance collaborative automation in manufacturing. Focus on machine interoperability and flexibility | Case study in PickNPack food manufacturing line with a system achieving 17 packages/min and potential for 30 packages/min. Reduced human operators from 6 to 2 | Integration of IoT technologies and collaborative automation is effective, but challenges remain in mechanical integration and domain-specific configurations |
| Sun et al. (2020) | RRUM for reducing chatter in milling processes | Analytical model, experimental setup with aluminum alloy plates (Al7075-T7) | 133% improvement in stability region, reduced vibrations leading to better machining quality and longer tool life | Influence of ultrasonic vibration parameters on milling stability, need for broader material testing |
| Ferreras-Higuero et al. (2020) | Robot-process precision modeling in flexible manufacturing cells for drilling tasks | Quaternions-based model, multibody system for computational efficiency, experimental validation | Improved position tolerance for drilled holes, identified key factors influencing precision | Impact of environmental factors on precision, extension to other manufacturing operations beyond drilling |
| Amersdorfer et al. (2020) | Real-time freeform surface and path tracking for force-controlled robotic tooling | Geometric approach using sparse distance measurements, force control integration, experimental setup with KUKA LBR iiwa 14 robot | Effective tracking of freeform surfaces, adaptive real-time adjustments, successful integration of force control | Challenges in adapting to highly dynamic environments, improvement in scaling to larger surfaces |
| Engemann et al. (2020) | Autonomous mobile manipulators for flexible production tasks in industrial environments | Design of OMNIVIL robot, sensor setup for localization, human-robot collaboration with workspace monitoring system | Improved efficiency in logistics and handling tasks, safe and adaptive collaboration with humans, zone-based navigation | Need for further optimization in dynamic environments and unpredictable human actions |
| Shahzad et al. (2020) | Vision-based path planning and object tracking for 6-DOF robotic manipulators in industrial automation, particularly in bottling applications | Developed an ensemble robotic framework using a stereo vision system for tracking colored objects with blob analysis and ML. Used a neural network to reduce geometric errors in stereo vision | Tested on industrial robotic tasks, achieving 91.8% path prediction accuracy. Combined color region tracking and neural networks for better performance | Real-time calibration and precise manipulation still require improvements. Further optimization for handling diverse industrial objects needed |

**Table 2.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Bänziger et al. (2020) | Optimization of human-robot task allocation in manufacturing using simulation tools for better efficiency and ergonomics | Developed a simulation tool modeling human-robot interactions based on standardized work descriptions. Validated using Volkswagen's assembly line data | Optimized task allocation reduced completion time from 57.5s to 43.0s. Genetic algorithms improved sequencing and distribution efficiency | Expansion to more complex workplaces involving multiple robots and workers is needed. Further real-world validation beyond automotive applications |

### 7.2. Advancements in Automation and Digitalization in Manufacturing (2021–2022)

Kozlova et al. (2021) focused on the automating technological processes in mechanical engineering were concerned with controlling automation across multiple production lines. The benefits they found were improved production capacity, higher quality products, and decreased prices due to technologies like automated cutting and grinding. Our case study on casting showed how automation could reduce defects, increase safety, and optimize the working environment. In contrast, Khrustaleva et al. (2021) created a simulation model for custom and small-batch production to show the potential of simulation and optimization in order to increase production efficiency. Their scheme included three levels: production control, processing routing planning and modelling, and rational cutting parameters by Taguchi for a more consistent product quality and less waste. These findings suggested that simulation modeling was an effective tool for reducing time to market and maximizing production in an agile environment. Popova and Popov (2021), by contrast, investigated the role of digitalization in production planning and called for ongoing education of workers to prepare them for automation. Their industrial employees had expressed an appetite for professional education because they understood how much education was necessary to remain competitive in an age of technological change. What they found was that implementing automation in production only worked if workers were capable of successfully negotiating technology.

Bedaka et al. (2021) introduced a camera-based position correction system to enhance autonomous production line inspection accuracy. The research applied automatic hand–eye calibration together with a perspective-n-point (PnP) algorithm to correct position errors during real-time operations, which resulted in greater reliability and efficiency in automatic optical inspection (AOI) tasks. Manufacturing environments experienced enhanced productivity and quality control through the implementation of this system. In contrast, Seitz et al. (2021) introduced a multi-agent system (MAS) aimed at enhancing flexibility and adaptability within Industry 4.0 production networks. They demonstrated the dynamic reconfiguration abilities of the MAS for production resources according to customer requirements and operational changes through seamless platform communication with the OPC UA standard. Their research findings demonstrated that the myYoghurt demonstrator system could effectively handle production processes throughout various facilities while ensuring manufacturing systems remained robust and adaptable. De Blasi et al. (2021) examined the application of Deep Reinforcement Learning (DRL) in automating a foosball system to simulate industrial process complexities. The research demonstrated that DRL could transfer simulation-trained control policies to real systems and showed promise for improving manufacturing automation.

The study by Koehler and Jing (2021) applied ML techniques to create automated improvement proposals for PLC-controlled manufacturing systems within automotive production. After examining production logs for inefficiencies, their method achieved cycle time reductions between 2.1 and 12.5 seconds per cycle. The implementation of expert knowledge during data preprocessing and the decision tree classifier resulted in a 99% accuracy rate for identifying improvement areas. Holubek et al. (2021) covered using Virtual Reality (VR) in the design of robotic workstations, which is a technology that can make designing a little easier than traditional approaches. The work showed that VR was an effective way to cut preproduction time, provide intuitive object control, and enable real-time inter-team communication to maximize the production yield. In contrast, Breaz et al. (2021) studied how industrial robots can be used in an incremental formwork process and studied kinematic simulation for manufacturing efficiency and accuracy. It was shown that the robots with six degrees of freedom could sufficiently cope with the high-level movement involved in incremental forming and even overcome singularity avoidance. This study focused on robots' agility and accuracy, making them more efficient in making complex parts. Selvi et al. (2021) focused on designing and manufacturing a multi-material 3D printer for soft robotics that could optimize production by making complex geometries and quickly curing silicone. Their work also ruled out molds, which are normally expensive and time-consuming, reducing production time. The research also revealed that the printer could print both conductive and non-conductive silicone, which would allow for soft robotics and medical uses.

Vasilev et al. (2021) introduced an advanced multi-robot system for automated welding, which incorporates real-time motion correction along with in-process Non-Destructive Evaluation (NDE) to enhance defect detection while reducing rework rates and production inefficiencies. The researchers showed that their system was capable of conducting inspections throughout multiple manufacturing steps, which enabled the early identification of defects and in-process repair opportunities. Inverse reinforcement learning (IRL) techniques allowed Sugisawa et al. (2022) to model manual decision-making processes in computer-aided process planning (CAPP) systems to solve machining sequence planning issues. The IRL-based methodology developed by the researchers effectively replicated human decision-making patterns in planning and confirmed its validity with limited data samples to achieve improved accuracy and efficiency in machining sequences. Naverschnigg et al. (2022) created a robot-based in-line measurement system for high-precision optical surface inspection, which achieved micrometer-level accuracy with a combined measurement uncertainty of 1.2 µm. The system demonstrated its ability to manage process variability effectively through its adaptable nature and seamless integration into production lines.

Guo et al. (2022) created an automatic method to develop a machining process knowledge base by using knowledge graphs and a hybrid algorithm to automate knowledge extraction, classification, and fusion. This method demonstrated superior knowledge extraction efficiency and quality, which resulted in higher F values compared to conventional techniques. In contrast, He et al. (2022) enhanced energy efficiency in manufacturing settings through the integration of multiple AGVs into their job-shop scheduling framework. The effective multiobjective evolutionary algorithm (EMOEA) developed by the researchers improved both AGV transport and machine setup operations while optimizing processing tasks to minimize machine waiting times alongside economic and environmental goals. The scheduling model showed better results compared to existing algorithms and highlighted the importance of AGVs in sustainable manufacturing practices. On the other hand, Qamsane et al. (2022) worked on merging Open Process Automation (OPA) with DT technologies to improve performance monitoring for process manufacturing systems. Their DT framework for real-time monitoring identified equipment and process anomalies to facilitate proactive maintenance and minimize downtime. The research demonstrated how DT technology can enhance manufacturing operations and boost productivity through timely system health information.

Pulatov et al. (2022) covered automation of production processes using energy-efficient asynchronous electric drives (and smart converter technology). They investigated how to build a pumping station operational algorithm that saves energy and is greener. The research focused on the business possibilities of harnessing these drives to optimize industrial performance. In contrast, Ismail et al. (2022) was about the rollout of Industry 4.0 in INCOM Egypt to reduce the "Handle a Product" inefficiencies in the wire and cable production line. They used Ould's Riva process model and discovered major inefficiencies due to manual data entry. Their idea of automating the process with an Enterprise Resource Planning (ERP) system made communication better, wasted less, and made the process more sustainable, economically and environmentally. Kukushkina et al. (2022), meanwhile, focused on multi-axis machine tools and CNC machining centers to automate manufacturing with rolling sheets. Their work concerned geometric parameter analysis, cost reduction, and volumetric error minimization through machine tools that gave them more precise and less expensive production processes.

The research by Fedosovsky et al. (2022) introduced a conceptual framework focused on sustainable hyperautomation within high-tech manufacturing operations for linear electromechanical actuators (LEMA). The researchers demonstrated how combining digital tools with modular designs and forward integration leads to production systems that make autonomous decisions through intelligent processes. The research clearly demonstrated that hyperautomation can optimize mass customization processes without compromising production efficiency. Kim et al. (2022) introduced a data-driven approach to estimate machine reliability parameters within smart production systems despite the failure of automated measurement systems. Production systems maintained productivity during equipment failures through continuous mathematical model updates enabled by buffer-related data from neighboring machines in their indirect estimation approach. In 2022, Gerling et al. (2022) investigated the implementation of ML techniques through the PREFERML AutoML system for error prediction automation in manufacturing settings. The study demonstrated that the system could improve algorithm optimization for predicting errors, which boosted production efficiency and cut costs, especially in countries where resource efficiency is essential due to high wages.

Binder et al. (2022) explored how to incorporate AI into adaptable production systems as part of Industry 4.0 development. Their research developed an Information Layer architectural framework for Reference Architecture Model Industrie 4.0 (RAMI 4.0) to connect production systems with information engineering. The authors validated their proposed architecture by conducting a real-world case study, which showed notable improvements in data management capabilities, AI integration efficiency, and production process optimization. The researchers Garouani et al. (2022) created AMLBID as a meta-learning solution to automate the selection and setup of ML algorithms to tackle ML implementation issues in manufacturing. The study showed that AMLBID outperformed competing AutoML tools when tested on 400 manufacturing datasets by delivering better predictive performance and computational efficiency while reducing reliance on human ML expertise. Wurster et al. (2022) investigated automation techniques for disassembly systems in remanufacturing by developing a hybrid system that merges manual and autonomous workstations. The research team used RL to control uncertainty in the disassembly process while simulation helped to evaluate RL versus established heuristic approaches. The research demonstrated that RL substantially decreased operational failures and achieved resource cost optimization, which indicates its capability to boost efficiency in complex manufacturing settings. Zhou et al. (2022) developed DL techniques for 3D point cloud analysis to enable object detection and localization in collaborative mobile robot manipulators within small and medium-sized enterprises (SMEs) for automation enhancement. The system they developed demonstrated success during name tag production and plug-in charging experiments by solving issues with uneven lighting and unpredictable object placement to improve production efficiency. The research team led by Liu et al. (2022) developed two forward dynamics algorithms to counter positioning errors in industrial robots with flexible joints by estimating deflections. The researchers applied Lie theory to simulate a 6-DOF serial robot, which demonstrated that their algorithms achieved better machining accuracy by effectively compensating for dynamic coupling effects.

Balanji et al. (2022) introduced a vision-based calibration system that improves industrial robotic manipulators' precision over time by rectifying positional and orientational errors with ArUco markers and kinematic modeling. The study showed that calibration errors decreased substantially, reaching 2.5 mm for positioning and 0.2° for orientation. Izagirre et al. (2022) conducted predictive maintenance research through the design of a synchronized data acquisition network for assembly line industrial robots with the help of programmable logic controllers to identify degradation patterns. The automotive manufacturing line deployment demonstrated the practicality of torque signal measurements combined with one-class novelty detection models to identify faults. Funes-Lora et al. (2022) investigated educational robotics integration by building their first-year engineering course on manufacturing applications of industrial robots along with CAD design and additive manufacturing and utilized a flipped classroom approach to increase student engagement.

Xie (2022) used multisensor data fusion with binocular vision to improve the versatility and accuracy of industrial robots for material handling. It was possible to design a five-axis robotic system with high-resolution vision to aid object recognition and grasping in motion. Kinematics modeling and the new camera calibration algorithms all helped us calibrate the cameras accurately, showing that the convergence of vision and information helped the robot to perform better in dense environments. In contrast, Heuss et al. (2022) devised the REpac framework, a skills-based solution for industrial robots that facilitates the easy setup and scaling of robotic tasks. This model minimizes expertise so that the task can become gradually more complex, from simple actions to self-directed planning. The experiment had shown to be successful in practical cases, such as LEGO assembling, in which robots did not fail to transition from predefined functions to more advanced, customized functions. The research demonstrated how the architecture enhances agility and utilization in dynamic production environments. Alghloom and Ay (2022) aimed at the design and simulation of a robotic arm for precision microfriction stir welding. The study focused on the robotic arm's capabilities of precision, sustainability, flexibility, and affordability when it came to welding. The structural and transient analysis in ANSYS during the design validated the arm's endurance in service. This robotic arm was much more accurate and smaller in operation compared to a traditional welder and benefited from huge increases in production capacity.

Novák and Vyskočil (2022) created a DT for increasing flexibility and efficiencies in industrial production systems of Industry 4.0. They had already demonstrated that DTs were able to be integrated successfully into production planning, with the data being analyzed in real time, production lines adjusted dynamically, and downtime due to errors minimized. This strategy was based on flexibility in a dynamic market environment. Gualtieri et al. (2022) focused on human-robot collaboration created an algorithm for job assignment in manual assembly systems. They did their research to ensure that workers were safe, ergonomically optimized, and efficient by using the human brain. The efficacy of the algorithm was revealed in an industrial case study as better working conditions for operators and better performance for the company, which led to sustainable and efficient production.

The following table offers a comparative analysis of research papers on manufacturing advancements in automation and digitalization during the years 2021 and 2022. The table provides detailed information about each research paper including study focus and application alongside methodology and dataset as well as key findings and metrics and any unresolved issues or gaps that remain.

**Table 3.** Comparison of Studies on Advancements in Automation and Digitalization in Manufacturing (2021–2022).

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Kozlova et al. (2021) | Automation of technological processes in mechanical engineering for enhancing efficiency, product quality, and reducing operational risks | Outlined key stages for realizing automatic control systems in mechanical engineering with a focus on case studies, such as casting process automation | Improved production efficiency, product quality, and reduced defects. Automation led to cost savings and reduced workforce needs | Automation's broader applicability was demonstrated, but more work is needed on implementing these systems across different industries |
| Khrustaleva et al. (2021) | Automating production engineering for custom and small-batch production through simulation modeling and optimization techniques | Developed a simulation model using a multi-level approach to control production elements, select cutting parameters, and analyze system constraints with the Taguchi method | Simulation model showed improved production planning, cutting accuracy, and reduced waste. Enhanced operational efficiency and product quality | Although the model demonstrates clear benefits, further refinement is needed for scalability and adaptation to more diverse production systems |
| Popova and Popov (2021) | Automation of production planning and importance of continuing education for employees in the context of digitalization | Survey with 40 employees from industrial enterprises, Ural Polytechnic Institute | 80% of respondents aspire to become production managers, 95% recognize the importance of digitalization; need for continuous education | Unresolved issues on how to ensure effective integration of education with automation, addressing concerns about job losses and complexity in operations |
| Bedaka et al. (2021) | A Camera-Based Position Correction System for Autonomous Production Line Inspection | Developed an autonomous robot-guided inspection system with automatic position correction using a calibration process and PnP algorithm | Improved accuracy in optical inspection tasks with robot-guided systems. Enhanced product quality evaluations despite position errors in production | Successful in experimental setups but may require further development for varying production environments with different types of positioning errors |
| Seitz et al. (2021) | Development of a MAS for Industry 4.0 to enhance production networks | Use case of the myYoghurt demonstrator, OPC UA for communication standards | MAS can effectively manage production across different facilities; system adapts to failures and changes in layout | Unresolved issues around the scalability of MAS and how to handle more complex real-world production environments |
| De Blasi et al. (2021) | Use of DRL to control a Foosball system as a manufacturing process model | Simulation-based DRL with domain randomization | DRL algorithms can effectively control physical systems and improve training speed and safety | Unresolved issues in transferring learned policies to broader and more complex industrial systems |
| Koehler and Jing (2021) | Automating improvement suggestions for legacy PLC-controlled manufacturing equipment using ML | Analysis of PLC event logs using Python, decision tree classifier | 99% accuracy in classifying log data, potential improvements of 2.1 to 12.5 seconds per cycle | Unresolved issues around generalizing findings to all types of manufacturing processes and integrating expert knowledge into automated systems |
| Holubek et al. (2021) | Using VR for designing robotic production systems to enhance efficiency and reduce design errors. | Compared traditional CAD-based design with immersive VR simulations. Tested on robotic workstations for welding and placement operations | VR-based design reduced preproduction time and enabled real-time modifications. Provided immediate feedback on dimensions, enhancing safety and efficiency | Broader application of VR for complex robotic systems is needed. Cost-benefit analysis for VR implementation in different industries |
| Breaz et al. (2021) | Use of industrial robots in incremental forming, focusing on kinematic simulation and movement precision | Simulated incremental forming using industrial serial robots with six degrees of freedom, ensuring proper movement coordination and singularity avoidance | Simulation results indicated improved flexibility and precision in manufacturing complex shapes. Robots effectively avoided singularities in movement | Further experimental validation in real-world manufacturing settings is required. Optimization for material-specific forming challenges needs exploration |
| Selvi et al. (2021) | Designing a multi-material 3D printer for soft robotic structural elements to enhance production efficiency and enable complex geometries | Development of a multi-material 3D printer with a mixing chamber for silicone and conductive materials; mechanical and electrical testing (ASTM D412) | Eliminated need for molds, reduced production time by 40%, achieved electrical resistivity of $1.87\times10^{-4}$ Ωm, and maintained high mechanical strength | Further research needed on optimizing material properties and integration with larger production systems |

**Table 3.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Vasilev et al. (2021) | Sensor-enabled multi-robot system for automated welding with in-process NDE | Development of a real-time multi-robot system with external positional control; defect detection tested in three welding stages | Improved defect detection, enabled in-process repair, reduced rework rates, and enhanced production efficiency | Challenges remain in integrating the system into various industrial welding setups and improving sensor fusion techniques |
| Sugisawa et al. (2022) | Machining sequence learning via IRL for CAPP systems, enhancing quality and cost efficiency | IRL, Markov Decision Process (MDP), convolutional networking. Dataset: Small dataset for validation | Validated IRL method successfully mimics planner's decision-making process; enhances machining sequence planning | Challenges in managing rule interference and processing challenges in existing methods |
| Naverschnigg et al. (2022) | Flexible robot-based in-line measurement system for high-precision optical surface inspection | Laser triangulation, 2D-scanning, Lissajous trajectories, edge detection for feature detection. Dataset: 25x25 mm scan area | High accuracy: Measurement uncertainty 6.4 µm, accuracy 2.2 µm. Combined standard uncertainty of 1.2 µm | Adaptability to varying production environments |
| Guo et al. (2022) | Automatic method for constructing a machining process knowledge base using knowledge graphs for intelligent process design | Knowledge graph construction, BERT-BiLSTM-CRF, fuzzy comprehensive evaluation, hybrid algorithm for knowledge fusion. Dataset: Process texts and machining domain data | Improved efficiency and quality in knowledge extraction; F values increased by 7.35% over BiLSTM-CRF | Redundancy elimination during knowledge fusion; handling of large datasets |
| He et al. (2022) | Energy efficiency optimization in job-shop environments with AGVs using multiobjective evolutionary algorithms | EMOEA, Taguchi analysis, computational experiments on benchmark instances and real-world case | Improved energy efficiency, reduced machine waiting times, and optimal balance between economic and environmental objectives. Outperformed other algorithms | Scalability of the model for larger production systems with more AGVs |
| Qamsane et al. (2022) | OPA and DT technologies for performance monitoring in process manufacturing systems | DT framework for monitoring pump, control loop, and process performance. Dataset: Process data for performance monitoring | Successful real-time performance monitoring; proactive maintenance and reduced downtime. KPIs used for pump health monitoring | Extension of the model to include more measurements and integration with physical systems for enhanced monitoring |
| Pulatov et al. (2022) | Automation using energy-efficient asynchronous electric drives for production mechanisms, particularly pumping stations | Comparative analysis of electric drives, algorithm development for pumping stations | Improved energy efficiency and cost reduction in production mechanisms, enhanced by intelligent converter technology | Future research needed on integration with other automation systems and expansion to other industries beyond pumping stations |
| Ismail et al. (2022) | Implementation of Industry 4.0 at INCOM Egypt to enhance sustainability and automate production processes | Process modeling using Ould's Riva method, interviews for qualitative data collection, and proposal of ERP system for automation | Proposed ERP system could improve data accuracy, reduce delays, and enhance environmental and economic sustainability | Challenges in fully automating production and the integration of new technologies with legacy systems |
| Kukushkina et al. (2022) | Optimization of manufacturing processes using multi-axis machine tools and CNC machining centers for cost-effectiveness | Geometric parameter calculation for bending objects, analysis of multi-axis machining tools, and error reduction techniques in CNC systems | Significant improvements in design flexibility, precision, and reduced material costs, with error reduction enhancing manufacturing accuracy | Integration of advanced machining technologies in smaller or less advanced production setups |
| Fedosovsky et al. (2022) | Sustainable hyperautomation in high-tech manufacturing with a focus on LEMA | Development of a conceptual framework, implementation of digital tools, modular design, and forward integration for enhanced customization and automation | Development of a 3-level factory model, mass customization for up to 1000 variants of LEMAs, and autonomous decision-making | Integration of advanced digital tools across all production stages and balancing cost-effectiveness with innovation in globalized markets |
| Kim et al. (2022) | Automated estimation of machine parameters in production systems for enhanced reliability | Indirect estimation approach using buffer data from neighboring machines and overall system information | Continuous updating of the mathematical model of production systems, even in the absence of direct measurements | Improvement of indirect estimation methods for real-time accuracy in large-scale production systems |
| Gerling et al. (2022) | Automated ML (AutoML) for predicting errors in manufacturing processes | Use of PREFERML AutoML system for model selection and hyperparameter optimization, with a focus on cost-based metrics | Improved error prediction accuracy, optimized models leading to cost reductions, and better decision-making for quality control | Optimization trade-offs between computational efficiency and prediction accuracy in diverse industrial contexts |
| Garouani et al. (2022) | Using meta-learning for automated algorithms selection and configuration: an experimental framework for industrial big data | Introduces AMLBID, a meta-learning tool for automating ML algorithms selection. Tested on 400 real-world manufacturing datasets | AMLBID outperforms TPOT and Auto-sklearn in predictive performance and computational efficiency | No exploration of potential limitations in diverse industrial datasets or scalability for larger systems |

**Table 3.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Binder et al. (2022) | Towards a domain-specific information architecture enabling the investigation and optimization of flexible production systems by utilizing AI | Proposes an architecture for integrating AI in flexible production systems within Industry 4.0. Real-world case study for validation | Significant improvement in RAMI 4.0 application. Enhanced AI integration and better data management | Challenges in implementing RAMI 4.0 in real-world scenarios, requiring further practical applications |
| Garouani et al. (2022) | Using meta-learning for automated algorithms selection and configuration: an experimental framework for industrial big data | Introduces AMLBID, a meta-learning tool for automating ML algorithms selection. Tested on 400 real-world manufacturing datasets | AMLBID outperforms TPOT and Auto-sklearn in predictive performance and computational efficiency | No exploration of potential limitations in diverse industrial datasets or scalability for larger systems |
| Wurster et al. (2022) | Modelling and condition-based control of a flexible and hybrid disassembly system with manual and autonomous workstations using RL | Proposes a hybrid disassembly system with manual and autonomous workstations. Tested with a RL-based control approach | RL significantly reduced operational failures, improved resource cost balancing, and optimized decision-making | Integration of RL with other complex systems and long-term performance evaluation in real-world settings |
| Zhou et al. (2022) | Learning-based object detection and localization for mobile robot manipulators in SMEs | Use of 3D point clouds, DL, and 2D camera calibration for object detection; experiments on name tag production and plug-in charging | Enhanced automation in SMEs, improved object detection accuracy, and successful implementation in real-world production tasks | Challenges in scaling the solution for complex industrial environments with dynamic object interactions |
| Liu et al. (2022) | Deflection estimation of industrial robots with flexible joints to improve machining accuracy | Two forward dynamics algorithms (implicit numerical integration and numerical iterative estimation) using Lie theory; simulations on a 6-DOF robot | Developed effective deflection estimation algorithms, improving positioning accuracy in industrial robots | Need for experimental validation in real industrial applications and further refinement of algorithms for dynamic loads |
| Balanji et al. (2022) | Vision-based calibration framework for industrial robotic manipulators | Uses a single camera and ArUco markers for tracking; employs the product of exponentials method for kinematic modeling; tested on a 6-DOF UR5 robotic manipulator | Position errors reduced to 2.5 mm and orientation errors to 0.2°; improved robot accuracy in real-world applications | Potential improvements in real-time calibration speed and adaptability to different robot types |
| Izagirre et al. (2022) | Synchronized data acquisition network architecture for industrial robot predictive maintenance | Uses PLC-based synchronization for extracting robot signals; implemented in an automotive assembly line; employs one-class novelty detection models | Effectively detects robot joint failures in production; first study using torque signals for one-class models | Enhancement of AI models for better predictive accuracy; scalability to multiple manufacturing sites |
| Funes-Lora et al. (2022) | Integration of industrial robots in a first-year engineering course | Course includes CAD, additive manufacturing, and robot programming; flipped classroom model applied during the pandemic | Positive student feedback; improved engagement and understanding of manufacturing concepts | Scaling the approach for larger student groups; optimizing flipped classroom methodologies for technical courses |
| Xie (2022) | Enhancing industrial robot grasping using multisensor data fusion and binocular vision | Development of a five-axis robot with binocular vision, camera calibration, kinematics analysis, and communication protocol setup | Improved grasping accuracy, successful 3D point cloud matching, and real-time object identification | Limited adaptability to highly unstructured environments; further work needed on sensor robustness |
| Heuss et al. (2022) | Extensible framework (REpac) for skills-based industrial robot applications | Three-stage framework: primitive skills execution, shared memory (skills blackboard), and automated task planning; tested on LEGO assembly tasks | Allows companies to gradually expand robot capabilities with minimal expertise; robots can autonomously determine action sequences | Integration with AI-driven optimization for better decision-making and expanding use cases beyond predefined tasks |
| Alghloom and Ay (2022) | Design and analysis of a novel 6-DOF robotic arm for high precision micro friction stir welding | Designed with high-speed motors and revolute joints; analyzed using ANSYS for structural and transient performance | High precision, sustainability, flexibility, and cost-effectiveness in welding; compact operational footprint | Further studies needed for real-world validation in various materials and long-term durability testing |
| Novák and Vyskočil (2022) | Digitalized Automation Engineering of Industry 4.0 Production Systems and Their Tight Cooperation with DTs | Focuses on DT-based automation and integration for Industry 4.0. Uses a testbed to validate the approach | Enhanced production flexibility and efficiency with DT integration, reduced manual re-initialization, and improved planning through process mining | Limited focus on scaling DT applications in larger and more diverse manufacturing environments |

**Table 3.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Gualtieri et al. (2022) | Integration of collaborative robots (cobots) in manual assembly systems for safety, ergonomics, and efficiency | Developed an algorithm for human-robot task allocation, validated through an industrial case study | Improved working conditions, reduced cognitive and physical load, enhanced company performance, and overcame technical barriers to Industry 4.0 adoption | Needs further validation in diverse industries; real-time adaptability of the algorithm remains unexplored |

### 7.3. Advancements in Industrial Automation and Control (2023–2024)

Nwulu et al. (2023) dedicated themselves to maximizing plant reliability and safety with the right process automation and control engineering. Their work focused on the control technology (PLCs and Distributed Control Systems, DCS) to monitor and regulate industrial processes to avoid human error and optimize processes. Incorporation of safety equipment, including Safety Instrumented Systems (SIS), added to the risk control. Toro et al. (2023) investigated the automation of quality control in manufacturing by optical character recognition (OCR). Their eDOCr tool for engineering drawing read accurately with a 94% F1 score in text recognition. This system improved quality control processes by automating data extraction from intricate mechanical drawings.

The research conducted by Fowler et al. (2023) demonstrated that 5G technology improves AGV operations in smart factories by enabling high-resolution video streaming and long-distance teleoperation, which increases the flexibility and mobility of industrial systems. The team established a private 5G network testbed to enable real-world experimentation and benchmarking against Wi-Fi technology for assessing 5G's capabilities in factory automation. Eckhart et al. (2023) enhanced CPPS security by infusing quality control protocols into security measures through their QualSec method. The researchers developed a framework to detect security risks that affect product quality, employing Petri nets for attack path analysis and cascading effect evaluation. The study showed that implementing security-by-design methods can effectively reduce vulnerabilities present in CPPSs. Borkin and et al. (2023) studied brain-computer interface (BCI) systems used to operate production manipulators, which allowed physically disabled individuals to control industrial equipment. The researchers proved that electroencephalogram (EEG) signals processed through ML algorithms can achieve real-time control with 100% experimental accuracy but require individualized calibration.

Vapski and Pandilov (2023) automated part of a line with a new profile studs packaging machine and realized a 4% increase in speed of production, even though maximum achievable speed was decreased slightly. They found that partial automation brought productivity, savings, and safety improvements through the use of machine guards and safety features. In contrast, Evtushenko et al. (2023) automated the terrain model generation for earthworks by applying algorithms and big data to flood-prone zones, solar radiation, and infrastructure. They showed that automated terrain modeling could be used for a variety of engineering problems and that data and algorithmic processing were crucial for ensuring that models could be effective and available. Annisa et al. (2023) automated charcoal briquette production in Kampoeng Oase with an automatic press machine, increasing production from 3 kg/day to 50 kg/week. The research showed the benefit of automation in labor reduction, productivity improvement, and sustainability.

The team led by Naranjo et al. (2023) conducted research on hauler automation for tunnel debris removal that resulted in the development of a 25-ton autonomous truck capable of operating in manual, teleoperated, and autonomous modes. The study exhibited a substantial increase in safety and productivity through enhanced operational efficiency in debris removal, which was validated by successful real-world testing in civil engineering contexts. Deng et al. (2023) investigated mass customization methods in manufacturing using RL techniques. Through their RL-based system, production lines were autonomously reconfigured according to live customer demand, resulting in quicker setup times and higher throughput along with improved flexibility. Simulation results demonstrated that RL systems performed better than traditional methods by achieving faster production speeds and enhanced adaptability. The research by Wilk-Kołodziejczyk and colleagues in 2023 (Wilk-Kołodziejczyk et al., 2023) utilized ML for casting production to forecast the mechanical properties of Austempered Ductile Iron (ADI). The researchers developed models that used gradient boosting and random forest algorithms to optimize production parameters, which minimized the need for physical testing and enhanced foundry efficiency. The research demonstrated ML methods as efficient tools for prediction while highlighting the significance of managing missing data.

The study by Thylén et al. (2023) investigated the human and organizational challenges that occur when AGVs are introduced into production facilities and demonstrated that a comprehensive approach combining human elements with technological and organizational aspects is essential. The team highlighted several critical challenges for AGV integration, such as new work procedure requirements, operator training needs, and employee acceptance support while providing actionable recommendations to overcome these obstacles. The research by Vasilko and Murčinková (2023) focused on decreasing production cycle duration through improved tool exchange procedures within manufacturing operations. The researchers found that redesigned tool holders, which enable faster and more precise tool exchanges, can substantially minimize machining time. The study found that automation within tool exchanges resulted in a 2.4 times faster machining process for parts with specific surface roughness parameters. Makris et al. (2023) developed a solution to automate the assembly process for non-rigid objects. The combination of computer vision and advanced robotic manipulation techniques enabled the development of an automated system that precisely assembles flexible materials. The system succeeded in both decreasing assembly time and enhancing reliability when compared to traditional techniques.

Bi et al. (2023) explored technical debt within automation systems by examining its origins and effects as well as its defining properties. Technical debt build-up from inadequate documentation alongside changing requirements and tight timelines results in increased maintenance expenses while diminishing both system agility and software quality. The mixed-methods study showed that regular code reviews are crucial for maintaining productive automation systems within production engineering to manage technical debt effectively. Gürel et al. (2023) were concerned with scheduling a two-gripper material handling robot and emphasized energy savings. Using a scheduling algorithm that saved the least amount of energy and the most productivity, they saved up to 30% of energy. Their work stressed the necessity of energy efficiency in robotic processes, which led to savings and sustainability in manufacturing. However, Anciferov et al. (2023) devoted themselves to the engineering analysis of a robot cell for machine-building production with Simcenter 3D software for CAD and Computer-Aided Engineering (CAE) analysis. They had written about how we should conduct an exhaustive engineering analysis of robotic design to make sure that the structure, stability, and effectiveness are maintained. They determined the design was safe and functional, and this shows that the tools of high-level analysis work well to develop reliable robots in production.

Mueller et al. (2023) proposed a novel manufacturing paradigm with collaborative robotics and additive manufacturing in Industry 4.0 that can make production more flexible and sustainable. They described a system of real-time data acquisition in the Karlsruhe Institute of Technology that allowed manufacturing processes to be monitored and optimized in real time. This synergy was found to support value chains by making production processes responsive to demand variations. In contrast, Mohanty et al. (2023) focused on industrial robotic programming in additive manufacturing, for example, of aerofoil wing manufacturing. They tended to focus on using multi-phase 3D printing to create complex geometries with high accuracy and showed how robotics can design complex parts that are impractical to manufacture. Furthermore, Nagy et al. (2023) explored robotics in smart manufacturing, especially in SMEs, by addressing barriers to Industry 4.0 technologies. In their experience, economics, shortage of human capital, and cybersecurity problems are the biggest challenges facing SMEs in Europe when trying to implement sophisticated robotics and automation technologies. Collaboration with larger companies and government backing, the research suggested, might make some of these problems less problematic.

Yao et al. (2023) introduced a new mixed-integer linear programming (MILP) model for the job shop scheduling problem with mobile robots (JSPMR) that focuses on optimizing both machine scheduling and transport logistics in intelligent workshops. Through validation with benchmark instances and real-world applications, their model showed considerable makespan minimization improvements by merging transport and processing activities effectively. Rahman et al. (2023) investigated semi-automated assembly line balancing problem (SAALBP) by integrating human-robot teamwork alongside sustainability and processing time variation considerations. A memetic algorithm that merges Q-learning with Monte Carlo simulation enhanced their MILP model, which surpassed traditional methods in achieving better optimization of economic, environmental, and social goals. Peralta et al. (2023) developed advanced vision-based techniques for robotic (un)screwing tasks, which leveraged segmentation neural networks and force feedback to boost performance accuracy and adaptability across different conditions. The research findings indicated almost flawless detection rates combined with real-time processing capabilities, which enhanced both precision and dependability in automated manufacturing systems.

Zhou et al. (2023) devised a hierarchical adaptive solution for industrial robot positioning error compensation that integrates incremental learning with a fixed-length memory window and model reconstruction updates. Continuous model optimization enabled their study to achieve substantial gains in positioning accuracy for industrial robots by addressing both geometric and non-geometric errors in machining applications. Xie et al. (2023) developed a parallel machining robot (PMR) with an attitude coupling adjustment mechanism and a new control method to improve machining efficiency and accuracy for curved part production. In complex machining tasks that involve open-and-close angle conversion features, their approach excelled by delivering better toolpath execution than traditional serial machine tools (SMTs). Malhan et al. (2023) investigated trajectory generation for robotic manipulators along semi-constrained Cartesian paths by creating an iterative graph-based technique that included several tool center points (TCPs) to enhance trajectory planning for industrial tasks like cutting and welding. The method improved robotic operations both in flexibility and efficiency through simplified trajectory computations. Lin et al. (2023) explored real-time charging scheduling for AGVs within cyber-physical smart factories through feature-based RL to maximize utilization without increasing congestion. This investigation defined the problem using a Markov decision process framework and showed that their new algorithm surpassed both traditional rule-based and model-based methods to boost AGV efficiency.

The research by Saroar et al. (2024) focused on automation tools used in software production through GitHub Marketplace that provide developers access to over 8,000 tools. The research analysis of tools and academic studies demonstrated a gap between industry automation priorities for continuous integration tasks and academic research that examines code quality and testing methods. Real-world production environments need research on automation to better align with practical applications. In contrast, Alvarado et al. (2024) studied how automation could be applied to the evaporation process during sugar cane production without centrifugal methods in Colombia. The researchers developed a system that combines sensors and automation strategies to maintain optimal sugar levels and syrup quality while controlling temperature, which leads to better production efficiency and sustainable operations. The research demonstrates that automation improves economic and environmental performance within production systems through sustainable practices that align with Sustainable Development Goal 9.

Kandalova (2024) studied automation in fuel and energy complexes with a focus on software modeling and client-server systems to improve data management and process control. These technologies, the research concluded, can be integrated to make energy operations much more efficient and affordable. In contrast, Janecki et al. (2024) discussed issues faced while adopting virtual engineering for production planning in the automotive space. Their studies showed a lack of quality assurance due to manual activities and noted the need for standardization to bring out the full capabilities of virtual engineering. This study suggested that by overcoming these issues, production planning and ramp-up could be automated more effectively. Gusev et al. (2024) focused on the production of beer, looking at the potential of automation to increase efficiency, consistency, and quality control. The results they found were that automation made operations more efficient and cheaper but also that it was difficult to adopt, particularly because of the high upfront costs and skill required.

Dihovični and Miščević (2024) tried bringing Industry 4.0 practices into production engineering using CNC machines and industrial robots in an adaptable cell. They found that real-time Computer-Aided Manufacturing (CAM) programming, tool path optimization, and numerical control (NC) code generation led to higher efficiency, shorter cycle times, and extended tool life thanks to their studies. The most important part was the simulation and optimization via a DT, which sped up production without changing the code. In contrast, Lora et al. (2024) focused on design automation of cyber-physical manufacturing systems in the DeFacto project. They invented new modeling paradigms, scalable algorithms, and service-based software architectures for computing and physical systems to be joined in production. Their findings suggested that system-level models and assume-guarantee contracts can be key to making better use of complex production networks and were useful for future research and use in CPS. Burduk et al. (2024) investigated smart systems in production engineering and maintenance. Their work showed how to leverage the power of algorithms and intelligent solutions to better manage resources, mitigate downtime, and automate workflows. The research was all about being interdisciplinary, bringing together knowledge from multiple fields to enhance productivity and effectiveness in manufacturing facilities.

In a recent study by Wei et al. (2024), researchers examined the impact of automation upgrades on worker well-being within Guangdong Province's manufacturing industry and discovered that automation leads to extended working hours while causing "deskilling," which results in the loss of workers' specialized skills through dependence on automated systems. The researchers showed labor unions and human capital help to safeguard workers but expressed worries about negative mental health impacts from excessive workloads and challenging wage systems under automation. Abicht et al. (2024) introduced a cognitive robotic system for improving production automation in brownfield settings. This system replicates human operator functions without demanding extensive control system changes and provides flexible automation options for industries dealing with labor shortages and demand fluctuations. The research showed cognitive robots can boost productivity through operator behavior replication and serve as a budget-friendly automation solution for economically challenging environments.

Li et al. (2024) developed robotic assembly line balancing methods that included carbon footprint considerations and introduced both a mixed-integer programming model and an optimized particle swarm algorithm for better production planning. The team's findings demonstrated better performance than traditional methods and highlighted the need to maintain operational efficiency while protecting the environment. The study by Polonara et al. (2024) demonstrated how collaborative robotics integration into automotive parts production at SMEs led to enhanced production performance and safety while also showing adaptability through a detailed case study. SMEs experienced benefits but also faced challenges because of resource constraints.

Tripathi (2024) gave an excellent description of robotics applications in the automotive industry, with applications including material handling, welding, painting, and assembly line automation. The paper emphasized using cobots and ML to optimize robot functionality, citing a robotized screw tightening case study. The work of Ashmitha and Arumugasamy (2024) focused on the production of cars, on the other hand, was devoted to examining how robotics performed better than humans. Statistical research found that robots were much more productive, safer, and cheaper to use than human employees and that robots needed to constantly be upgraded to optimize their usage. Smith et al. (2024) discussed industrial robotics in mechanical engineering in general and its transformative effect on accuracy and efficacy. They pointed to technical constraints, cost, and workforce migration as barriers but also to the possibilities of AI-based robots, cobots, and advanced sensor systems.

Ade-Omowaye et al. (2024) analyzed how robotics and automation were changing engineering in the digital economy. They did a systematic literature review on current technologies and their application and emphasized the economic, social, and moral value (cutting costs, productivity, displacement of workers). Bai (2024) documented the history of robotics, from the earliest industrial robot, Unimate, and looked at how it shifted from mere machines to systems with impact across industries. Bai spoke of the multidisciplinary nature of robotics and its use in industry, medicine, and spaceflight, as well as public problems such as displacing workers and privacy issues. Jović et al. (2024) focused on VR as a means to apply it to production robotics in order to optimize training, human-robot cooperation, and overall productivity. Then they discovered that VR simulations can provide real-world training scenarios to reduce mistakes and better model robotic behavior in production.

The study by Bručienė et al. (2024) showed that robot-assisted sugar beet production resulted in less greenhouse gas (GHG) emissions at 27.18 kg $CO_2$eq per ton and achieved a sustainability index of 13.72 to demonstrate solar-powered robotic systems offer environmental advantages in farming. Yao et al. (2024) focused on task reallocation between humans and robots in production workshops by using a dynamic model of human fatigue to enhance both efficiency and worker safety. The research applied a fatigue feature extraction method along with an upgraded genetic algorithm to achieve more adaptable task allocation. In 2024, Guo (2024) carried out research on human-robot team collaboration during aircraft assembly by using MILP and constraint programming (CP) to handle scheduling with various constraints. CP demonstrated superior performance to MILP when addressing real-world scheduling problems, which led to improved efficiency in synchronized production-logistics operations. Nguyen and Duy (2024) developed a contour-matching approach using Hu moments to determine moving objects' positions in low-cost production lines through robotic grasping with incomplete visual data. Their approach delivered centroid estimation with 2.2-pixel precision in image space and 1.8 mm precision in 3D space, which enhanced robotic precision when manipulating objects.

The following table presents a comparative review of recent studies on industrial automation and control, highlighting their focus areas, methodologies, key findings, and unresolved research gaps.

**Table 4.** Comparative Analysis of Papers on Advancements in Industrial Automation and Control (2023–2024).

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Nwulu et al. (2023) | Promoting plant reliability and safety through effective process automation and control engineering practices | Examines process automation in industrial plants using PLCs, DCS, and safety systems to enhance plant reliability and safety | Reduced human error, improved safety through automation, integration of SIS and ESD, and enhanced real-time decision-making | No detailed exploration of challenges in integrating automation and control systems in different types of plants or their long-term effectiveness |
| Toro et al. (2023) | Automation of quality control in manufacturing through OCR on engineering drawings | Development of eDOCr tool, five-stage methodology, image processing, and text recognition | Precision and recall of 90%, F1-score of 94%, character error rate of 8%, effective automation for interpreting EDs | Challenges in handling special symbols and complex layouts in mechanical drawings, further refinement of OCR tools |
| Fowler et al. (2023) | Integration of 5G in AGVs for smart factories, enhancing automation and teleoperation | Development of 5G private network testbed, comparison with Wi-Fi, experimental evaluation | 5G enhances AGVs with long-distance teleoperation and high-resolution video streaming, improving operational efficiency and adaptability | Challenges related to sustainability and supply chain resilience in digital manufacturing |
| Eckhart et al. (2023) | Automation in CPPS, integrating quality with security for risk identification | Introduction of QualSec method, semantic representation of engineering knowledge, Petri nets for risk analysis | QualSec improves security risk identification in CPPSs by considering quality aspects, helping protect product quality from malicious activities | Need for broader application and scalability of QualSec in diverse industrial settings |
| Borkin et al. (2023) | Use of BCIs in controlling production manipulators, particularly for individuals with physical disabilities | EEG signal analysis, ML algorithms, experimental testing with human participants (4 subjects) | 100% accuracy in command identification, proof of concept for BCI-PLC integration for inclusive automation | Personalized calibration and expanding command range needed for broader real-world applications |
| Vapski and Pandilov (2023) | Partial automation of production line to improve productivity, safety, and competitiveness | Design and implementation of automated packaging machine, analysis of pre-automation process efficiency | 4% increase in production speed, improved efficiency, safety enhancements through machine guarding | Full automation not yet achieved, need for further improvements in operational consistency |
| Evtushenko et al. (2023) | Automation of the process of preparing the production of earthworks. The paper focuses on automating terrain model preparation for tasks like flooding modeling, solar radiation, and infrastructure planning | Development of analog-discrete terrain models using big data processing and algorithms. Examples of structured data sources for model creation | Enhanced decision-making in engineering, including applications in flooding analysis, solar radiation calculation, and infrastructure planning. Introduction of algorithmic techniques for terrain model construction | Unresolved gaps in the real-time application of these models and scalability for large infrastructure projects |
| Annisa et al. (2023) | Automation of the Bricket Charcoal Press Machine in Kampoeng Oase, Surabaya. The research aims to increase production efficiency of charcoal briquettes and reduce labor needs | Design and implementation of an automatic press machine including a milling machine and a press machine for briquette production. Data on labor reduction and output improvement | Reduction in labor from 6-8 workers to 2-4 workers. Increased production capacity to 50 kg per week. The use of waste materials for briquette production | Unresolved issues related to scaling up the system for larger production volumes and potential impacts on environmental sustainability |
| Naranjo et al. (2023) | Automation in tunnel construction with a focus on debris removal using an autonomous 25-ton hauler truck | Development and testing of an autonomous hauler truck for tunnel construction. Real-world testing in civil engineering companies | Key features include flexible operational modes (manual, tele-operation, autonomous), obstacle detection, and GPS integration. Positive impact on safety and operational efficiency in tunnel construction | Unresolved gaps include integration with different types of tunnel construction projects and further improvements in obstacle detection algorithms |
| Deng et al. (2023) | Mass customization with RL in production engineering. The study focuses on the automatic reconfiguration of production lines | Implementation of a RL framework to optimize production line configurations. Simulated production environment for testing | Improved production line efficiency, reduced setup times, and increased throughput. RL outperformed traditional methods in production speed and flexibility | Potential for future research on more complex RL algorithms and MASs for further adaptability |
| Wilk-Kołodziejczyk et al. (2023) | Selection of casting production parameters using ML and data supplementation methods to improve foundry production efficiency | Use of ML algorithms (Random Forest, Gradient Boosting, Multilayer Perceptron) to predict mechanical properties in casting processes. Experimental validation with laboratory melts | Gradient Boosting achieved the best predictive performance for mechanical properties. Successful validation of predictions with laboratory melts | Unresolved issues related to the handling of missing data in large-scale industrial settings and the generalizability of the model across different foundries |

**Table 4.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Thylén et al. (2023) | Challenges in introducing AGVs in production facilities, focusing on human and organizational challenges | Case studies in production settings, Human, Technology, and Organisation (HTO) model application | Identified challenges include new work procedures, operator knowledge requirements, and employee acceptance. Suggested actions for successful AGV implementation | Need for further research into the long-term impacts of AGVs on employee roles and organizational structures |
| Vasilko and Murčinková (2023) | Reduction in production cycle time through automated cutting insert exchanges and tool holder designs in machining | Experiments with new tool holder designs and different cutting conditions on a conventional lathe | 2.4x decrease in machining time using a double cutting tool holder, reduction in tool change times. Impact of tooltip radii on machining time | Need for validation of the findings across different manufacturing environments and materials |
| Makris et al. (2023) | Automated assembly of non-rigid objects using robotics and algorithms to handle complex shapes and materials | Robotic manipulation, computer vision, and sensor data for assembly of non-rigid objects | High accuracy in assembling non-rigid objects, faster and more reliable than manual methods. Significant reduction in assembly time | Exploration of the adaptability of the system for different industries and material types |
| Bi et al. (2023) | Characteristics, causes, and consequences of technical debt in automation systems, focusing on software quality and project management | Mixed-methods approach with qualitative interviews and quantitative surveys | Technical debt accumulation due to time constraints, lack of documentation, and evolving requirements. Leads to higher maintenance costs, reduced agility, and quality issues | Strategies for mitigating technical debt in automation projects need further exploration, including more specific case studies |
| Gürel et al. (2023) | Scheduling optimization of a dual gripper material handling robot with energy efficiency considerations | Developed a scheduling algorithm integrating simulation and optimization techniques to minimize energy use | Energy consumption reduced by up to 30%; improved throughput due to dual gripper design | Exploration of adaptive scheduling and ML integration for real-time decision-making |
| Anciferov et al. (2023) | Engineering analysis of a robotic cell in machine-building production using Simcenter 3D for structural analysis and optimization | Utilized Simcenter 3D platform for CAD and CAE analysis, focusing on structural integrity and operational loads | Confirmed structural reliability through strength and stiffness coefficients; emphasized collaborative engineering for complex product development | Need for further validation using experimental data and complex mathematical models |
| Mueller et al. (2023) | Integration of collaborative robotics and additive manufacturing for scalable, sustainable production | Experimental setup at KIT using four robotic systems, real-time data acquisition, and fused filament fabrication | Demonstrated scalable and flexible manufacturing, enhancing value chains within Industry 4.0 | Need for further studies on long-term scalability and wider industry adoption |
| Mohanty et al. (2023) | Robotic programming in additive manufacturing, applied to aerofoil wing production | Case study on robotic programming for 3D printing, focusing on multi-phase printing processes | Validated the feasibility of robotic 3D printing for complex geometries; proposed a structured workflow | Further research on automation improvements and material optimization |
| Nagy et al. (2023) | Barriers to implementing Industry 4.0 technologies in SMEs, focusing on machine intelligence and robotics | Secondary data analysis on financial, labor, and cybersecurity challenges in SMEs | Financial constraints, lack of skilled labor, and cybersecurity issues hinder Industry 4.0 adoption | Strategies to bridge the technology gap between SMEs and large corporations |
| Yao et al. (2023) | JSPMR to enhance efficiency in intelligent workshops | Developed a MILP model, tested on 82 benchmark instances and 40 real-world cases | First MILP model to obtain optimal solutions for all tested instances, significantly improving scheduling efficiency | Scalability for larger, more complex industrial applications needs assessment |
| Rahman et al. (2023) | SAALBP with a focus on sustainability and ergonomics | Developed a MILP model incorporating uncertainty in processing times; used Q-learning and Monte Carlo-assisted genetic algorithms | Outperformed existing algorithms in optimizing assembly line balancing, achieving better Pareto-front solutions | Requires real-world testing; impact of long-term human-robot collaboration not fully explored |
| Peralta et al. (2023) | Robotic fastener detection in (un)screwing applications using vision and force feedback | Developed a vision system with neural networks; tested on fasteners from M6 to M24 in industrial settings | Achieved 99.86% vertex detection accuracy and 100% center detection accuracy; effective under varying lighting and sizes | Adaptability to non-hexagonal fasteners and real-time implementation in dynamic environments needs improvement |
| Zhou et al. (2023) | Industrial robot positioning error compensation for long-term accuracy improvement | Developed an adaptive hierarchical compensation method using incremental learning and fixed-length memory window | Reduced position error from 0.85mm to 0.13mm (Stäubli) and 2.11mm to 0.17mm (UR robot), significantly improving accuracy | Real-time adaptation in rapidly changing industrial environments needs further testing |

**Table 4.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Xie et al. (2023) | Development of a PMR for machining curved parts with high efficiency and accuracy | Designed a 5-DoF PMR with an attitude coupling adjustment mechanism and developed a new control method | Improved machining accuracy and efficiency compared to traditional five-axis SMTs | Future work needed on broader industrial applications and refinement of control methodologies |
| Malhan et al. (2023) | Trajectory generation for robotic manipulators following semi-constrained Cartesian paths in production engineering | Iterative graph construction method incorporating multiple TCPs; tested on industrial cases | Near-optimal solutions with fewer nodes and edges, enhancing efficiency in cutting, sanding, welding, and painting | Further optimization of computational efficiency and real-time adaptability |
| Lin et al. (2023) | Real-time charging scheduling of AGVs in cyber-physical smart factories using RL | Feature-based RL approach using five key feature functions; tested against existing strategies | Improved AGV utilization rates, reducing congestion and enhancing efficiency in production | Scalability and adaptability to diverse smart factory environments |
| Saroar et al. (2024) | GitHub Marketplace for Automation and Innovation in Software Production | Descriptive analysis of GitHub Marketplace, comparison of tools with academic literature. Dataset: 8,318 automated production tools, 515 academic papers | Tools in GitHub Marketplace differ from academic focus areas. Key tools used for Continuous Integration, Utilities, while academic focus is on Code Quality, Testing | Need for alignment between academic research and practical tools in software production |
| Alvarado et al. (2024) | Evaporation Automation in Non-Centrifugal Sugar Cane Production | Descriptive-correlational quantitative methodology, analysis of productive variables in evaporation process. Dataset: Sugar cane production variables | Optimal sugar levels and syrup characteristics for quality production. Automation proposed to enhance efficiency, safety, and sustainability | Unresolved: Further validation of automation strategies across different regions and scalability |
| Kandalova (2024) | Automation in production processes within fuel and energy complexes. Use of software modeling and client-server architectures for data management | Software modeling using various programming languages (C++, Java, Python, .NET). Two-tier or three-tier client-server architecture | Improved operational efficiency, enhanced data management, and reduced costs in fuel and energy complexes | No specific unresolved issues identified |
| Janecki et al. (2024) | Challenges and potentials of planning automation through Virtual Engineering in production facilities | Conducted a literature review and expert interviews (7). Focus on Virtual Engineering's role in the automotive sector | Challenges identified: functionality of virtual models, equipment selection, safety issues, KPI establishment | Need for standardization in work steps for optimizing Virtual Engineering's use |
| Gusev et al. (2024) | Automation of the beer production process. Focus on efficiency, consistency, and quality control | Analysis of automation features in beer brewing, including fermentation, filtration, and packaging | Automation increases efficiency, quality control, and cost reduction. Challenges: initial investment costs, skilled personnel for system maintenance | Future research needed on AI and ML to further enhance automation |
| Dihovični and Miščević (2024) | Automation in production engineering through Industry 4.0, using CNC machines and industrial robots | Utilization of CNC machines, industrial robots, real-time CAM programming, optimized tool paths, and NC code generation | Improved machine utilization, longer tool life, and reduced cycle times using real-time CAM programming | No unresolved issues identified |
| Lora et al. (2024) | Design automation for CPPS. Focus on innovative modeling paradigms and scalable algorithms | Development of scalable algorithms and service-oriented software architectures. System-level modeling | Successful modeling of system interactions, effective service-oriented architectures, and methodologies for system analysis and optimization | Need for further refinement in real-time application of service-oriented approaches in manufacturing |
| Burduk et al. (2024) | Intelligent Systems in Production Engineering and Maintenance III | Interdisciplinary research combining engineering, computer science, and operational management. Case studies and examples explored | Integration of intelligent systems improves efficiency, reduces downtime, and increases productivity. Future AI and ML advancements will shape production engineering | Unresolved: Further exploration of AI and ML in production engineering, and their impact on maintenance processes |
| Wei et al. (2024) | Production Automation Upgrades and the Mystery of Workers' Overwork | Analysis of employer-employee matching survey in Guangdong Province, China. Dataset: Survey data on workers' responses to automation upgrades | Increased working hours, deskilling, and mental health concerns. Labor union protection and human capital can mitigate labor degradation | Unresolved: Further research on the long-term effects of automation on worker mental health and job satisfaction |

**Table 4.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Abicht et al. (2024) | New Automation Solution for Brownfield Production | Cognitive robotic system development. Dataset: Cognitive robot behavior emulation in brownfield production | Successful development of cognitive robots for automation without integration with existing systems. Flexible and cost-effective automation solution for brownfield production | Unresolved: Potential challenges in scaling the system to larger production environments and integration with more complex tasks |
| Li et al. (2024) | Robotic assembly line balancing with a focus on carbon footprint reduction | Mixed-integer programming model and Particle Swarm Optimization (PSO) algorithm to optimize assembly line design considering environmental impact | The PSO algorithm efficiently reduces carbon footprint and optimizes assembly line operations. Demonstrates improved efficiency over classic algorithms | Further exploration of cross-station design and integration with other environmental considerations |
| Polonara et al. (2024) | Introduction of Collaborative Robotics in the Production of Automotive Parts: A Case Study | The integration of collaborative robotics in automotive parts production, especially in SMEs to enhance performance, safety, and competitiveness | Case study; exploration of collaborative robotics' role in production efficiency | Enhanced production line performance; improved efficiency; new perspectives in automotive parts design. Challenges in implementing collaborative robotics in SMEs due to limited resources |
| Tripathi (2024) | Applications of robotics in the automotive industry, including material handling, welding, and assembly. | Case study on robotized screw tightening; industry analysis of robotics adoption. | Robots improve precision, speed, and efficiency in automotive manufacturing, with a focus on collaborative robots. | Integration of AI-driven decision-making for adaptive robotic systems. |
| Ashmitha and Arumugasamy (2024) | Effectiveness of robotics in automobile manufacturing compared to human labor | Survey-based study using statistical methods (ANOVA, Kruskal-Wallis, Wilcoxon signed-rank test) | Robots outperform human labor in productivity, consistency, and safety. Recommendations for industry adoption | Workforce transition strategies and cost-benefit analysis of full automation |
| Smith et al. (2024) | Industrial robotics in mechanical engineering, focusing on challenges, opportunities, and emerging technologies | Review of current industrial robotics applications, identification of technical limitations, cost implications, and workforce adaptation challenges | Robotics enhances precision, productivity, and safety. Emerging technologies like AI and cobots improve efficiency and innovation in manufacturing | Limited adaptability of current robots, high initial costs, need for workforce reskilling |
| Ade-Omowaye et al. (2024) | Robotics and automation's impact on engineering practices in the digital economy | Literature review of robotics and automation technologies and their integration into engineering processes | Robotics and automation drive efficiency, reduce costs, and reshape engineering practices. Ethical and social implications of workforce displacement | Need for responsible integration and reskilling of workforce to handle automation |
| Bai (2024) | Advancements in robotics engineering and its transformative impact on industries and society | Review of robotics history, current applications, and interdisciplinary developments in the field | Robotics, from Unimate to current systems, revolutionize industries like manufacturing, healthcare, and space exploration. Ethical concerns about job displacement and human-robot interaction | Ethical concerns on job loss, privacy, and the societal impact of robotic technologies |
| Jović et al. (2024) | Application of VR with production robotics for enhanced efficiency and safety | Experimental research on VR simulations and its integration with production robots for training and operational improvements | VR improves training, enhances collaboration between humans and robots, and boosts efficiency in production environments | Need for further research on VR's long-term impact and potential in different industries |
| Bručienė et al. (2024) | Comparative environmental analysis of sugar beet production using a solar-driven robot versus conventional systems | Life Cycle Assessment (LCA) of robotic and conventional sugar beet production | Robotic system had lower GHG emissions (27.18 kg CO2eq t–1), higher sustainability index (13.72), better efficiency in weed control and yield | Need for further optimization in fossil fuel usage and long-term economic feasibility of robotic systems |
| Yao et al. (2024) | Task reallocation in human-robot collaborative production workshops using a dynamic human fatigue model | Fatigue feature extraction, evaluation network, improved genetic algorithm for task reallocation | Improved safety and efficiency in human-robot collaboration, real-time fatigue assessment, effective task reallocation | Limited validation in real-world industrial settings, need for integration with broader ergonomic models |

**Table 4.** *Cont.*

| Author(s) and Year | Study Focus and Application | Methodology and Dataset | Key Findings and Metrics | Unresolved Issues/Gaps |
|---|---|---|---|---|
| Guo (2024) | Fast scheduling of human-robot teams collaboration in aircraft assembly using optimization techniques | MILP and CP, 1200 independent tests on 80 benchmark instances | CP approach outperformed MILP in scheduling efficiency, better coordination of human-robot teams, improved safety and productivity | Potential computational complexity in large-scale implementations, need for adaptive real-time scheduling solutions |
| Nguyen and Duy (2024) | Grasping moving objects with incomplete information in a low-cost robot production line | Contour matching using Hu moments, centroid estimation, calibration for robot grasping | Centroid estimation accuracy of 2.2 pixels in image space, 1.8 mm in 3D space, improved grasping accuracy in production lines | Challenges in handling more complex object shapes and high-speed conveyor systems |

## 8. Challenges and Future Directions of Automation in Production Engineering

The path forward for automation in production engineering demands solutions to existing limitations while integrating AI and responding to changing market demands (C et al., 2024; Nakamoto & Takasugi, 2023; Ojha, 2023).

### 8.1. Challenges

- Integration of New Technologies: The implementation of new automation technologies requires substantial investments to upgrade infrastructure and train staff (Adeleke et al., 2024).
- Data Quality and Availability: The implementation of AI in manufacturing faces significant obstacles related to maintaining high data quality and availability (Parmar, 2022).
- Workforce Adaptation: The resolution of workforce adaptation issues that encompass ethical dilemmas and job displacement remains essential (Dupare & Sangole, 2024; Ojha, 2023).
- Maintaining System Security: As reliance on CPS expands for automation and control, protecting those systems from cyber threats becomes essential (Lo et al., 2024; Malik et al., 2021).
- Complexity of CPPS: The complexity of CPPSs presents a substantial challenge because they need solutions from multiple disciplines (Feichtinger et al., 2022).
- Limitations in Design and Manufacturing: Manufacturing and design must advance beyond current limitations to succeed in the changing marketplace (Xiaokun, 2019).
- Lack of Engineering Expertise: The lack of understanding data scientists have about control systems and process engineering limits their ability to design effective AI solutions.
- Data Silos and Integration: The integration of real-time data faces challenges as data remains isolated within individual silos even though organizations have tried to establish enterprise data lakes (Hollender et al., 2024).
- Software Maturity: The development of adaptable automation software that reaches maturity continues to pose difficulties for manufacturers in the machine and plant sectors (Vogel-Heuser et al., 2022).

### 8.2. Future Directions

- AI and ML: Upcoming industry trends encompass AI and ML along with collaborative robots that have the potential to boost production processes (C et al., 2024). AI methods aim to enhance operational efficiency while enabling product launches and customized designs and facilitate financial planning for the future (Nakamoto & Takasugi, 2023).
- DTs and Simulation: The application of DTs and simulation tools for virtual process simulation and optimization helps speed up product development while reducing necessary experimentation (Adeleke et al., 2024).
- Robotics: The combination of AI with robotics will create industrial revolutions through clinical enhancements and more accurate minimally invasive surgical procedures (Husainy et al., 2023).
- Focus on Sustainability: Emerging processes must undergo thorough sustainability evaluation during development to prevent environmental damage and conserve resources. Adopting circular economy principles leads to improved resource management and waste minimization throughout all phases of a product's existence.

- Industry 4.0 Initiatives: Industry 4.0 propels academic, industrial, and governmental partnerships to develop research initiatives that create sustainable connected manufacturing systems.
- Advanced Materials: The development of advanced materials such as composites and biomaterials creates opportunities for lightweight structures along with performance enhancements and customized functionalities (Adeleke et al., 2024).
- Integration with IoT and Edge Computing: Upcoming developments will include combining IoT technology with edge computing while advancing into new manufacturing sectors and enabling fully autonomous quality control systems (Parmar, 2022).
- CPS: The implementation of CPS presents a potential solution to tackle challenges in planting operations as well as crop maintenance and harvesting processes (Bakar et al., 2021).
- IPA: The move from RPA to IPA requires integrating advanced technologies and capabilities (Siderska et al., 2023).
- Addressing Human-Automation Challenges: The solution involves identifying methods to resolve human-automation challenges to enhance operators' ability to understand automatic system functioning (Andersson, 2011).
- Development of Intelligent and Adaptive Robots: The development of intelligent and adaptive robots for industrial automation requires careful consideration of sensor integration along with control algorithms and ML as well as human-robot interaction (Mulla & Ansurkar, 2023).
- Use of 3D Printing: The integration of 3D printing technology with additional automation systems enables improved efficiency and cost-effectiveness in construction while also reducing environmental impact (Akkoyun & Günal, 2025).
- AI-driven Demand Forecasting and Inventory Management: Organizations implement AI technology to enhance demand forecasts and manage inventory systems while optimizing energy usage (Parmar, 2022).

## 9. Conclusions

The review of automation in production engineering identifies important trends as well as advancements and future directions that are transforming the industry. The past five years brought substantial progress in automation technologies, which demonstrates a move towards more efficient and sustainable manufacturing processes. Smart technologies and digital solutions have been essential to this transformation because multiple studies show that they lead to improved operational capabilities and decreased environmental impact. The emergence of DTs working together with AutomationML technology represents a key element for advancing intelligent manufacturing capabilities. Improved data exchange and connectivity in CPPS through these technologies results in enhanced decision-making processes and better system performance. Studies show industrial robots have reached 30% energy savings by optimizing movement patterns and minimizing idle periods. Anticipated technological developments will integrate renewable energy sources to boost sustainable production processes. FMS that employ collaborative automation demonstrate potential for better machine interoperability alongside minimizing human involvement. High-mix, low-volume production scenarios require systems to adapt effectively. Real-time monitoring systems combined with anomaly detection techniques have demonstrated effectiveness in sustaining operational reliability. The systems employ statistical learning techniques to deliver stable performance without requiring continuous recalibration. The review underscores the rising need to tackle cybersecurity threats alongside the expanding adoption of automation technologies. Production safety and operational continuity face significant challenges from cyber threats, which require strong security solutions. The research paper advocates for ongoing research and development efforts within automation technologies. The future of production engineering demands concentrated efforts on better decision-making processes while advancing system interoperability and cybersecurity measures. The advancement of these technologies will prove essential for developing manufacturing systems that maintain efficiency and sustainability while remaining strong against future challenges. This review summarizes the evolving field of production engineering automation while pointing out its accomplishments and upcoming challenges. Analyzing recent studies reveals key guidance for the next developments within this field.

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## Automatyzacja i Przemysł 4.0 w Inżynierii Produkcji: Kompleksowy Przegląd


### Streszczenie

W artykule przedstawiono kompleksowy przegląd rozwoju automatyzacji w inżynierii produkcji i zaprezentowano różne metodologie oraz zastosowania automatyzacji z różnych okresów historycznych. Artykuł omawia wyzwania stojące przed przemysłem, proponując jednocześnie przyszłe ścieżki badawcze i praktyczne zastosowania automatyzacji. Przedstawiono w jaki sposób narzędzia automatyzacji, takie jak robotyka, sztuczna inteligencja i Internet Rzeczy, rewolucjonizują wydajność produkcji i zarządzanie zasobami. Poddano analizie funkcjonowanie systemów cyberfizycznych w systemach zautomatyzowanych, ze szczególnym uwzględnieniem środków bezpieczeństwa niezbędnych w środowisku Przemysłu 4.0. Naukowcy, praktycy i specjaliści z branży mogą wykorzystać te ustalenia do analizy automatyzacji i stymulowania innowacji w tej dziedzinie. Niniejszy przegląd integruje zarówno historyczne wyniki badań, jak i współczesne osiągnięcia, aby lepiej zrozumieć, jak automatyzacja zwiększa wydajność i zrównoważony rozwój w systemach wytwarzania.


**Słowa kluczowe:** automatyzacja, digitalizacja, automatyzacja procesów robotycznych, Przemysł 4.0, systemy cyberfizyczne