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Advanced Decision-Making Strategies and Technologies for Manufacturing: Case Studies, and Future Research Directions

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Abstract

This article presents a review exploring decision-making strategies and technologies in the manufacturing sector, examining both traditional and emerging approaches. The article critically analyses the current landscape of decision-making in the manufacturing sector, highlighting innovative technologies and practical applications through case studies and the challenges associated with their implementation. By investigating the intersection of technological advances and strategic decision-making, the study provides insights for improving industrial competitiveness and identifies critical areas for future research and development.

Keywords: decision-making, digital twins, manufacturing strategies.

1 Introduction

Decision-making is an essential phase of the manufacturing process that has a major impact on the productivity, quality, cost and on-time delivery of a product [13, 21, 22]. In the traditional approach, decisions in the manufacturing industry were based primarily on the experience, knowledge, intuition and judgement of managers and staff. However, as modern manufacturing processes have become more complex and dynamic, it is no longer sufficient to base judgements solely on intuition and experience [6, 29].

The evolution of decision-making technologies reflects a significant transformation in industrial strategic planning. From methods and tools of production management and operations research, such as statistical process control, queuing theory, dynamic programming, and linear programming [13, 21], to programming to advanced technologies such as data analytics, artificial intelligence, and optimization tools, manufacturers are continuously adapting to more sophisticated decision-making paradigms [5, 10, 24, 30].

The use of cutting-edge technology and techniques such as data analytics, simulation and optimization, quality management, and supply chain integration has emerged as the latest technology in industrial decision-making in recent years [6, 22, 29]. These technologies and strategies enable manufacturing decision-makers to collect and analyze large amounts of relevant data, model and analyze different scenarios and alternatives, and make more informed and effective decisions.

For example, data analytics and artificial intelligence have emerged as important decision-making tools in the manufacturing sector [24, 30]. Data analytics provides decision-makers with the ability to collect and examine relevant data from various sources, including information systems, equipment, and sensors, to gain insights into important details about the functioning of the production system. On the other hand, artificial intelligence provides decision-makers with the ability to evaluate massive amounts of unstructured data and derive relevant information for decision-making by using machine learning algorithms and natural language processing. Optimization helps decision-makers to select the optimal option using mathematical and computational tools.

Quality management and supply chain integration are also important decision-making strategies in the manufacturing industry [6, 29]. Quality management enables decision-makers in the manufacturing industry to identify and correct quality problems promptly, using tools and techniques such as statistical process control, root cause analysis, and quality management systems. Supply chain integration, on the other hand, enables decision-makers in the manufacturing industry to improve visibility and coordination of the different stages of the production process, from raw material procurement to delivery to the customer. This enables decision-makers to make more informed and effective decisions throughout the entire production process.

This article presents both traditional strategies and advanced innovative methods and tools for decision-making in the manufacturing sector. Through detailed case studies and critical analysis, they illustrate the practical applications of emerging technologies, evaluate their transformative potential, and offer strategic guidance for effective implementation. The paper's objective is to enhance understanding of advanced decision-making approaches, identify critical adoption challenges, and outline promising research directions that can drive industrial competitiveness in an increasingly dynamic global marketplace.

2 Methods of Decision-Making in Manufacturing

2.1 Traditional Methods of Decision-Making in Manufacturing

Traditional methods are formed by *experience-based* methods and *quantitative approaches*, as illustrated in Figure 1. The former includes *intuition*, *prior experience* and *trial and error* methods.

Traditional methods in manufacturing decision making also include quantitative approaches, including *linear programming*, which is a very popular method that allows decision makers to schedule production and allocate resources optimally given specific objectives and constraints [21]. *Dynamic programming* also allows for a gradual improvement in the performance of the manufacturing system [13]. Another traditional approach is the use of *queuing theory* to model and analyze manufacturing

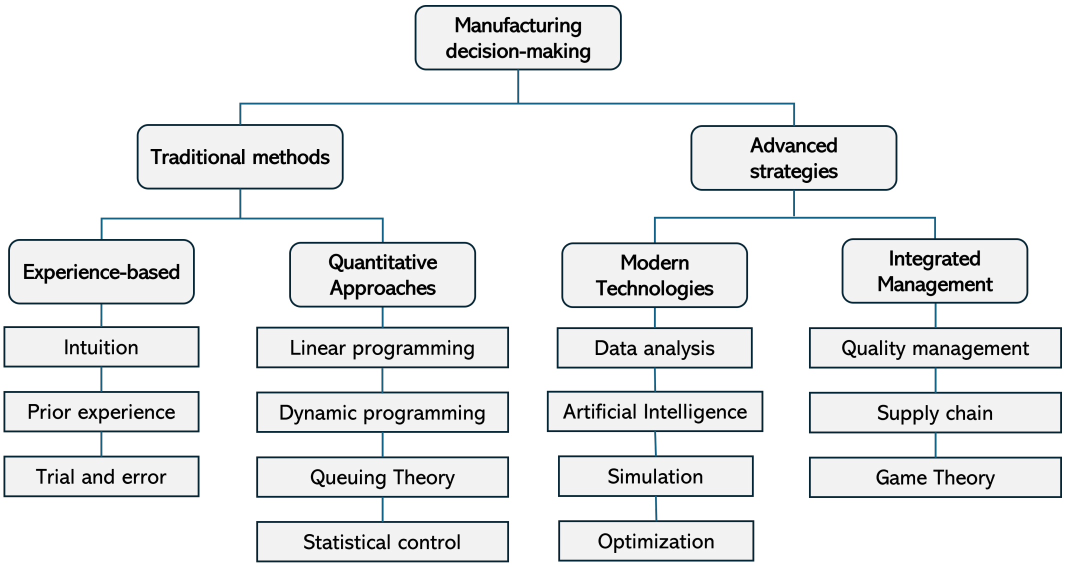

Figure 1: Manufacturing Decisions Making Methods

systems. Queuing theory allows decision makers to analyze the interaction between different components of the manufacturing system such as machines, workers, and inventories and to make more effective decisions to improve system performance. *Statistical process control* also belongs to quantitative approaches and is used as a traditional tool that allows quality control monitoring in the production process to identify and correct quality problems in time. Furthermore, it also uses decision rules and scenario analysis approaches based on knowledge and experience [22].

The above methods have proven useful in the past. However, with massive data, *advanced strategies*, as described in Figure 1, using *modern technologies* have allowed decision makers in the manufacturing sector to collect and analyze large amounts of relevant data, model and analyze different scenarios and alternatives, and make more informed and effective decisions.

There are still challenges and limitations associated with the adoption and implementation of these new technologies and strategies. One of the most important challenges is to have high quality and relevant data for decision making. If the quality of the data is incomplete, inaccurate or biased, it can lead to wrong decisions. The complexity and dynamics of modern manufacturing systems are challenging and information can make it difficult to predict the impact of different decisions on system performance and make timely decisions [29]. Resistance to change is always a major issue in the adoption, trust, and implementation of new technologies and strategies in manufacturing decision making [6]. Many workers and managers may resist change because they do not have information and may think this is a threat to their position or job security.

Manufacturing companies must have an approach to decision making. This involves high-quality data, a model, an analysis of different scenarios, and the implementation and monitoring of the decisions made. Companies must promote continuous improvement by training workers and managers in the use of decision making. There are still challenges and limitations associated with the adoption and implementation of these new technologies and strategies, and manufacturing companies need to take a systematic and strategic approach to manufacturing decision-making.

2.2 Advanced Decision-Making Strategies in Manufacturing

One of the most important technologies for decision making in manufacturing (Fig. 1) is *data analysis* and *artificial intelligence*. Data analytics allows for the analysis of relevant data from different sources, such as sensors, machines, and information systems, of the performance of the manufacturing system. Machine learning and natural language processing algorithms allow us to analyze large sets of unstructured data and obtain useful information for decision-making. Siemens uses machine learning algorithms to predict machine failures and reduce downtime [24, 30].

Simulation and *optimization* are strategies for decision-making in manufacturing. Simulation allows us to model and analyze different scenarios and alternatives virtually, before implementing them in the real manufacturing system [5]. Then, it can evaluate the impact of different decisions on the performance of the manufacturing system and make decisions more effective and timelier. Optimization permits the use of algorithms and mathematical techniques to find the best solution among a set of feasible alternatives. For example, Ford Motor Company uses simulation and optimization to improve production efficiency and reduce costs. Quality management and integration of the supply chain are also important decision-making strategies in manufacturing [6, 29].

Within *integrated management, quality management* allows identifying and correcting quality problems in time, using tools and techniques such as statistical process control, root cause analysis and quality management systems. *Supply chain* integration improves the visibility and coordination of the different stages of the production process, from the acquisition of raw materials to delivery to the customer. The decisions throughout the production process are more informed and effective. For example, the Toyota company uses supply chain integration to improve production quality and efficiency [30].

Game theory facilitates the analysis and forecasting of the actions of various participants in the industrial system, enabling more efficient decision-making in intricate and ever-changing scenarios. The efficiency and quality of production can be increased by allowing various players in the manufacturing system to collaborate and share information pertinent to decision-making. Decision-making is improved by both methods [22].

These advanced strategies enable more informed and effective decisions. However, there are also challenges and limitations associated with the adoption and implementation of these new technologies and strategies, such as the lack of relevant and high-quality data, the complexity and dynamics of modern manufacturing systems, and resistance to change. To address these challenges and limitations, manufacturing companies need to adopt a systematic and strategic approach to decision-making in the manufacturing industry, including the collection and analysis of relevant and high-quality data, the modeling and analysis of different scenarios and alternatives, and the implementation and monitoring of the decisions made.

3 Case studies

3.1 Airbus SE's Decision-Making in Manufacturing

Airbus SE is a European multinational aerospace corporation and one of the largest aircraft manufacturers in the world. The company operates across a variety of sectors, including commercial aircraft, defense and space (Fig. 2) and helicopters, and has a strong focus on innovation, sustainability, and digitalization. In recent years, it has been implementing various advanced manufacturing decision-making strategies and technologies to improve its competitiveness and efficiency in the global market. Some of the key strategies and technologies that the company has adopted are described below [1]:

Digital Twin Technology:
Airbus SE has been using digital twin technology to optimize its manufacturing processes and improve the quality of its products. In particular, to optimize the design and manufacturing of its aircraft, reduce aircraft downtime and maintenance costs, and improve the efficiency and flexibility of its production lines. The company has also been using digital twin technology to monitor and predict the performance of aircraft in service and to offer new and innovative services and solutions to its customers.

Artificial Intelligence and Machine Learning:
Airbus SE has been using artificial intelligence (AI) and machine learning (ML) algorithms to analyze and interpret large amounts of data from its manufacturing operations and make more informed and effective decisions. The company has been using AI and ML to optimize its production planning and scheduling, predict and prevent equipment failures, improve the quality and consistency of its products, and reduce waste of energy and materials. The company has also been using AI and ML to develop and implement new and innovative solutions and services for its customers, such as predictive maintenance, energy management, and quality control.

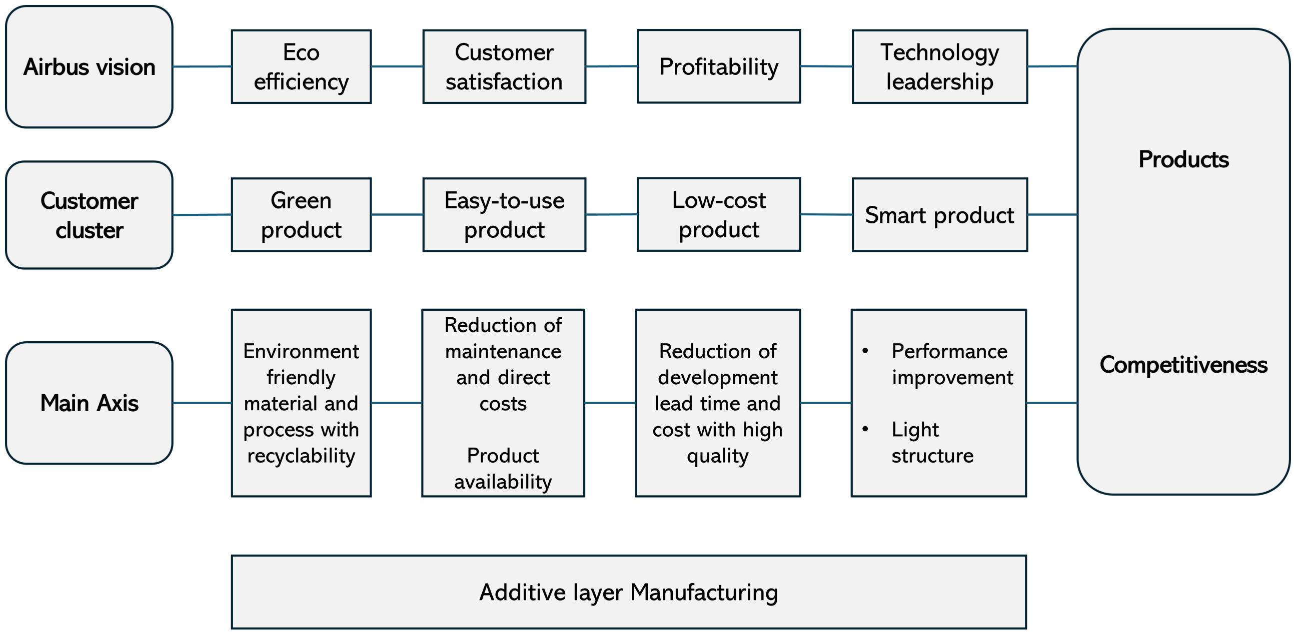

Figure 2: Airbus SE advanced manufacturing decision-making strategies

Additive Manufacturing:
Airbus SE has been using additive manufacturing, also known as 3D printing, to produce complex, customized parts and products for its operations and for its customers. The company has been using additive manufacturing to produce parts for its aircraft, such as struts, fuel nozzles, and cabin components, and to reduce the time and cost of prototyping, tooling, and production. The company has also been using additive manufacturing to offer new and innovative solutions and services to its customers in various industries.

Collaborative Robotics:
Airbus SE has been using collaborative robots, or cobots to assist and support its human workers in various manufacturing tasks, such as assembly, inspection, and painting. The company has been using cobots to reduce the physical and mental strain on its workers, to improve the quality and consistency of its products, and to increase the flexibility and agility of its production lines. The company has also been using cobots to deliver new and innovative solutions and services to its customers in various industries.

Lean and Agile Manufacturing:
Airbus SE has been using lean and agile manufacturing principles and practices to improve the efficiency, quality, and responsiveness of its manufacturing operations. The company has been using lean and agile manufacturing to eliminate waste and improve the flow of its production process, and lean manufacturing to enable the production process to adapt and respond to changes and uncertainties in the market and environment. The company has been using lean and agile manufacturing to reduce lead times and inventory levels, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations.

The implementation of these advanced manufacturing decision-making technologies and strategies has not been without challenges and limitations. Some of the challenges that Airbus SE has faced are [2]:

Data and Analytics:
The availability, quality and security of data and analytics are critical to the success of advanced manufacturing decision-making technologies and strategies. Airbus SE has been investing in the development and implementation of advanced data and analytics capabilities, such as data lakes, data warehouses, data integration, data governance and data security, to support and enable its decision-making processes.

Talent and skills:
The adoption and implementation of advanced manufacturing decision-making technologies and strate-

gies require a new set of talents and skills, such as data science, software engineering and digital manufacturing. Airbus SE has been investing in the training and development of its existing workforce, and in the recruitment and integration of new talents and skills, to support and enable its decision-making processes.

Change management:
The adoption and implementation of advanced manufacturing decision-making technologies and strategies require significant organizational, cultural and mindset change and transformation. Airbus SE has been using various change management techniques and tools, such as communication, participation and feedback, to involve its employees, customers and partners in decision-making processes and to ensure the success and sustainability of change and transformation. Despite these challenges and limitations, Airbus SE has achieved significant improvements and benefits by implementing advanced manufacturing decision-making strategies and technologies. Some of the improvements and benefits that the company has reported are [14]:

Efficiency and Productivity:
The company has managed to reduce downtime, energy and material consumption, and lead time of its manufacturing operations, and increase the performance, efficiency, and flexibility of its production lines.

Quality and Innovation:
The company has managed to improve the quality, consistency, and customization of its products, and increase the speed, scope, and success of its product innovation and development.

Customer Satisfaction:
The company has managed to improve the responsiveness, reliability, and transparency of its manufacturing operations, and offer new and innovative solutions and services to its customers in various industries.

Sustainability:
The company has managed to reduce the carbon and environmental footprint of its manufacturing operations and contributes to the achievement of global sustainability goals and targets. While advanced decision-making strategies and technologies offer significant potential benefits to the manufacturing industry, their widespread adoption faces several practical barriers that need to be addressed:

Cost considerations:
Implementing advanced systems such as digital twins, AI, and robotics often requires a substantial upfront investment. For example, a Deloitte study found that 55% of manufacturers cited high implementation costs as a major barrier to Industry 4.0 adoption [2]. Smaller manufacturers may struggle to justify these costs in the face of uncertain returns on investment.

Technical complexity:
The intricate nature of these systems demands specialized expertise for implementation and maintenance. A McKinsey and Company survey revealed that 70% of manufacturers reported that a lack of digital talent was a major obstacle to their digital transformation efforts [3]. This complexity extends to data integration, system interoperability, and the need for continuous workforce upskilling.

Organizational resistance:
Cultural barriers within manufacturing organizations can significantly impede adoption. Concerns about job displacement and reluctance to change established processes are common. Research from the Manufacturing Institute showed that 78% of manufacturers believe that resistance to change is one of the main challenges in implementing new technologies [4].

Airbus SE's manufacturing decision-making is a case study of how a large, diversified aerospace corporation can adopt and implement advanced manufacturing decision-making strategies and technologies to improve its competitiveness, efficiency and sustainability in the global marketplace. The company's focus on innovation, digitalization and collaboration and its ability to overcome implementation challenges and constraints are key drivers of the success and sustainability of its decision-making processes [14].

3.2 General Electric's Implementation of Decision-Making in Manufacturing

General Electric (GE) is one of the world's largest industrial corporations, headquartered in Boston, Massachusetts, USA, where it was founded in 1892 [10]. The Company uses predictive analytics to improve its decision-making strategies. The company has manufacturing facilities, research and development centres, and sales and marketing offices in several countries and operates in many sectors, including renewable energy, electricity, aviation, and healthcare.

To implement predictive analytics, the company uses many tools and technologies, such as machine learning, artificial intelligence (AI), and the Internet of Things (IoT), as well as data analytics and visualization, to collect, process, and utilize data from its manufacturing operations. Predictive analytics has both advantages and disadvantages in this strategy. These tools and technologies enable GE to predict and anticipate various scenarios and outcomes and make more informed and effective decisions regarding its manufacturing operations.

GE's manufacturing operations are a critical part of its business, enabling it to produce and deliver the high-quality, high-performance products its customers demand. GE's manufacturing operations involve the use of complex and sophisticated processes, such as casting, forging, and machining, to create the various components and systems of its products. These processes require a high degree of precision, accuracy, and control, as well as a significant amount of data and information, to ensure that products meet desired specifications and quality standards [11].

For example, GE uses predictive analytics to predict and anticipate maintenance and repair needs for its manufacturing equipment and machinery. Using predictive analytics, GE can monitor and analyze various performance and health indicators of its equipment and machinery, such as temperature, vibration, and pressure, and can predict and anticipate any issues that may arise (Figure 3). This, in turn, allows GE to schedule and perform necessary maintenance and repairs more proactively and efficiently, reducing the costs and downtime associated with unscheduled maintenance and repairs.

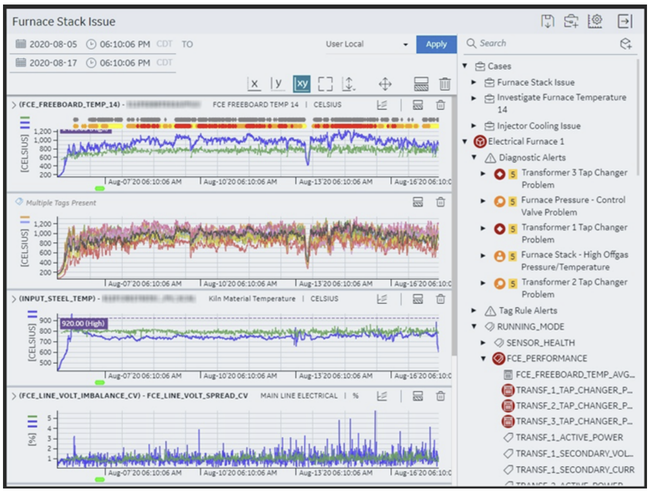

Figure 3: GE Predictive analytics metrics [11]

Another example of how GE uses predictive analytics for manufacturing decision-making is in the area of quality control. GE uses predictive analytics to predict and anticipate the quality and consistency of its products and to identify and diagnose any issues that may arise. By using predictive analytics, GE can monitor and analyze various process and product indicators, such as dimensions, tolerances, and surface finish, and can predict and anticipate any deviations or defects that may occur. This, in turn, allows GE to adjust and optimize process parameters and settings more proactively and efficiently, and improve the quality and consistency of its products. GE's implementation of predictive analytics for manufacturing decision-making has yielded several benefits for the company: improved quality and consistency, increased efficiency and productivity, and greater innovation and agility. GE's implementation of predictive analytics for decision-making in manufacturing has also resulted in several challenges for the company, such as [11]:

Data Quality and Integrity:
GE's use of predictive analytics depends on the quality and integrity of the data it collects and analyzes. However, ensuring data quality and integrity can be a significant challenge, as data can be subject to errors, omissions, and biases that in turn can impact on the accuracy and reliability of the predictions and recommendations it generates. To address this challenge, GE implements robust and reliable data management practices, such as data validation, data cleansing, and data integration, to ensure the quality and integrity of its data.

Technical Complexity and Expertise:
GE's use of predictive analytics involves the use of multiple tools and technologies, such as data analytics and visualization, machine learning and artificial intelligence, and IoT, which can be technically complex and require specialized expertise. For example, GE's use of predictive analytics to monitor and analyze various process and product indicators can be technically complex and require specialized expertise in areas such as materials science, physics, and computer science. To address this challenge, GE needs to invest in and develop its technical capabilities and expertise, and collaborate with third-party partners and suppliers, to ensure it has the skills and resources to effectively implement and leverage predictive analytics.

Organizational Culture and Change Management:
GE's use of predictive analytics requires a significant change in the way the company makes decisions and operates its manufacturing processes. This change can be challenging for the company's employees and stakeholders, who may resist the change or lack the skills and knowledge to use predictive analytics effectively. To address this challenge, GE needs to implement a comprehensive change management strategy—including training and development, communication and engagement, and incentives and rewards—to ensure that its employees and stakeholders are prepared and motivated to use predictive analytics effectively.

GE's implementation of predictive analytics for decision making in the manufacturing industry has brought with it several benefits to the company, such as improved quality and consistency, increased efficiency and productivity, and greater innovation and agility. However, GE's implementation of predictive analytics has also brought with it several challenges to the company, such as data quality and integrity, complexity and technical expertise, and organizational culture and change management. To address these challenges, GE needs to implement robust and reliable data management practices, invest in and develop its technical capabilities and expertise, and implement a comprehensive management strategy. By doing so, GE can continue to leverage predictive analytics to improve its decision making in the manufacturing industry and maintain its competitive advantage in the global industrial market [22, 29].

GE's ambitious digital transformation initiative, aimed at positioning the company as a leader in the Industrial Internet of Things (IIoT), faced significant challenges. Despite investing billions of dollars in its Predix platform, GE faced organizational resistance, complexity in integrating diverse industrial assets, and difficulty demonstrating a clear return on investment to customers. This led to a downsizing of the initiative and a restructuring of the GE Digital division [12].

3.3 Ford Motor Company's Implementation for Decision-Making in Manufacturing

Ford Motor Company was founded in 1903 and is one of the world's oldest and largest automobile manufacturers, headquartered in Dearborn, Michigan, USA. The company owns a diverse portfolio of cars, SUVs, trucks, and electric and autonomous vehicles. With a global presence with manufacturing facilities, research and development centers, and sales and marketing offices in multiple countries around the world, Ford has been at the forefront of using digital twin technology to improve its manufacturing decision-making. The company's implementation of digital twin technology involves creating a virtual replica of a physical product or process, which can be used to simulate, analyze, and optimize various scenarios and outcomes. In this case study, we will take a closer look at Ford's implementation of digital twin technology for manufacturing decision-making and explore the benefits and challenges of this approach.

Ford's manufacturing operations are a critical part of its business, enabling it to produce and deliver the high-quality, high-performance vehicles its customers demand. Ford's manufacturing operations involve the use of complex and sophisticated processes, such as stamping, welding, and painting, to create the various components and systems of its vehicles. These processes require a high degree of precision, accuracy, and control, as well as a significant amount of data and information to ensure that vehicles meet desired specifications and quality standards [8]. Ford's implementation of digital twin technology for decision-making involves the use of various tools and technologies, such as 3D modeling and simulation, data analytics and visualization, and machine learning and artificial intelligence (AI) to create and leverage virtual replicas of its products and processes. These tools and technologies enable Ford to simulate and analyze various scenarios and outcomes and make more informed and effective decisions regarding its manufacturing operations [9, 23].

For example, Ford uses digital twin technology to simulate and analyze the stamping process used in body panels and frames. By using digital twin technology, they can simulate and analyze the various process parameters and settings such as the temperature and pressure of the stamping dies, the thickness and shape of the metal parts, and identify the optimal settings and conditions for the process. This, in turn, allows the company to improve the quality and consistency of stamped components and reduce the costs and time associated with the process [8].

Another example of how Ford uses digital twin technology for manufacturing decision-making is in predictive maintenance. They use digital twin technology to create virtual replicas of its manufacturing equipment and machinery and to monitor and analyze their performance and status in real time. Any issues or problems with the equipment and machinery are quickly and accurately identified and diagnosed, and necessary maintenance and repairs can be scheduled and performed more proactively and efficiently. This, in turn, improves the reliability and availability of its equipment and machinery and reduces the costs and downtime associated with unscheduled maintenance and repairs (Fig. 4).

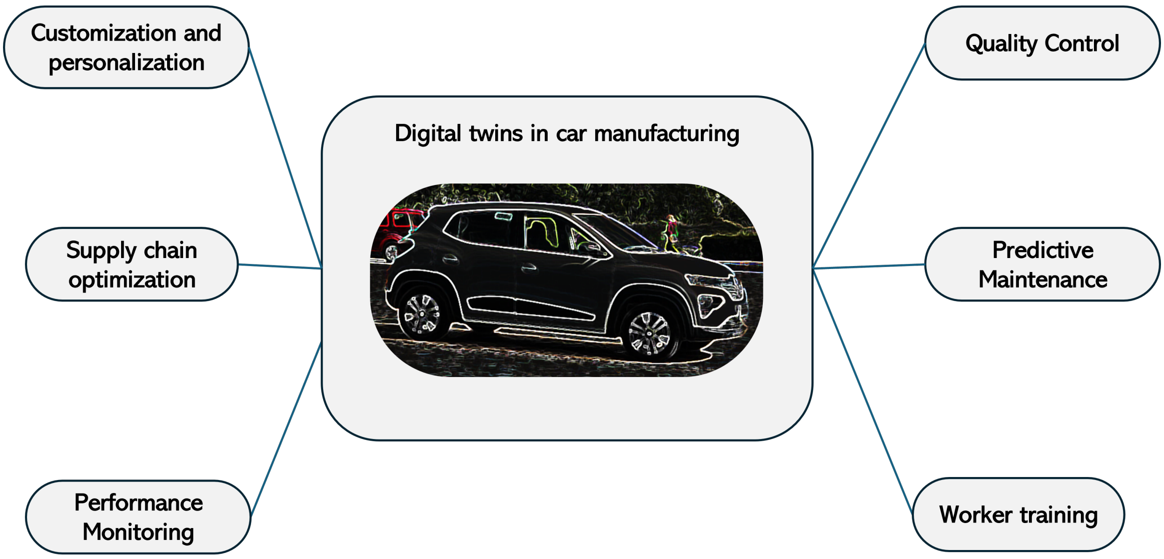

Figure 4: Ford's implementation of digital twin technology

Ford's implementation of digital twin technology for decision-making in manufacturing has resulted in several benefits for the company, such as [20]:

Improved Quality and Consistency:
Ford's use of digital twin technology has enabled the company to improve the quality and consistency of its products, thereby meeting the demands and expectations of its customers [28]. For instance, simulating and analyzing the stamping process has resulted in a significant improvement in the quality and consistency of stamped components, which in turn has resulted in a significant improvement in the quality and consistency of its vehicles.

Increased Efficiency and Productivity:
Ford's use of digital twin technology has enabled it to increase the efficiency and productivity of its manufacturing operations, reducing the costs and time associated with producing its products. For example, using digital twin technology to schedule and perform necessary maintenance and repairs

more proactively and efficiently has resulted in a significant increase in the reliability and availability of its equipment and machinery, which in turn has resulted in a significant increase in the efficiency and productivity of its manufacturing operations.

Increased Innovation and Agility:
Ford's use of digital twin technology has enabled it to improve its innovation and agility capabilities and respond more quickly and effectively to changing customer demands and expectations. For example, using digital twin technology to simulate and analyse various scenarios and outcomes has enabled it to test and evaluate new and innovative ideas and concepts bringing new and innovative products to market more quickly and effectively.

Ford's implementation of digital twin technology for decision-making in manufacturing has also resulted in several challenges for the company, such as:

Data Quality and Integrity:
Ford's use of digital twin technology depends on the quality and integrity of the data it collects and analyzes. However, ensuring data quality and integrity can be a significant challenge as data can be subject to errors, omissions and biases. For example, using digital twin technology to monitor and analyze the performance and health of its equipment and machinery can be impacted by the quality and integrity of the data it collects and analyzes, which in turn can impact on the accuracy and reliability of the predictions and recommendations it generates. To address this challenge, Ford implements data management practices such as data validation, cleansing and integration to ensure data quality and integrity.

Technical Complexity and Expertise:
Using digital twin technology involves the use of multiple tools and technologies, such as 3D modelling and simulation, data analysis and visualization, and machine learning and artificial intelligence, which can be complex and require specialized expertise. Using digital twin technology to simulate and analyze the stamping process requires expertise in areas such as materials science, physics, and computer science. To address this challenge, the company is developing its technical capabilities and expertise and collaborating with third-party partners and suppliers to ensure that it has the skills and resources to implement and leverage digital twin technology effectively.

Organizational Culture and Change Management:
Using digital twin technology requires a significant shift in the way the company makes decisions and operates its manufacturing processes. This change can be challenging for the company's employees and stakeholders, who may resist the change or lack the skills and knowledge to use digital twin technology effectively. To address this challenge, Ford has needed to implement a comprehensive management strategy, including training and development, communication and engagement, and incentives and rewards to ensure its employees and stakeholders are prepared and motivated to use the technology effectively.

3.4 Intel Decision-Making in Manufacturing

Intel Corporation was founded in 1968 and headquartered in Santa Clara, California, USA and is one of the world's leading technology companies. It is a leading provider of semiconductor chips and other advanced technologies such as artificial intelligence (AI), cloud computing, and the Internet of Things (IoT). Intel has a global presence, with manufacturing facilities, research and development centers, and sales and marketing offices in several countries.

The company has been at the forefront of using data-driven decision making to optimize its manufacturing processes. The company's approach to data-driven decision making involves using various tools and technologies, such as data analytics and visualization, simulation and optimization, and digital twins, to collect, analyze, and leverage data from its manufacturing operations. In this case study, we will take a closer look at Intel's use of data-driven decision making for manufacturing optimization and explore the benefits and challenges of this approach [15].

Intel's manufacturing operations are a critical part of its business, enabling the company to produce and deliver the high-quality, high-performance products its customers demand. Intel's manufacturing operations involve the use of complex processes such as lithography, etching, and deposition to create intricate, precise structures and patterns on its semiconductor chips. These processes require a high degree of precision, accuracy, and control, as well as a significant amount of data and information, to ensure that the chips meet the desired specifications and quality standards. Its data-driven decision-making approach to manufacturing optimization involves the use of several tools and technologies to collect, analyze, and leverage data from its manufacturing operations. These tools and technologies include [16]:

Data Analytics and Visualization:
Intel uses data analytics and visualization tools, such as Tableau and Power BI, to collect and analyze data from its manufacturing operations. These tools allow Intel to gain insights and knowledge about the performance and quality of its manufacturing processes and identify areas for improvement and optimization. Intel uses data analytics and visualization to monitor and track the performance and yield of its semiconductor chips and to identify and diagnose the root causes of any defects or failures (Fig. 5).

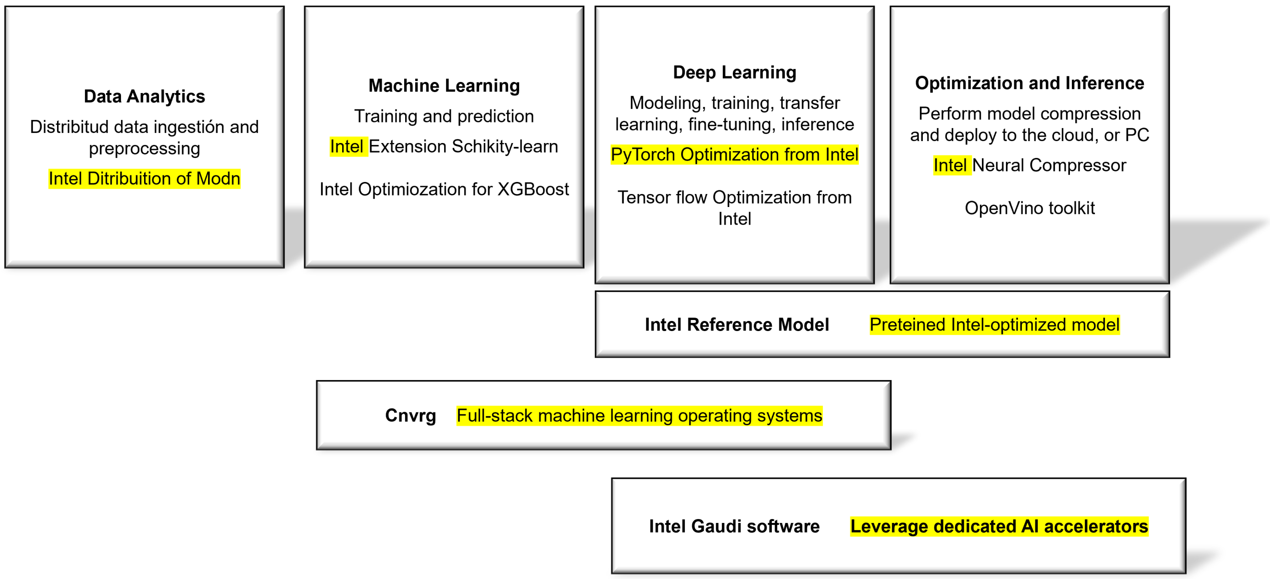

Figure 5: Intel Data Analytic tools

Simulation and Optimization:
Intel uses simulation and optimization tools, such as MATLAB and Simulink, to model and simulate its manufacturing processes and optimize the performance and quality of its products. These tools allow Intel to test and evaluate different process parameters and configurations and identify the optimal configurations and conditions for its manufacturing operations. For example, it uses simulation and optimization to model and simulate the lithography process and optimize the resolution and accuracy of the patterns and structures on its semiconductor chips.

Digital Twin:
Intel uses digital twin technology to create virtual replicas of its manufacturing equipment and processes and to monitor and control the performance and quality of its products in real time. Digital twin technology enables it to gain a more detailed and accurate understanding of its manufacturing operations and to identify and diagnose any issues or problems more quickly and efficiently. It uses digital twins to monitor and control the temperature and humidity of its clean rooms and to ensure that conditions are optimal for the production of its semiconductor chips.

Improved Performance and Quality:
Intel's use of data-driven decision making has enabled it to improve the performance and quality of its products and meet the demands and expectations of its customers. For example, the use of simulation and optimization has resulted in a significant improvement in the resolution and accuracy of the patterns and structures of its semiconductor chips, which in turn results in a significant improvement in the performance and quality of its products.

Increased Efficiency and Productivity:
Intel's use of data-driven decision making has enabled it to increase the efficiency and productivity of

its manufacturing operations, and reduce the costs and time associated with producing its products. The use of data analytics and visualization has enabled it to identify and eliminate bottlenecks and inefficiencies in its manufacturing processes, which in turn has resulted in a significant increase in the efficiency and productivity of its operations.

Increased Innovation and Agility:
Using data-driven decision making has enabled the company to improve innovation and agility capabilities and respond more quickly and effectively to changing customer demands and expectations. For example, using digital twin technology has enabled Intel to test and evaluate new innovative process parameters and configurations more quickly and effectively, and bring new products to market more quickly and efficiently.

Intel's use of data-driven decision-making for manufacturing optimization has also resulted in several challenges for the company, such as [17]:

Data Quality and Integrity:
Intel's use of data-driven decision making depends on the quality and integrity of the data it collects and analyzes. However, ensuring data quality and integrity can be challenging, as data can be subject to errors, omissions, and bias. For example, Intel's use of data analytics and visualization can be impacted by data quality and integrity, which in turn can impact the accuracy and reliability of the insights and knowledge it generates.

Data Security and Privacy:
Intel's use of data-driven decision making can also raise significant security and privacy concerns, as data can be sensitive and confidential and subject to unauthorized access, use, and disclosure. For example, its use of digital twins can be subject to significant security and privacy concerns, as virtual replicas of its manufacturing equipment and processes can be sensitive and confidential and subject to unauthorized access, use, and disclosure.

Data Integration and Interoperability:
Intel's use of data-driven decision making can also be impacted by the integration and interoperability of the various tools and technologies it uses to collect, analyze, and leverage data. Intel's use of simulation and optimization can be impacted by the integration and interoperability of the various tools and technologies it uses to model and simulate its manufacturing processes and to optimize the performance and quality of its products [17, 18].

Intel's use of data-driven decision making to optimize manufacturing has led to several benefits for the company, such as improved performance and quality, increased efficiency and productivity, and greater innovation and agility. However, the use of data-driven decision making has also led to several challenges such as data quality and integrity, data security and privacy, and data integration and interoperability. To address these challenges, Intel will need to continue to invest in and develop its data-driven decision making capabilities and ensure that its approach to data-driven decision making is robust, reliable, and secure [19].

3.5 Siemens AG's Decision-Making in Manufacturing

Siemens AG is a German multinational conglomerate and one of the largest industrial manufacturing companies in Europe. The company operates in various sectors, including energy, industry, mobility, and healthcare, and has a strong focus on innovation, sustainability, and digitalization (Fig. 6).

In recent years, Siemens AG has been implementing various advanced manufacturing decision-making strategies and technologies to improve its competitiveness and efficiency in the global market. Some of the key strategies and technologies that the company has adopted are described below [25]:

Digital Twin Technology:
Siemens AG has been using digital twin technology to optimize its manufacturing processes and improve the quality of its products. A digital twin is a virtual replica of a physical asset, such as a machine, production line, or factory, which is created using data and analytics. The digital twin can be used to simulate and test different scenarios and configurations, and to monitor and predict the performance of the physical asset. Siemens AG has been using digital twin technology to optimize the

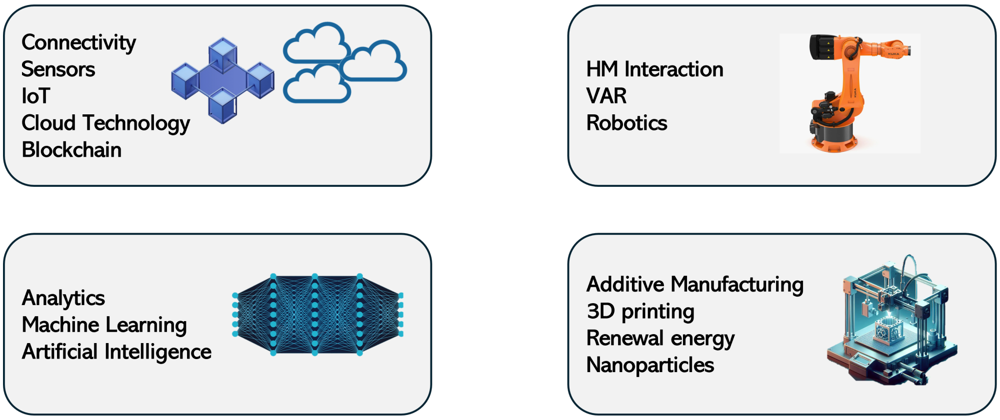

Figure 6: Industry 4.0 Foundational technologies Siemens

design and layout of its factories, reduce downtime and maintenance costs, and improve the efficiency and flexibility of its production lines.

Artificial Intelligence and Machine Learning:
Siemens AG has been using artificial intelligence (AI) and machine learning (ML) algorithms to analyze and interpret large amounts of data from its manufacturing operations and make more informed and effective decisions. The company has been using AI and ML to optimize its production planning and scheduling, predict and prevent equipment failures, improve the quality and consistency of its products, and reduce waste of energy and materials. Siemens AG has also been developing and implementing AI-based solutions and services for its customers, such as predictive maintenance, energy management, and quality control.

Additive Manufacturing:
Siemens AG has been using additive manufacturing, also known as 3D printing, to produce complex, customized parts and products for its operations and for its customers. Additive manufacturing enables the creation of parts and products with high precision, low weight, and high strength, and can be used to reduce the time and cost of prototyping, tooling, and production. Siemens AG has been using additive manufacturing to produce parts for its gas turbines, trains, and medical equipment, and has also been offering additive manufacturing services and solutions to its customers in various industries.

Collaborative Robotics:
Siemens AG has been using collaborative robots, or cobots, to assist and support its human workers in various manufacturing tasks, such as assembly, inspection, and packaging. Cobots are designed to work alongside humans and interact with them safely and intuitively. They can be used to reduce physical and mental strain on workers, improve product quality and consistency, and increase the flexibility and agility of production lines. Siemens AG has been using cobots in its own operations and has also been offering cobot-based solutions and services to its customers.

Agile and Lean Manufacturing:
Siemens AG has been using agile and lean manufacturing principles and practices to improve the efficiency, quality, and responsiveness of its manufacturing operations. Lean manufacturing is a philosophy and set of techniques that aim to eliminate waste and improve the flow of the production process. Agile manufacturing is a philosophy and set of techniques that aim to enable the production process to adapt and respond to changes and uncertainties in the market and environment. Siemens AG has been using lean and agile manufacturing to reduce lead times and inventory levels, improve customer satisfaction and product innovation, and increase the resilience and sustainability of its operations.

The implementation of these advanced manufacturing decision-making strategies and technologies has not been without challenges and limitations. Some of the challenges that Siemens AG has faced are [26]:

Data and Analytics:
The availability, quality, and security of data and analytics are critical to the success of advanced manufacturing decision-making strategies and technologies. Siemens AG has been investing in the

development and implementation of advanced data and analytics capabilities, such as data lakes, data warehouses, data integration, data governance, and data security, to support and enable its decision-making processes.

Talent and Skills:

The adoption and implementation of advanced manufacturing decision-making strategies and technologies requires a new set of talents and skills, such as data science, software engineering, and digital manufacturing. In this regard, Siemens AG has been investing in the training and development of its existing workforce and in the recruitment and integration of new talents and skills to support and enable its decision-making processes.

Change Management:

The adoption and implementation of advanced manufacturing decision-making strategies and technologies require significant organizational, cultural, and mindset change and transformation. Siemens AG has been using various management techniques and tools, such as communication, participation and feedback, to involve its employees, customers and partners in decision-making processes and to ensure the success and sustainability of change and transformation.

Despite these challenges and limitations, Siemens AG has achieved significant improvements and benefits by implementing advanced decision-making strategies and technologies in manufacturing. Some of the improvements and benefits the company has reported are [27]:

Efficiency and Productivity:

The company has managed to reduce downtime, energy and material consumption, and lead time of its manufacturing operations, and increase the performance, efficiency, and flexibility of its production lines.

Quality and Innovation:

The company has managed to improve the quality, consistency, and customization of its products, and increase the speed, scope, and success of its product innovation and development.

Customer Satisfaction:

The company has managed to improve the responsiveness, reliability, and transparency of its manufacturing operations, and offer new and innovative solutions and services to its customers in various industries.

Sustainability:

The company has managed to reduce the carbon and environmental footprint of its manufacturing operations and contributes to the achievement of global sustainability goals and targets.

Siemens AG's decision-making in the manufacturing sector is a case study of how a large diversified industrial manufacturing company can adopt and implement advanced manufacturing decision-making strategies and technologies to improve its competitiveness, efficiency, and sustainability in the global marketplace. The company's focus on innovation, digitalization, and collaboration, and its ability to overcome implementation challenges and constraints, are key drivers for the success and sustainability of its decision-making processes [27].

4 Best Practices to Overcome Barriers

To address these challenges, manufacturers can consider the following strategies:

1. Phased implementation: Start with pilot projects to demonstrate value and build organizational buy-in before full-scale implementation.

2. Cross-functional teams: Form teams that include both technical experts and operational staff to ensure new systems address real business needs.

3. Partnerships: Collaborate with technology vendors, academic institutions, or industry consortia to access expertise and share implementation costs.

4. Clear ROI metrics: Develop and communicate clear metrics to measure the impact of new technologies on productivity, quality, and cost reduction.

5. Continuous learning programs: Implement ongoing training initiatives to build internal digital capabilities and reduce reliance on external expertise over time.

Future lines of research. To further address adoption barriers, future research should focus on:

- Developing cost-effective implementation models for small and medium-sized manufacturers.
- Creating frameworks to simplify the integration of complex systems in manufacturing environments.
- Investigating effective change management strategies specific to digital transformation in manufacturing environments.

5 Comparison of the Cases of study

In this section, we compare the decision-making processes of five large diversified industrial manufacturing companies: General Electric (GE), Ford, Intel, Siemens, and Airbus. We focus on the advanced manufacturing decision-making strategies and technologies these companies have implemented to improve their competitiveness and efficiency in the global market. Finally, the main findings of the comparison will be summarized in Table 1.

Similarities:

- They use digital twin technology to optimize their manufacturing processes and improve the quality of their products.
- They use artificial intelligence (AI) and machine learning (ML) algorithms to analyze and interpret large amounts of data from their manufacturing operations and make more informed and effective decisions.
- They employ additive manufacturing, also known as 3D printing, to produce complex, customized parts and products for their operations and their customers.
- They use collaborative robots, or cobots, to assist and support their human workers in various manufacturing tasks, such as assembly, inspection, and painting.
- They employ agile and lean manufacturing principles and practices to improve the efficiency, quality, and responsiveness of their manufacturing operations.

Differences:

GE has been using digital twin technology to optimize the design and performance of its wind turbines, reduce downtime and maintenance costs, and improve the efficiency and reliability of its wind farms. Ford has been using digital twin technology to optimize the design and manufacturing of its vehicles, reduce the time and cost of prototyping, tooling, and production, and improving the quality and customization of its vehicles. Intel has been using digital twin technology to optimize the design and manufacturing of its semiconductors, reduce the time and cost of prototyping, tooling, and production, and improve the quality and performance of its semiconductors. Siemens has been using digital twin technology to optimize the design and layout of its factories, reduce downtime and maintenance costs, and improve the efficiency and flexibility of its production lines. Airbus has been using digital twin technology to optimize the design and manufacturing of its aircrafts, reduce the downtime and maintenance costs of its aircrafts, and improve the efficiency and flexibility of its production lines.

GE has been using AI and ML to optimize the performance and maintenance of its wind turbines, predict and prevent equipment failures, and improve the efficiency and reliability of its wind farms. Ford has been using AI and ML to optimize its production planning and scheduling, predict and

Table 1: Comparison of Decision-Making : General Electric, Ford, Intel, Siemens, and Airbus

Decision-Making Strategy/Technology	General Electric	Ford	Intel	Siemens	Airbus
Digital Twin Technology	Optimize wind turbine design and performance, reduce downtime and maintenance costs, improve wind farm efficiency and reliability	Optimizing vehicle design and manufacturing, reduce time and cost of prototyping, tooling, and production, improve vehicle quality and customization	Optimize semiconductor design and manufacturing, reduce time and cost of prototyping, tooling, and production, improve semiconductor quality and performance	Optimize factory design and layout, reduce downtime and maintenance costs, improve production line efficiency and flexibility	Optimize aircraft design and manufacturing, reduce downtime and maintenance costs of aircraft, improve production line efficiency and flexibility
Artificial Intelligence and Machine Learning	Optimize wind turbine performance and maintenance, predict, and prevent equipment failures, improve wind farm efficiency and reliability	Optimize production planning and scheduling, predict, and prevent equipment failures, improve vehicle quality and consistency, reduce energy and material waste	Optimize semiconductor performance and manufacturing, predict, and prevent equipment failures, improve semiconductor quality and performance	Optimize production planning and scheduling, predict, and prevent equipment failures, improve product quality and consistency, reduce energy and material waste	Optimize production planning and scheduling, predict, and prevent equipment failures, improve product quality and consistency, reduce energy and material waste, develop, and implement new and innovative solutions and services for customers
Additive Manufacturing	Produce parts for wind turbines, such as blades and nacelles, reduce time and cost of prototyping, tooling, and production	Produce parts for vehicles, such as brackets, fuel nozzles, and cabin components, reduce time and cost of prototyping, tooling, and production	Produce parts for semiconductors, such as heat sinks and interconnects, reduce time and cost of prototyping, tooling, and production	Produce parts for gas turbines, trains, and medical equipment, reduce time and cost of prototyping, tooling, and production	Produce parts for aircraft, such as brackets, fuel nozzles, and cabin components, reduce time and cost of prototyping, tooling, and production
Collaborative Robotics	Reduce physical and mental strain of workers, improve wind turbine quality and consistency, increase wind farm flexibility and agility	Reduce physical and mental strain of workers, improve vehicle quality and consistency, increase production line flexibility and agility	Reduce physical and mental strain of workers, improve semiconductor quality and consistency, increase production line flexibility and agility	Reduce physical and mental strain of workers, improve product quality and consistency, increase production line flexibility and agility	Reduce physical and mental strain of workers, improve product quality and consistency, increase production line flexibility and agility, offer new and innovative solutions and services to customers in various industries
Lean and Agile Manufacturing	Reduce lead time and inventory levels of wind turbines and wind farms, improve customer satisfaction and product innovation, increase resilience and sustainability of operations	Reduce lead time and inventory levels of vehicles, improve customer satisfaction and product innovation, increase resilience and sustainability of operations	Reduce lead time and inventory levels of semiconductors, improve customer satisfaction and product innovation, increase resilience and sustainability of operations	Reduce lead time and inventory levels of products, improve customer satisfaction and product innovation, increase resilience and sustainability of operations	Reduce lead time and inventory levels of products, improve customer satisfaction and product innovation, increase resilience and sustainability of operations, enable production process to adapt and respond to changes and uncertainties in market and environment

prevent equipment failures, improve the quality and consistency of its vehicles, and reduce energy and material waste. Intel has been using AI and ML to optimize the performance and manufacturing of its semiconductors, predict and prevent equipment failures, and improve the quality and performance of its semiconductors. Siemens has been using AI and ML to optimize its production planning and scheduling, predict and prevent equipment failures, improve the quality and consistency of its products, and reduce energy and material waste. Airbus has been using AI and ML to optimize its production planning and scheduling, predict and prevent equipment failures, improve the quality and consistency of its products, and reduce energy and material waste. However, Airbus has also been using AI and ML to develop and implement new and innovative solutions and services for its customers, such as predictive maintenance, energy management and quality control.

GE has been using additive manufacturing to produce parts for its wind turbines, such as blades and nacelles, and to reduce the time and cost of prototyping, tooling, and production. Ford has been using additive manufacturing to produce parts for its vehicles, such as brackets, fuel nozzles, and cabin components, and to reduce the time and cost of prototyping, tooling, and production. Intel has been using additive manufacturing to produce parts for its semiconductors, such as heat sinks and interconnects, and to reduce the time and cost of prototyping, tooling, and production. Siemens has been using additive manufacturing to produce parts for its gas turbines, trains, and medical equipment, and to reduce the time and cost of prototyping, tooling, and production. Airbus has been using additive manufacturing to produce parts for its airplanes, such as brackets, fuel nozzles, and cabin components, and to reduce the time and cost of prototyping, tooling, and production.

GE has been using cobots to reduce the physical and mental strain of its workers, to improve the quality and consistency of its wind turbines, and to increase the flexibility and agility of its wind farms. Ford has been using cobots to reduce the physical and mental strain of its workers, to improve the quality and consistency of its vehicles, and to increase the flexibility and agility of its production lines. Intel has been using cobots to reduce the physical and mental strain of its workers, to improve the quality and consistency of its semiconductors, and to increase the flexibility and agility of its production lines. Siemens has been using cobots to reduce the physical and mental strain of its workers, to improve the quality and consistency of its products, and to increase the flexibility and agility of its production lines. Airbus has been using cobots to reduce the physical and mental strain of its workers, to improve the quality and consistency of its products, and to increase the flexibility and agility of its production lines. However, Airbus has also been using cobots to deliver new and innovative solutions and services to its customers in a range of industries.

GE has been using agile and lean manufacturing to reduce lead time and inventory levels for its wind turbines and wind farms, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations. Ford has been using agile and lean manufacturing to reduce lead time and inventory levels for its vehicles, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations. Intel has been using agile and lean manufacturing to reduce lead time and inventory levels for its semiconductors, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations. Siemens has been using agile and lean manufacturing to reduce lead time and inventory levels for its products, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations. Airbus has been using agile and lean manufacturing to reduce lead time and inventory levels of its products, to improve customer satisfaction and product innovation, and to increase the resilience and sustainability of its operations. However, Airbus has also been using agile and lean manufacturing to enable the production process to adapt and respond to changes and uncertainties in the market and the environment.

Some of the key challenges and limitations of advanced decision-making strategies and technologies in the manufacturing sector are:

Data availability and quality:
Advanced decision-making strategies and technologies often rely on large amounts of accurate and relevant data. However, in many cases, data can be incomplete, noisy, biased or outdated, which can lead to incorrect or suboptimal decisions.

Modeling and simulation:
Simulation and optimization-based decision-making strategies are typically based on mathematical or computational models that represent the real-world system or process. However, models can be inaccurate, incomplete, or oversimplified, which can lead to incorrect or suboptimal decisions.

Complexity and uncertainty:
Advanced decision-making strategies and technologies often aim to address complex and uncertain problems or situations. However, complexity and uncertainty may be too high for models or algorithms to fully capture or predict, which can lead to incorrect or suboptimal decisions.

Human factors:
Advanced decision-making strategies and technologies often involve or interact with human decision makers, such as operators, engineers, or managers. However, human decision makers may have different levels of experience, preferences, or biases, which can affect the quality or consistency of decisions.

6 Conclusions

This article presents an overview of decision making in the manufacturing sector, including traditional methods and advanced technologies and strategies. Case studies illustrating the practical application of these technologies and strategies are also provided, as well as an analysis of the challenges and limitations associated with their adoption and implementation.

The state of the art in decision making in the manufacturing sector has evolved significantly in recent years, driven by technological advances and the changing needs and expectations of customers and society. The adoption and implementation of advanced technologies and decision-making strategies in the manufacturing sector can significantly improve the competitiveness of manufacturing companies in the global market, enabling them to make more informed, efficient and faster decisions.

While the potential for advanced decision-making techniques in the manufacturing sector is clear, this article has highlighted the significant challenges that hinder their widespread adoption. The tension between the promise of these technologies and the practical difficulty of implementation highlights the need for a balanced strategic approach. Manufacturers must carefully weigh the benefits against the costs, complexities, and organizational changes required. Future success will likely depend on the industry's ability to develop more accessible and cost-effective solutions, as well as strategies to overcome resistance and develop the necessary digital capabilities within its workforce. The challenges and limitations associated with these technologies and strategies must be carefully considered and addressed to ensure their successful adoption and implementation. Practical recommendations have been provided on how to improve their decision-making processes and increase their competitiveness in the global marketplace, as well as identifying and discussing some possible future research directions in the field of decision-making in the industry.

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