Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/GC03.20250543
Published: February 2, 2026

Mass Adoption of AI in Automotive Manufacturing: Pathways to a Bright Future

Corrie Floyd II
Department of Industrial Engineering
Master's Student in Systems Engineering
Wayne State University
Detroit, Michigan, USA
gr4166@wayne.edu

Abstract

Artificial Intelligence is redefining automotive manufacturing, assembly, and design by enabling predictive analytics, real-time fault detection, and generative design workflows. At GM, AI-driven systems support predictive maintenance and production optimization, improving efficiency and enabling mass customization. AI-powered vision systems, such as Ford's MAIVS, detect millimeter-scale defects in real time, thereby reducing rework and enhancing design feedback. Generative design and additive manufacturing platforms, such as those from Autodesk, help deliver lightweight, optimized structures, while other automakers explore generative AI for rapid ideation. These capabilities accelerate development cycles, improve quality, and promote sustainability. However, high infrastructure costs, legacy system integration, and workforce skill gaps remain challenges. Recommendations include phased deployment, workforce training, and secure, scalable infrastructure. These transformations enable intelligent factories, adaptive assembly lines, and AI-enhanced design studios in which human creativity and AI capabilities converge.

Keywords
Artificial Intelligence, Automotive Manufacturing, Automotive Assembly, Generative AI, Predictive Maintenance

1. Introduction
The automotive industry has consistently been at the forefront of technological advancements, from Henry Ford's introduction of the moving assembly line to the emergence of robotics in the 20th century. Today, artificial intelligence (AI) represents the next inflection point. Unlike innovations focused on mechanical efficiency, AI possesses cognitive capabilities such as pattern recognition, prediction, and adaptive learning. These capabilities enable the addressing of complex challenges, such as minimizing production downtime, personalizing vehicle design, identifying human errors within quality assurance, and ensuring supply chain resilience. The urgency of this research stems from three converging pressures: the global demand for smart manufacturing, rigorous regulatory standards, and the increasing complexity of production in gas, electric, and autonomous vehicles. Traditional methods, though proven, are no longer sufficient to meet these challenges at scale. AI adoption, therefore, is not optional but rather necessary for manufacturers who want to remain competitive. The central research question guiding this study is: How can artificial intelligence be effectively integrated into the automotive industry to enhance manufacturing efficiency, design personalization, and supply chain resilience?

This paper will explore how AI is transforming automotive **manufacturing, assembly, and design**, detailing its benefits, challenges, and future implications. By analyzing recent case studies and industry reports, the promise of AI and the risks associated with its mismanagement will be highlighted. Ultimately, the objective is to show that when properly implemented, AI is not just a tool for optimization; it is the foundation for the next era of automotive innovation. It is not clear who is leading in the global automotive manufacturing sector. I will conduct thorough research to investigate and identify who has the strongest automotive production power by resources. I will also identify who is leading the market in creating AI solutions to problems resulting from an increase in customer demand. There are numerous benefits to integrating this technology into the automotive industry, along with the new challenges it presents.

1.1 Objectives

This research aims to discuss market trends, surveys, and industry practices, demonstrating that AI technology addresses issues during the manufacturing, assembly, and design of automobiles and provides a sufficient solution to these issues. This includes predictive maintenance, quality inspection, and dynamically adjusting production schedules.

2. Literature Review

Title: Artificial Intelligence in Manufacturing: State of the art, perspectives, and future directions

Overview: This narrative review analyzes themes from 297 papers about artificial intelligence in manufacturing. The key themes found in the literature: Production Planning and Scheduling, AI for Smart Manufacturing, AI for Quality Assurance (QA) and maintenance, and Unsupervised Learning from unlabeled data. After presenting the key themes, the authors recommend that those implementing these technologies take an educational approach to understanding how AI works before using it in manufacturing to identify its potential (N.N., 2024).

3.Methods

Research methods include surveys, questionnaires, case studies, cross-sectional studies, and historical research.

4. History and Shift: Industry 4.0 to 5.0

Industry 4.0, also known as the Fourth Industrial Revolution, was first unveiled in 2011. It is defined by the emergence of digital industrial technology, primarily centered on cyber-physical systems. This era focused on integrating machines and digital technology to create "smart" operations.

Industry 5.0, or the Fifth Industrial Revolution, was introduced in 2021. It is a development that builds upon Industry 4.0 technologies but introduces a fundamental shift in focus from purely technological efficiency to incorporating human and planetary well-being. This shift is largely driven by the European Union's push towards sustainability and global goals like climate neutrality.
The primary objective of the Industry 4.0 phase is to achieve highly innovative and efficient manufacturing through data and connectivity.

The ultimate goal of Industry 4.0 is to:

- Create tailored, versatile manufacturing solutions by leveraging data-driven insights.
- Facilitate efficient collaboration between humans and machines.
- Enable the creation of smart, integrated factories and operations.

Key technologies like the Internet of Things (IoT), Artificial Intelligence (AI), Big Data & Data Analytics, and Additive Manufacturing (3D Printing) are utilized to create a cohesive, data-optimized manufacturing environment.
Industry 5.0 emphasizes using advanced technologies (the foundation of 4.0) while ensuring that production adheres to the welfare of both workers and our planet. It seeks to bring the human and environmental elements back to the forefront of manufacturing goals.

The core objectives and ethical guidelines of Industry 5.0 include:

1. Prioritizing Worker Welfare: Ensuring workers have the ongoing education (often through VR/simulation training) needed to work with rapidly advancing technologies, and focusing on improving human-machine interactions for increased productivity and safety.
2. Mitigating Ethical Risks: Reviewing and overseeing AI and algorithms to mitigate inherent biases.
3. Addressing Ecological Footprint: Incorporating green materials and sustainable operation strategies, with a focus on moving to a circular manufacturing system to cut back on waste.
4. Managing Employment Shifts: Training employees in new areas to address the changing needs of organizations as technological advancements reduce the need for traditional roles.

Migrating to the next phase of the Industrial Revolution, Industry 5.0 represents a monumental shift in the way technology will be fully integrated within industrial automotive manufacturing. In the fourth phase of the Industrial Revolution (Industry 4.0), a significant amount of emphasis is being placed on automating production processes in order to achieve three key objectives that corporate leadership prioritizes most: maximizing efficiency, increasing output, and enhancing ROI. However, with the next phase of the Industrial Revolution (Industry 5.0), the focus has shifted to moving production floor employees to the heart of the production process. This includes developing workspaces that prioritize and enhance human comfort while integrating technology that improves their ability to produce custom, reliable, high-quality products.

5. Artificial Intelligence Market Value and Investments

AI is proving itself to be a worthy investment. According to GlobalNewsWire, they are evaluating that investing in the AI market is projected to grow from 538.13 billion to 2,575.16 billion USD between 2023 and 2032, growing at a Compound Annual Growth Rate of 19%. From optimizing manufacturing processes to detecting the necessary maintenance of production equipment, AI technologies are reshaping every aspect of how vehicles are manufactured, assembled, and designed. The proof is in reality (Precedence Research, 2023) (Figure 1).

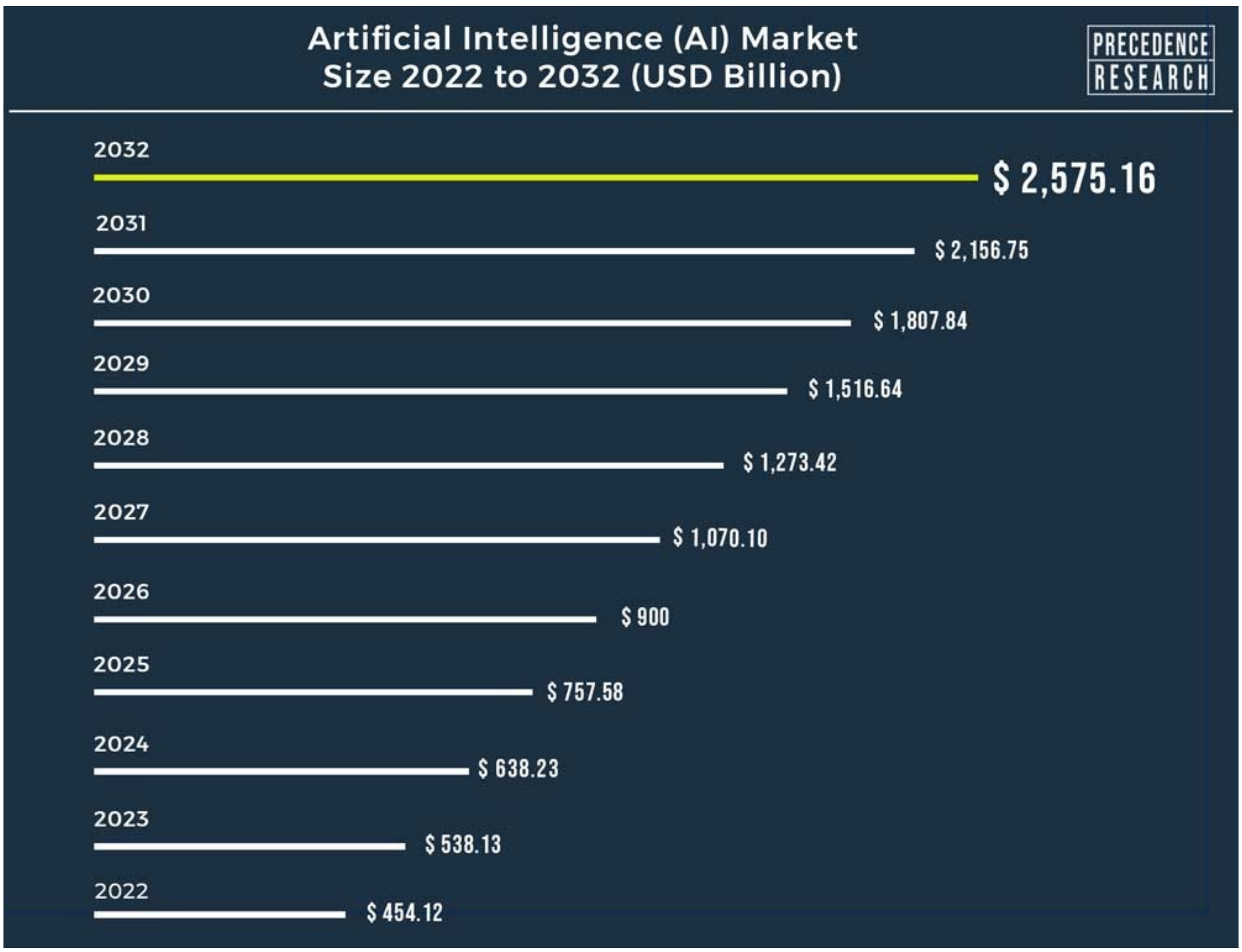

Figure 1. Artificial Intelligence Market

5.1 AI Technological Applications for US Automakers

To maximize production efficiency, organizations must design workspaces that enhance human quality of work and time management, taking into account the needs and preferences of both human and robotic resources. This, combined with digital twins, advanced robotics, LLMs for Machine Learning will completely shift the paradigm of product development, design, simulation, and testing, enabling the workforce to become more resilient and identify problems and solutions faster than humanly possible (Camarella et al., 2024).

AI applications are being developed to increase efficiency, reduce errors, decrease production downtime, optimize production schedules, and enhance predictive accuracy. Companies such as First, I'd like to begin with the company BMW Group.

The BMW group is AI for development using digital twin tech. Since its development ,they are able to perform extensive simulations: crash testing, aerodynamics and autonomous driving, for example. The group is becoming less dependent on physical prototypes and faster in terms of development cycles. (Source) BMW is also running tests to include AI in production. At the group plant in Spartanburg, South Carolina, the robots in beta testing can perform a variety of human-like tasks that require precision and dynamic manipulations, complex gripping and two-handed coordination, with full autonomy. These humanoid cobots can position a range of tricky components accurately to the millimetre and move flexibly while making the most of the efficiency of its design. The Figure 02 supports plant employees performing ergonomically awkward and exhausting tasks to take the strain off them. The safety of these humanoid robots in automotive production is under constant assessment (Source). BMW has seen impressive results utilizing PM applications as well, specifically at the group plant in Regensburg (German location). AI-supported systems monitoring conveyor technology during assembly feature an integrated ML maintenance system that identifies potential faults early, resulting in an average of eight hours of production downtime saved per year. Load carriers used to transport vehicles throughout the assembly send various data to the carrier control system. This data is then transmitted to the BMW Group's own PM cloud platform, where further analysis is to be conducted. The proprietary ML algorithm continuously scans for irregularities, such as fluctuations in power consumption, anomalies in conveyor movements, or illegible barcodes, which could trigger malfunctions in production equipment. If anomalies are found, the maintenance control centre receives a warning message, which gets assigned to a maintenance technician on duty. Since its inception, the group has developed in-house and issued two patents for that technology. Currently, it is being deployed at group plants located in Dingolfing, Leipzig, and Berlin (Gaser, 2023).

General Motors have deployed AI-driven predictive maintenance (PM) systems that can monitor machines in real-time to identify anomalies before breakdowns occur (Motors, 2025). The technique being used here is known as condition-based monitoring, where sensors collect data on the health and performance of assembly equipment. There is less public data on how this has been accomplished, however the context of how it should be done is rather the same across all OEMs. In terms of assembly line production data, Machine learning algorithms (ML) analyze these variables to detect early warning signs of potential issues that may halt production. Their embedded algorithms can then identify patterns and anomalies indicative of impending failure by continuously monitoring key indicators, such as temperature, vibration, voltage, and fluid level fluctuations and spikes (Neural Concept, 2025) The advantages of PM lie in its ability to maximize productivity: organizations can avoid costly unplanned equipment downtime and reduce unnecessary maintenance activities. This sort of maintenance prolongs an asset's lifespan by preventing premature failures of critical infrastructure, allowing companies to save on operating cost year over year.

General Motors even utilizes AI for inventory/ supply chain optimization. Over the past five years GM has faced several supplier chain disruptions. From 2020 through 2023, multiple automakers alike had to temporarily shut down their US production plants due to semiconductor chip shortages. In 2021, the shortage forced General Motors to cut production at eight facilities, which led to the company halting US truck production again in 2022. As a result, GM developed a four pronged system in house, capable of monitoring supplier events and disruptions ahead of time to identify resources that are needed and scheduled to be imported.. First, engineers built a digitized supply map and a coordinating machine-learning tool that constantly tracks relationships between tier-one suppliers and their sub-tier partners. Second, a centralized communication hub, monitored by risk analysts in Michigan, activates when the system identifies a disruption, having since triggered thousands of investigations. Third, named Risk Intelligence, General Motors' AI article scanner, reads and classifies thousands of daily news articles for potential impact on the company's supply chain. Finally, a dashboard to peer over supplier sites for indicators of trouble such as shipping delays, overdue parts, or missed schedules. (Source) With regards to robotic capabilities, Engineers and scientists from NASA and GM are working together through a Space Act Agreement at the Johnson Space Center in Houston to build new humanoid robots capable of working side by side with people (cobots). Using leading edge control, sensor and vision technologies, future robots could assist astronauts during hazardous space missions and help GM build safer cars and plants. The two organizations, with the help of engineers from Oceaneering Space Systems of Houston, developed and built the next iteration of Robonaut. Robonaut 2, or R2, is a faster, more dexterous and more technologically advanced robot. This new generation robot can use its hands to do work beyond the scope of prior humanoid machines. R2 can work safely alongside people, a necessity both on Earth and in space. The industry is currently awaiting a GM

inspired humanoid bot that will assist in automotive production. (Source). The K2 "Bumblebee" Kepler robot is built for the demands of modern factories. At SAIC-GM, it has already demonstrated its ability to perform intricate inspections, navigate complex factory layouts, and manage heavy automotive components with impressive autonomy. The robot can load stamped parts, manipulate mechanical fixtures, and adapt to new tasks using a combination of imitation and reinforcement learning. Its presence in the factory highlights a shift toward smarter, more efficient production lines, where robots and humans work side by side to achieve higher standards of quality and safety.
Ford Motor Company.

Ford has reported that they are working on a PM solution of their own, sponsored by the project to create Miniterms (dating back to 2020), sensors that are integrated with plant machinery to detect any reduction in performance and relay that information to engineers, direct to their phones. This development is being done in Europe. Miniterms was developed together with engineers at the robotics department of the Universidad CEU Cardenal Herrera (CEU UCH), in Valencia. The project was awarded funding by Ford Motor Company's University Research Program and the team is working with Ford's Global Data Insights and Analytics to make the data available for use in Ford facilities globally. Since its inception, In Valencia, more than 15,000 machines are employed in the production of vehicles including Ford Galaxy, Kuga, Mondeo, S-MAX and Transit. Most of these machines are now monitored through the use of miniterminals. Further innovations introduced at Ford's Valencia plant include a self-driving delivery robot that delivers spare parts to the production line. With regards to generative design and supply chain optimization, Ford has partnered with Google over the next six years (effective 2023) to accelerate modernization of product development and supply chain managemnt.

Ford aims to improve their QA with this technology after having led the automotive industry in recalls for four of the past five years. These AI tools could relieve a potential billion-dollar headache for Ford. In the past two years, the automaker has faced a substantial number of recalls, primarily affecting cars built before 2023. By the middle of this year, Ford had 45 recalls alone, which has (as of August) increased to 94 recalls (Team, 2025). This has been the largest number of recalls posted by any major car brand within a single calendar year ever, which is costing Ford millions of dollars. To cite a major recall, there was a fuel injector leak recall affecting 694,271 units of the popular Bronco Sport and Escape models combined, which will cost Ford approximately $570 million in damages (Perez, 2024). Ford sells the most demanded automotive vehicle in the nation, the Ford F-150, so production resources (whether human or robotic) are subject to temporary exhaustion. It's only natural that mistakes such as these would occur for a large OEM such as the Blue Oval, but we must find solutions to remediate such QA failures before automobiles are shipped to customers. Ford is leading the way with that (Figure 2).

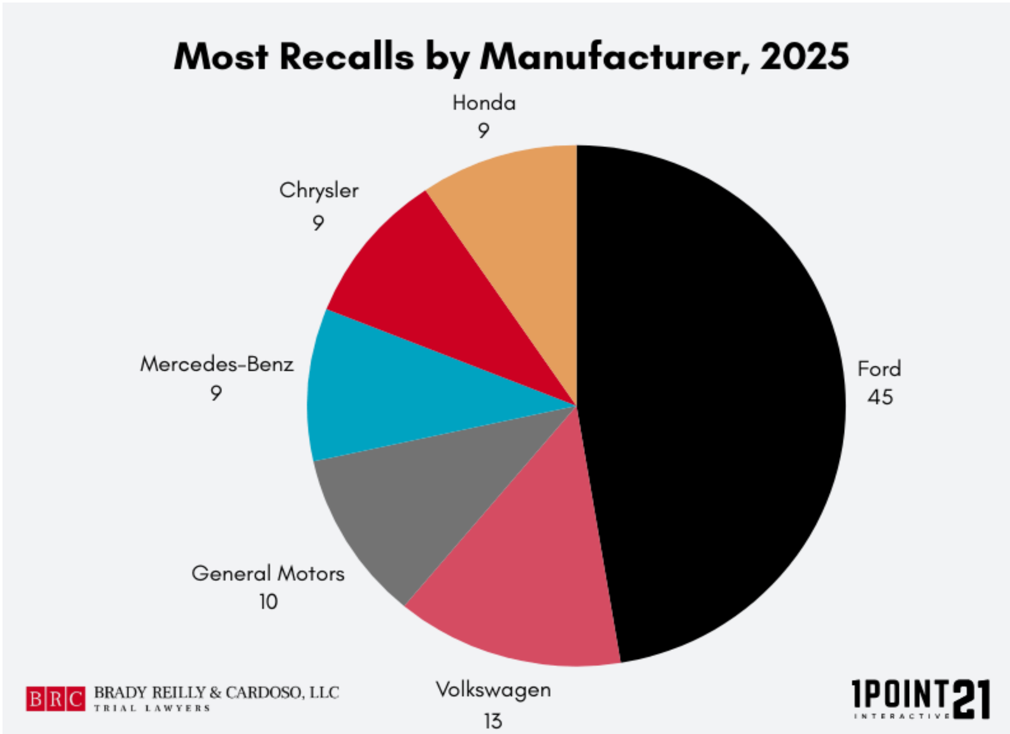

Figure 2. Recalls by manufacturer

Looking forward, "the company's AI-supported systems are already making a significant impact on the manufacturing floors", Patrick Frye, an engineering manager at the Dearborn plant, said. Both AI systems are being used during QA inspections, capable of using machine learning combined with still images and video streaming to catch millimeter-scale misalignments. **MAIVS** (Mobile Artificial Intelligence Vision System) is limited to still images taken on smart phones, whereas **AiTriz** (named after its creator, Beatriz Garcia Collado, who is based in Spain) utilizes a live video feed and still images to run QA inspections. Additionally, AiTriz offers greater precision and adaptability in inspections, particularly in instances of occlusions (such as production employees walking and obstructing a camera's field of view or in the case of some element of sheet metal chocks a necessary electrical connection). Both of these systems are now installed at dozens of stations across North America. AiTriz is deployed at 35 stations, while MAIVS is at nearly 700. With all of this being said, Ford executives remain unconvinced that this breakthrough will continue to work at scale. With cautious optimism, the pros outweigh the cons. While these systems are being adopted primarily across the organization, Ford's leadership also plans to retrain the production workforce to mitigate workforce shrinkage in the wake of advancements in AI and robotics (Shimkus, 2025). With respect to humanoid robotics, The Pretoria South Africa media center reports that five years ago, Ford partnered with Agility Robotics to acquire Digi. Digi aims to explore ways to help commercial vehicle customers, including autonomous vehicle businesses, make warehousing and delivery more efficient and affordable for their customers.

Mercedes-Benz takes the digital production ecosystem a step further. Artificial intelligence has made its way to Benz's paint shops, capable of identifying imperfections invisible to the human eye. This ensures a higher finish quality while cutting inspection time. With the help of a digital twin and virtual commissioning, the construction time and ramp-up of the "Next Generation Paintshop" can be significantly accelerated. Paint booths, dryers, and approximately 250 robots are integrated into the AI enabled MO360 Data Platform (Benz's digital production ecosystem). All production data is accessible and subject to real-time analysis by employees via the cloud, enabling immediate reaction to non-conformities before a vehicle reaches the end of the production line. This paint shop has the capacity to cover all special and large-scale painting processes, from high-tech cleaning immersion baths to corrosion protection sealing using the drop-on-demand process and surface finishing in the painting process (Mercedes-Benz Group, 2025). MO360 comprises several software applications as well. Two of them are currently fully integrated into the production ecosystem and are dedicated to QA (QUALITY LIVE) and production management (Shopfloor Management digital, SFMdigital). As applications, they also serve to support the structured problem-solving process in Benz's assembly plants. This is achieved through continuous process optimization, which involves making suggestions for efficient rework and identifying issues with vehicle quality before they reach the end of the production line (Automotive World, 2020). Robotics are being tested as well, to further the production capabilities of plants worldwide. Currently, the US based company Apptronik, is developing cobots for Benz. Per commercial agreement, Apptronik and Benz aim to "fill labor gaps in areas such as low skill, repetitive and physically demanding work and to free up our highly skilled team members on the line to build the world's most desirable cars," said Jörg Burzer, Member of the Board of Management of Mercedes-Benz Group AG, Production, Quality & Supply Chain Management.(Source). Apollo robots, developed by Apptronik and tested for production purposes, have been collecting data in a production environment to train for specific use cases within MO360. Mercedes-Benz employees with hands-on production experience have transferred their knowledge to Apollo using teleoperation processes and augmented reality. The next significant development at the Digital Factory Campus Berlin involves enabling Apollo's robots to perform autonomous operations, marking a technological milestone toward a flexible, intelligent assistance system for production.

In March of this year, the AI-powered humanoid robotics company Apptronik announced a strategic partnership agreement with the Google DeepMind robotics team to merge best-in-class artificial intelligence with cutting-edge hardware, advancing humanoid robots to be more helpful to people in dynamic environments. The AI M360 platform has provided enablement to the MO360 AI Factory (Berlin). The in-house "Digital Factory Chatbot Ecosystem" development has allowed employees to access production databases: Inquiries about machine maintenance or best-practice methods for manufacturing processes can simply be asked via chat, with the AI immediately providing precise answers in multiple languages.(Source).

AI's capabilities continue to increase daily as new models are updated and developed. Thanks to the ongoing efforts of developers, select models now possess the ability to optimize production scheduling. Traditional production schedule planning methods often struggle with sudden supply chain disruptions, disjointed data sets, fluctuating budgets, tariffs, and limited time to plan. C3 has a solution: an AI system capable of analysing vast dataset variables to adjust production schedules dynamically. This not only reduces waste but also strengthens resilience in the face of global uncertainties stemming from geopolitical tensions, tariffs, and inflation. The successful case study below highlights the capabilities of the **C3 AI Production Schedule Optimization** (C3, 2025). It demonstrates how it enables production schedulers to improve fill rates, line utilization, and profitability by creating dynamic production schedules. This application enhances production scheduling by integrating disparate data and applying best-in-class optimization techniques that account for thousands of constraints across capacity, materials, labor, and other factors. In the next paragraph, I will be reviewing a real case study, highlighting the value that C3 AI Production Schedule Optimization brings to manufacturers worldwide.

Nucor, a major steel manufacturer, faced significant challenges in planning and scheduling production at its steel mill. Previously, this process was manual, time-consuming, and inefficient. It took five days to complete, resulting in excess inventory. By partnering with C3 AI, Nucor implemented a new AI-powered application to optimize production scheduling. Within 26 weeks, the new system reduced planning time from five days to one hour. The AI optimizer, which considered over 300 variables and constraints, increased net production by 1%, resulting in the addition of over 1,000 tons of finished product per year. This translates to a $1 million annual benefit, with the potential for much more as the solution is expanded to other mills.

Finally, the joint team configured a multi-screen user interface. Live data connections were established to support ongoing scheduling work. The workflow-driven user interface enabled planners and schedulers to visualize optimization results and create planning scenarios. The application, in total, reduced the time required to plan and schedule production cycles from 5 to 7 days to 1 hour, thereby improving operational efficiency (C3, 2025). This integration of AI and data analytics offers valuable insights for this business, enabling it to make informed decisions and drive innovation.

AI is fundamentally changing vehicle design. Instead of being constrained by human limitations, designers can now leverage **generative design**, a process in which AI creates numerous design solutions based on performance and engineering criteria. By analyzing customer data, this technology can anticipate market trends, such as the demand for unique interior layouts for autonomous vehicles or highly customized seating, and translate those insights directly into new designs. This paradigm shift from **mass production** to **mass customization** is enabling automakers to differentiate themselves and meet evolving consumer demands more effectively than ever before. Companies such as

General Motors, in partnership with **Autodesk**, have used AI to design lightweight seat brackets that are 40% lighter yet stronger than their traditionally manufactured counterparts (General Motors, 2021). AI even accelerates product simulation and testing. In the past, engineers relied solely on costly prototypes and physical crash tests. AI-driven digital twins are capable of simulating how components and entire vehicles will perform under various conditions, such as heat, stress, and vibration, before a single prototype is built. This not only reduces cost but also allows engineers to explore innovative materials and configurations with less risk.

6. Challenges Posed by AI in Automotive Manufacturing

It is generally understood that AI enhances efficiency. However, its integration into manufacturing has several obstacles, the most pressing one being **data dependency**. AI systems rely on massive amounts of clean, labeled data to function correctly. Yet, many manufacturers struggle with fragmented legacy systems that do not capture consistent data, nor are they capable of real-time monitoring. Without reliable inputs, AI predictions risk being inaccurate or even harmful because this technology relies heavily on data to function effectively. It must draw upon vast datasets to train algorithms and optimize model performance, which is where data science comes into play. Data science plays a pivotal role in training and validating AI models because it shapes the models to generate realistic outputs. If AI inspection systems are trained on limited datasets, they may fail to detect defects in certain scenarios, creating blind spots that compromise quality and safety.

Secondly, AI challenges organizations across the vectors of **cost and scalability**. Deploying some AI-enabled PM or computer vision systems could require significant upfront investment in sensors, infrastructure, and training. Smaller suppliers may lack the resources to adopt AI at the same pace as global OEMs, leading to uneven adoption across the supply chain.McKinsey and Company has discovered that German automotive manufacturers are inclined to adopt general AI in the automotive sector. According to a survey conducted, the majority of companies (75 percent of survey respondents) are experimenting with at least one generative AI application, compared to those that do not plan to start within the next year (25 percent of respondents). This survey also indicates that further investments in general AI applications for R&D are substantial, with more than 40 percent of survey respondents reporting that their companies have invested up to €5 million or $5.8 million USD. In a few companies, more than 10 percent of respondents have invested over €20 million, or approximately $23.8 million USD (Cholewinski et al., 2024).

Thirdly, we have the challenge of **human-robot interaction**. While AI enables robots to adapt to real-time variability, ongoing safety concerns persist regarding humans and machines sharing the same workspace. Even with advanced vision systems, unpredictable human movement poses risks to production floor hazards. **Reskilling the workforce** to work with these systems and advanced robotics creates an even greater hurdle to adoption. Production line workers must transition from manual tasks to supervising AI systems, a shift that will require new technical literacy, which is not always readily available in the labor force. In a 2023 survey conducted by the Boston Consulting Group (BCG) Center for Customer Insight surveyed 21,000 Consumers Across 21 Countries on AI Awareness, Usage, and Sentiment (BCG, 2024. In the US, 75% of respondents were aware of tools such as ChatGPT, and 23% actively used it; meanwhile, respondents from other surveyed countries were far more educated about the tool and were already utilizing it in their daily work or leisure time (Figure 3- Figure 6).

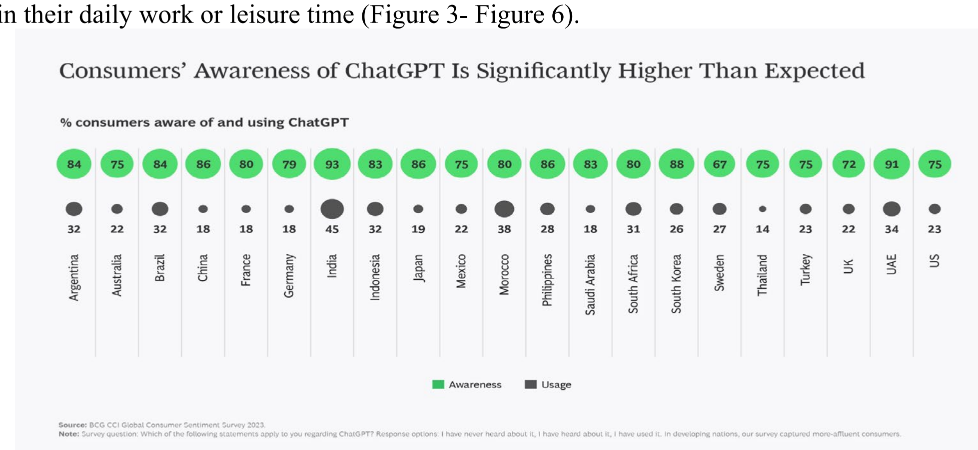

Figure 3. ChatGPT

While excitement about AI is prevalent, a notable portion of consumers surveyed displayed an insightful awareness of its potential downsides if not implemented responsibly. Approximately 30% of the surveyed consumers expressed excitement about the various uses of AI, and 30% reported feeling conflicted about it. Consumers also voiced outright concerns about AI, with 40% worried about the possibility of AI replacing workers in certain jobs. 10% percent of consumers expressed concern about the environmental impact of GenAI. 33% are worried about data security and ethics.

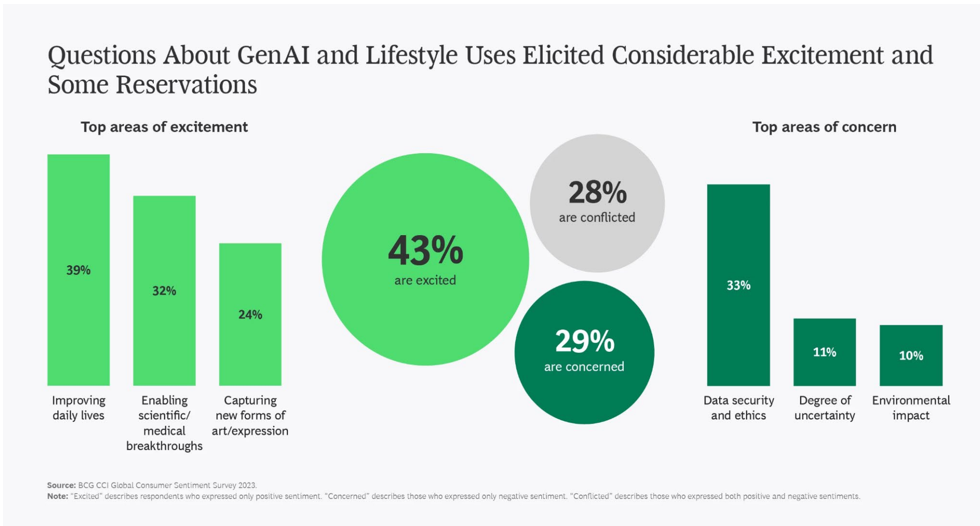

Figure 4. Gen AI and Lifestyle

BCG's study shows that there is a "misinformation-excitement-concern curve." With their increased experience and use of GenAI, consumers simultaneously exhibited more excitement and concern about the emerging technology.

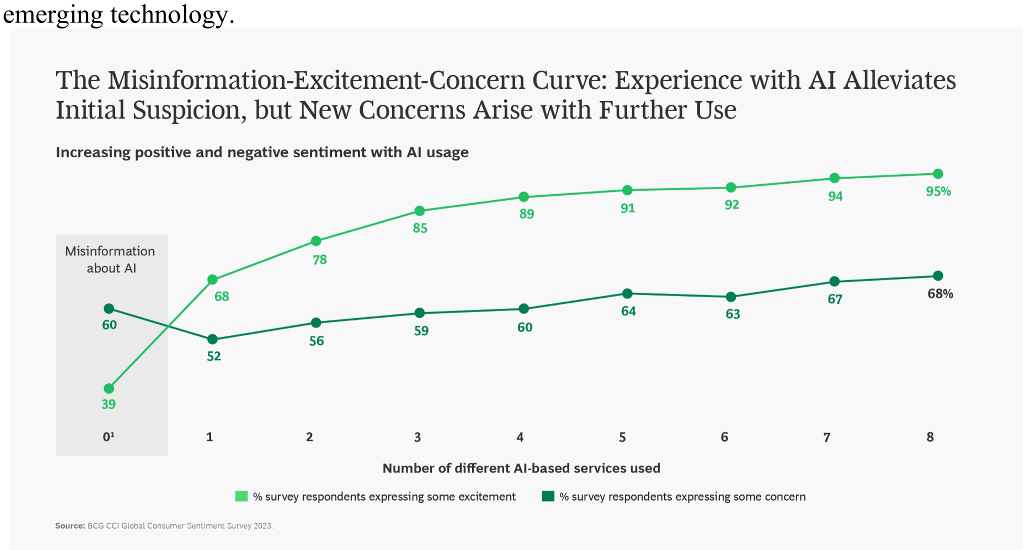

Figure 5. AI based service

Those surveyed recognized the value AI provided, with 39% of respondents expressing optimism about its impact. 55% anticipate increased workplace efficiencies, and 60% are excited to be educated and trained on GenAI tools. It's also important to note that workplace attitudes toward AI often correlate with job roles. More than half of respondents feel that AI or other technologies cannot replace them, while only 29% express feelings of vulnerability or concern about how it could negatively impact their job (BCG, 2024).

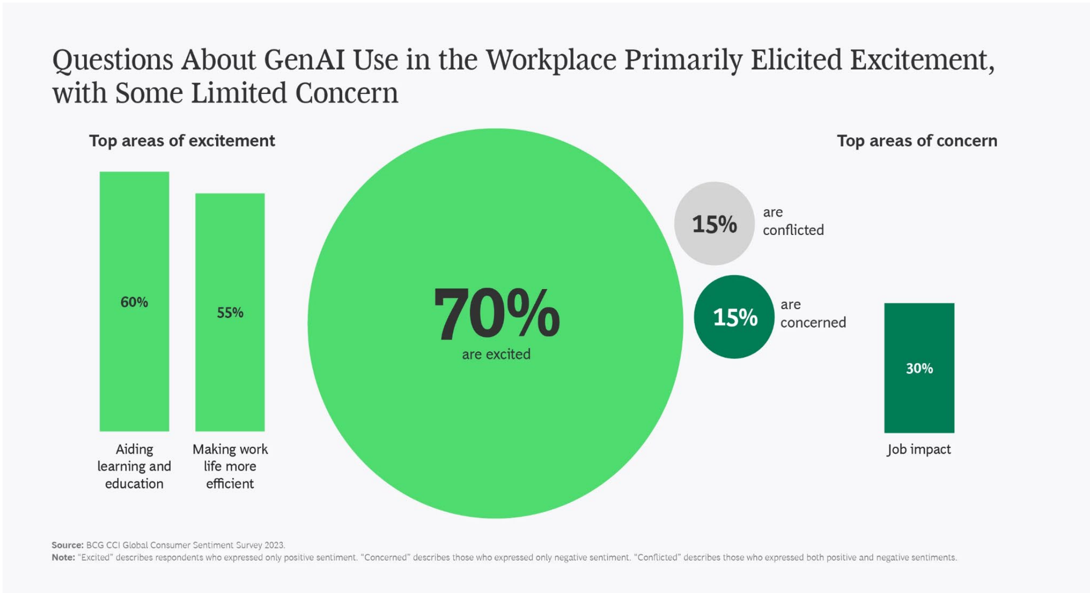

Figure 6. GenAI

7. Comparative Analysis of AI Applications in Automotive Manufacturing

The continued transformation of the automotive industry relies on the effective integration of Artificial Intelligence (AI) across core operational areas: design, assembly, and manufacturing. This comparative analysis of leading global manufacturers; General Motors (GM), Ford, BMW, and Mercedes-Benz, reveals distinct strategic approaches to AI adoption, highlighting accomplishments and identifying current gaps across key applications such as predictive maintenance, robotics, supply chain optimization, and quality assurance.

General Motors (GM)
Accomplishments:

- Supply Chain Optimization: GM is a leader in using AI for supply chain resilience. They have developed a proprietary four-pronged system that includes a digitized supply map and a machine-learning tool to track tier-one and sub-tier suppliers. Risk Intelligence, an AI article scanner that reads and classifies thousands of daily news articles to predict potential disruptions, which has been successful in triggering thousands of investigations and avoiding 75 events of potential business disruption in a single year.
- Predictive Maintenance (PM): GM has deployed AI-driven PM systems using condition-based monitoring, where machine learning (ML) algorithms analyze sensor data (e.g., temperature, vibration) to detect anomalies indicative of impending equipment failure.
- Design and Assembly: In partnership with Autodesk, GM has utilized generative design to create lightweight yet stronger components, such as seat brackets that are 40% lighter than traditionally manufactured counterparts.
- Robotics: While their advanced Robonaut 2 (R2) humanoid robot was developed with NASA for space exploration, GM is testing the externally developed K2 "Bumblebee" Kepler robot at its SAIC-GM plant in China for intricate inspections, component manipulation, and autonomous navigation.

Gaps and Future Objectives:

- Robotics in U.S. Production: GM's humanoid robot technology, while advanced, is currently not deployed for vehicle production in the United States.
- Wider Robotics Deployment: Up to this current data, The integration of the Kepler robot is currently limited to the SAIC-GM plant in China, suggesting a potential delay in widespread, autonomous production robotics deployment across all global facilities.

BMW
Accomplishments:

- Predictive Maintenance (PM): BMW is a leader in deploying successful, proprietary PM solutions. Their in-house ML maintenance system, integrated with conveyor technology at plants like Regensburg, monitors data for irregularities such as power fluctuations or illegible barcodes. This system has saved an average of eight hours of production downtime per year at the Regensburg plant alone and has been issued two patents.

- Design and Simulation: BMW utilizes AI with digital twin technology extensively in product development, allowing them to conduct technical tasks involving extensive simulations for areas like crash testing, aerodynamics, and autonomous driving. This reduces reliance on costly physical prototypes and accelerates development cycles.
- Robotics: BMW is actively testing humanoid robots for complex, precision, and ergonomically awkward tasks at its Spartanburg, S.C. plant.
- Assembly and QA: The company uses AI for tailored quality checks in vehicle assembly. They also use AI for inventory optimization.

Gaps and Future Objectives:

- Generative Design: While the paper highlights advanced digital twin use, a specific mention of the adoption of AI-driven generative design for novel component creation (similar to GM/Autodesk) is not explicitly detailed. The focus is primarily on simulation.
- Supply Chain Optimization: The provided data does not detail specific, proprietary AI systems for proactive, real-time supply chain disruption tracking similar to GM's Risk Intelligence.

Mercedes-Benz
Accomplishments:

- Quality Assurance (QA) and Assembly: Mercedes-Benz has advanced AI integration in its production ecosystem, MO360. Specifically, AI has been deployed in paint shops to identify imperfections invisible to the human eye, thereby ensuring higher finish quality while cutting inspection time.
- Digital Ecosystem: The MO360 platform, which integrates approximately 250 robots and paint equipment via AI, makes production data accessible and subject to real-time analysis via the cloud, allowing employees to immediately react to non-conformities. The platform includes a dedicated QA application QUALITY LIVE that supports continuous process optimization.
- Robotics: Mercedes-Benz is actively testing humanoid cobots, developed by Apptronik, in its production environment to fill labor gaps in repetitive, physically demanding work and free up highly skilled team members. The Apptronik Apollo robots are collecting data in the MO360 AI Factory (Berlin) to train for autonomous operations.
- Internal Knowledge Management: The "Digital Factory Chatbot Ecosystem" enables employees to access production databases and receive precise, multi-language answers to inquiries about machine maintenance or best-practice methods.

Gaps and Future Objectives:

- Predictive Maintenance: While Mercedes-Benz uses PM in production and embeds maintenance AI in its vehicles for customers, the scale and quantitative success of its in-house PM efforts, comparable to BMW's documented time savings, are not specified.
- Supply Chain Optimization: The provided text does not explicitly detail an AI system for managing and predicting external supply chain disruptions.
- Generative Design: The text focuses on digital twin/virtual commissioning for paint shops but does not confirm the use of generative design for product components.

Ford
Accomplishments:

- Quality Assurance (QA): Ford has addressed its recall challenges by implementing two AI-supported systems for QA inspections: MAIVS (Mobile Artificial Intelligence Vision System) and AiTriz. These systems use machine learning with still images and video streaming to catch millimeter-scale misalignments. MAIVS is deployed at nearly 700 stations, and AiTriz is at 35 stations across North America. AiTriz further offers greater precision and adaptability, particularly in instances of occlusions.
-
- Robotics/Cobots: Ford promotes human-cobot collaboration, utilizing AI-enabled robotic arms that can adapt to variability in QA by making real-time adjustments instead of halting production. They are also partnering with Agility Robotics for their Digi robot, aiming to improve warehousing and delivery efficiency.

- Predictive Maintenance (PM): Ford is working on a PM solution, the Miniterms project, which involves integrating small sensors with plant machinery to detect performance reduction and relay information to engineers' phones. This is an ongoing development in Europe.

Gaps and Future Objectives

- Supply Chain Optimization: Ford currently lacks the in-house capability for advanced, real-time AI supply chain management, relying on a six-year partnership with Google (effective 2023) to accelerate modernization in this area.
- Predictive Maintenance Deployment: The Miniterms PM solution is still a project under development and is not yet a complete, deployed capability at the scale of GM or BMW.
- Generative Design: Ford does not currently use generative AI in their design workflows, which means they are missing this key component for personalizing vehicle designs and achieving lightweight component optimization.
- Robotics for Production: Ford's current advanced robotics focus (Digi) is on warehouse maintenance and delivery, not on direct automotive production or assembly, unlike its competitors.

Comparative Results and Industry Standards

Based on the analysis, General Motors (GM) currently sets a strong standard in two critical, complex, and high-value areas:

1. Supply Chain Optimization: GM is the clear leader with its proprietary, real-time, four-pronged system that uses AI to predict and mitigate supply chain disruptions.
2. Generative Design: GM is a leader in applying generative AI to product design, yielding demonstrable results in weight reduction and performance.

BMW is the standard-setter for the efficacy and patenting of Predictive Maintenance systems, documenting significant savings in production downtime.

Mercedes-Benz establishes the standard for the full integration of AI into a digital production ecosystem (MO360), particularly for sophisticated Quality Assurance applications like paint-shop flaw detection.

The primary gap for many manufacturers, particularly Ford, lies in a lack of mature, in-house Supply Chain Optimization AI capabilities.

Recommendations for Automotive Manufacturers

1. Strategic AI Development (In-House vs. Outsource): Companies must make a strategic decision on whether to develop core AI solutions in-house, as BMW and GM have done with PM and supply chain, respectively, to maintain a competitive advantage and protect intellectual property. Conversely, outsourcing or partnerships (like Ford's with Google) for data analysis, artificial intelligence and machine learning, can accelerate adoption but may dilute proprietary knowledge.
2. Bridging the Workforce Skills Gap: The transition to AI-enabled manufacturing requires workers to shift from manual tasks to supervising AI systems. Manufacturers must launch continuous training programs and leverage partnerships with technical institutes to prepare the workforce for new technical literacy requirements. A human-centered approach is essential to ensure AI enhances job quality and does not simply replace workers, addressing a common concern among consumers.
3. Data Foundation and Governance: To overcome the challenge of data dependency, firms must focus on building robust data pipelines and establishing standardized data governance to ensure interoperability between legacy systems and new AI platforms. Without reliable, clean data, AI predictions risk being inaccurate and potentially harmful.
4. Adoption of Systems Engineering (MBSE): For complex AI integration projects, using model-based systems engineering (MBSE)-compliant tools is crucial. This approach helps properly define the AI transformation project using models (like the V model) to match goals with validation and verification activities, ensuring a robust, tested solution before costly real-time production deployment

8. Conclusions

Production leadership will largely depend on who integrates AI, robotics, and production equipment the best. Comparing robot capabilities. Who has larger data set, who manages data the best, who produces the fastest, To overcome the challenges of AI integration, manufacturers must adopt a holistic strategy. This begins with building robust data pipelines and ensuring interoperability between legacy systems and new AI platforms. By establishing standardized data governance practices, companies can minimize the risk of poor data inputs and create a reliable foundation for AI-driven insights. In the automotive assembly sector, a human-centered approach to AI is essential as adoption accelerates. This involves not only implementing clear safety protocols for human-robot collaboration but also launching continuous training programs to upskill the workforce. Partnerships with universities and technical institutes can be leveraged to bridge the skills gap and prepare students for future roles in the industry. When it comes to design, transparency and validation are paramount. Generative designs must undergo rigorous compliance and ethical reviews to ensure their integrity and reliability. Furthermore, legal and ethical concerns arise if design materials are used without consent. Therefore, developers of generative AI systems must secure proper licensing agreements to acquire and use data, particularly from copyrighted or proprietary sources, for training their models (Gerben, 2025). Across all three domains, success hinges on viewing AI not as a plug-in solution but as a strategic transformation. Firms that align AI adoption with clear goals (of sustainability, safety, customer personalization, work-life enhancement) will capture the full value of the technology while minimizing its risks. Data has proven to show that this strategic investment is not just a fad, but indeed a reality. Using approaches such as the V model will help properly define this AI transformation project and match ideas, goals, and initiatives with validation and verification activities of the solution. Development teams need to construct a detailed design of what AI systems will look like and how users will use them for QA inspection tests, predictive maintenance, and custom design layouts for automobiles. Integrated product development teams are also crucial for the success of these sorts of projects. The concept development phase will require tremendous integration across the different functions of the development team. The front-end process must include identifying customer needs, analyzing competitive AI products, establishing target specifications, generating and selecting concepts, setting final specifications, testing the idea, performing an economic analysis, and planning the remaining project activities (Ulrich et al., 2020). Organizations have two choices: finding ways to outsource this technology development or developing it in-house, as BMW has done. Although teams may find it cheaper to develop in-house, it may take some time to actually get AI solutions to work as expected in a test environment.

Using MBSE-compliant tools is essential, as these diagrams and process flows enable the production system and lifecycle to be mapped and brought to life. Relying on stale documentation to communicate complex engineering and project management activities and milestones to marketing, engineering, and manufacturing can limit the understanding of the activities necessary to reach the solution. This AI system and its integration with production equipment are a complex problem, which means the product will need a suitable development process. Upon beginning the system-level design, the system is decomposed into subsystems, which are then decomposed into smaller components, repeating this process until we are left with numerous components. Teams are then assigned to each component, and another development team will integrate them into the overall system (Ulrich et al., 2020). There needs to be a test environment for this, as halting real-time production leads to loss of revenue and production, while risking the failure of not working as expected. Training employees on the user interface will require time, as these employees will need space, training, and support to acquire new skills surrounding the software and hardware being deployed. Companies will need an on-site support team (tiger team) for this technology. These individuals must understand how the software was integrated into the hardware system to troubleshoot its effects on assembly/production line errors. Lastly, companies must make the strategic decision of whether to outsource their AI solution development. If AI solutions are developed in-house, this helps maintain competition, as competitors would be exempt from disclosing their intellectual property. On the contrary, if AI solutions are created and made available to others through contractual agreements, AI adoption will occur more quickly, giving companies another market advantage over those who decide to purchase their solutions. All in all, AI systems for auto manufacturing can be a win-win situation for corporate leadership and production if implemented responsibly: training AI systems on reliable and quality data while training a production workforce to use these tools to enhance their quality of work, rather than using the technology to replace them.

References

Agalianos, K., Ponis, S. T., Aretoulaki, E., Plakas, G., and Efthymiou, O., "Discrete event simulation and digital twins: Review and challenges for logistics," *Procedia Manufacturing*, vol. 51, pp. 1636–1641, 2020. https://doi.org/10.1016/j.promfg.2020.10.228

Ahmad, R., Amin, R. F. M., and Mustafa, S. A., "Value stream mapping with lean thinking model for effective non-value added identification, evaluation and solution processes," *Operations Management Research*, vol. 15, no. 3, pp. 1490–1509, 2022. https://doi.org/10.1007/s12063-022-00265-9

Alcaraz, J., and Rivera, R., "Integrating human factors into warehouse simulation models," *Journal of Industrial Engineering*, vol. 19, no. 1, pp. 45–58, 2022.

Amorim-Lopes, M., Guimarães, L., Alves, J., and Almada-Lobo, B., "Improving picking performance at a large retailer warehouse by combining probabilistic simulation, optimization, and discrete-event simulation," *International Transactions in Operational Research*, vol. 28, no. 2, pp. 687–715, 2021. https://doi.org/10.1111/itor.12852

AnyLogic, "Warehouse operations – DHL supply chain case study," 2025.

Automotive World, "Enhanced efficiency thanks to new family of applications: Digital Mercedes-Benz Production Ecosystem MO360: Global production networked in real time," 2020.

Barnes, R. M., *Motion and Time Study: Design and Measurement of Work*, 7th ed., Wiley, 1980.

BCG, "Of consumers, 70% are excited about GenAI in the workplace, but only 43% are enthusiastic about its impact on daily life," 2024.

Bett, D. K., Ali, I., Gheith, M., and Eltawil, A., "Simulation-based optimization of truck appointment systems in container terminals: A dual transactions approach with improved congestion factor representation," *Logistics*, vol. 8, no. 3, 2024. https://doi.org/10.3390/logistics8030080

Caballini, C., Gracia, M. D., Mar-Ortiz, J., and Sacone, S., "A combined data mining–optimization approach to manage truck operations in container terminals with the use of a TAS," *Transportation Research Part E*, vol. 142, 2020. https://doi.org/10.1016/j.tre.2020.102054

Camarella, S., Huntington, M., Goering, K., and Conway, M. P., "What is digital-twin technology?," McKinsey & Company, 2024.

Chen, J. C., Li, Y., and Shady, B. D., "From value stream mapping toward a lean/sigma continuous improvement process: An industrial case study," *International Journal of Production Research*, vol. 48, no. 4, pp. 1069–1086, 2010.

Cholewinski, P., Kellner, M., Richter, W., Roggendorf, M., Tschiesner, A., and Venus, A., "Automotive R&D transformation: Optimizing Gen AI's potential value," McKinsey & Company, 2024.

De Steur, H., Wesana, J., Dora, M. K., Pearce, D., and Gellynck, X., "Applying value stream mapping to reduce food losses and wastes in supply chains: A systematic review," *Waste Management*, vol. 58, pp. 359–368, 2016.

De Vito, P., Battista, U., Bolognesi, A., and Sanfilippo, S., "Multi-method approaches for simulation modelling of warehouse processes," *SIMULTECH 2024*, pp. 305–312, 2024.

Ganbold, O., Kundu, K., Li, H., and Zhang, W., "A simulation-based optimization method for warehouse worker assignment," *Algorithms*, vol. 13, no. 12, p. 326, 2020.

Gaser, S., "Smart maintenance using artificial intelligence," BMW Group PressClub, 2023.

Gerben, J. G. M., "IP in the age of AI: What today's cases teach us about the future of the legal landscape," American Bar Association, 2025.

Guasch, A., Piera, M. A., and Figueras, J., "Automatic warehouse modelling and simulation," *International Journal of Simulation and Process Modelling*, vol. 6, no. 4, pp. 288–296, 2011.

Johnson, C., and Smith, L., "Collaborative waste management: A review of successful partnerships," *Waste Management*, vol. 35, no. 8, pp. 198–210, 2020.

Liker, J. K., *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*, McGraw Hill Education, 2021.

Macal, C. M., and North, M. J., "Agent-based modeling and simulation: ABM for logistics and supply chain management," *Decision Support Systems*, vol. 50, no. 4, pp. 95–105, 2010.

Precedence Research, "Artificial intelligence (AI) market size estimated to reach USD 2,575.16 bn by 2032," 2023.

Shimkus, B., "AI cameras help Ford factory workers spot assembly errors and prevent costly recalls," Business Insider, 2025.

Skapinyecz, R., "Recent trends in the optimization of logistics systems through discrete-event simulation and deep learning," *Algorithms*, vol. 18, no. 9, p. 573, 2025.

Staudt, F. H., Alpan, G., Di Mascolo, M., and Rodriguez, C. M. T., "Warehouse performance measurement: A literature review," *International Journal of Production Research*, vol. 53, no. 18, pp. 5524–5544, 2015.

Sun, S., Zheng, Y., Dong, Y., Li, N., Jin, Z., and Yu, Q., "Reducing external container trucks' turnaround time in ports: A data-driven approach under truck appointment systems," *Computers & Industrial Engineering*, vol. 174, p. 108787, 2022.

Ulrich, K. T., Eppinger, S. D., and Yang, M. C., *Product Design and Development*, McGraw Hill Education (India) Private Limited, 2020.

Zhang, Y., and Zhao, L., "Multi-criteria decision analysis in logistics sustainability," *International Journal of Operations Research*, vol. 27, no. 4, pp. 201–219, 2023.