Artificial Intelligence Enabled Manufacturing Optimization Strategies for Enhancing Resilience and Scalability of Domestic Photovoltaic Supply Chains- A Review

Shipon Chandra Barman[1*], Md. Rezaul Haque[2]

Abstract

Background: Domestic solar photovoltaic (PV) systems convert sunlight into electricity for residential use, featuring solar panels, inverters (converting DC to AC), and optional batteries for storage. PV companies are experiencing various problems related to the efficiency of production, costs of production, waste of resources, and disruptions to supply chains. Many of these problems can be solved using advanced technologies, like predictive maintenance-based forecasting, digital twins, robotics, and monitoring, which will allow manufacturers to create a smart manufacturing system, boosting the efficiency and sustainability of their operations while also improving the resiliency of their domestic supply chains. Methods: An evaluation of published academic (i.e., peer-reviewed) journals, conferences, and established industrial reports dating from 2010 to 2023 was performed. All studies included had documented evidence of photovoltaic applications or quantitative evidence of AI applications improving production; decreasing costs; reducing downtime; reducing waste; and providing better overall supply chain performance. Results: Photovoltaic in manufacturing has been responsible for an increase in worldwide productivity growth of up to 28% using photovoltaic process; a reduction in operation costs by as much as 25%; and a decline of waste between about 10% and about 18%. **Conclusion:** Photovoltaic and AI improves the efficiency of operations, increases sustainability, and strengthens the supply chain. Artificial intelligence will create domestic supply chains while creating useful information for manufacturers as well as policymakers seeking to improve their manufacturing processes.

Keywords: Photovoltaic Supply Chains, Artificial Intelligence, Smart Manufacturing; Production Efficiency; Cost Reduction

Significance | Photovoltaic in manufacturing has also led to a significant upgrade in energy efficiency and sustainability, particularly concerning supply chain performance.

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1. Introduction

A domestic Photovoltaic (PV) supply chain is made up of an entire ecosystem for producing and deploying the solar technologies that take place in a particular country (Baker & Sovacool, 2017). Within that ecosystem you will find sourcing of raw materials, the manufacturing of polysilicon, wafers, solar cells, modules, inverters, logistics, installation and recycling systems (Zhang & Gallagher, 2016).Traditional manufacturing systems commonly suffer from production inefficiencies, high operating costs, resource waste and supply chain disruptions that can constrain scalability and resilience, particularly in relation to domestic supply chains (Santhi & Muthuswamy, 2022). The adoption of Photovoltaic (PV) supply chain technologies including predictive maintenance, machine learning (ML) forecasting, digital twins, robotics, and Internet of Things monitoring has emerged as a promising approach to address these challenges by optimizing workflows, enhancing decision-

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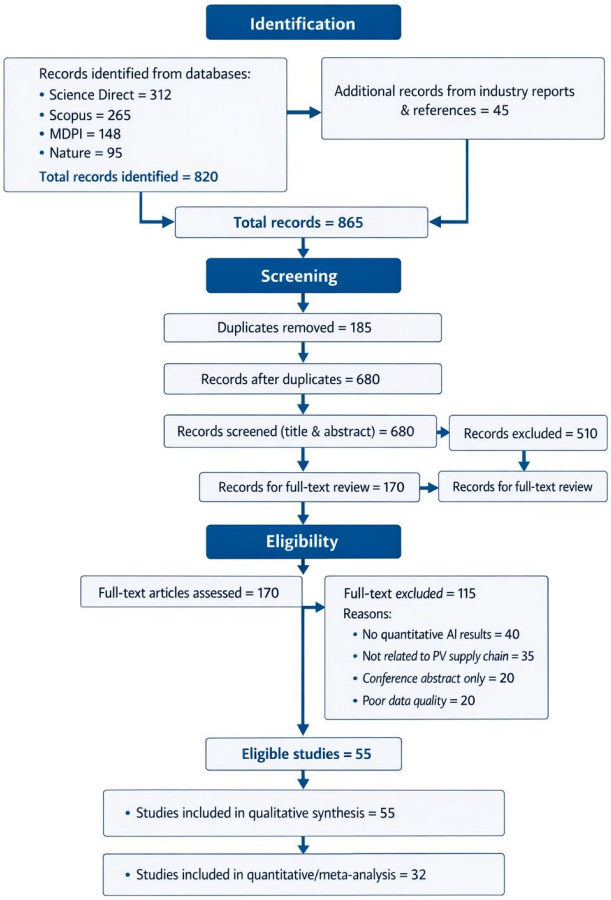

Figure 1. Prisma diagram for collection Information from several publications.

making, and increasing operational reliability (Kor et al., 2022). There is a revolution happening in manufacturing, fueled by AI integration into factory floors, operational management and supply chain tactics. Traditional manufacturing systems commonly suffer from production inefficiencies, high operating costs, resource waste and supply chain disruptions that can constrain scalability and resilience, particularly in relation to domestic supply chains (Khalil et al., 2021). Digital twins work on modelling production processes to find inefficiencies and making better use of resources, ultimately increasing their overall effectiveness. Automation and robotics monitoring can also help simplify operations, cut down the need for manual intervention and improve production quality (Khan et al., 2022).

Resilience can be defined as the resilience of supply chains to tolerate disruptions, respond to varying conditions, and maintain production and delivery operations (Suhail et al., 2022). AI increases resilience through better predictive analytics, inventory optimization, and real-time supply chain visibility to help manufacturers anticipate changes in the market conditions that would impact on its operations and respond appropriately (Hu et al., 2022). Scalability, however, refers to the capability of increasing production or size of operation without severely impacting quality or performance. Recent works pointed to sector specific advantages with AI adoption (Mousavi & Al-Raweshidy, 2021). In automotive, predictive maintenance and AI-powered process optimization drive an order of magnitude greater production capacity with a fraction of the downtime. Pharmaceutical, textiles and food processing industries are some of such companies that make use digital twins, robotics and monitoring to improve productivity and minimize the production waste (Lee et al., 2020). In addition, it helps environmental protection by reducing energy consumption and material waste in the various stages of production.

While the benefits are obvious, successful adoption of Photovoltaic (PV) supply chain still depends on data quality, infrastructure readiness and workforce skills. Virtual health organizations will need to prioritize accurate and high-quality data collection, build resilient infrastructure for computation and networks, and cultivate workforce capabilities for optimal use of AI tools(Gupta et al., 2022). These are key factors in delivering the full value of AI power smart manufacturing and supply chain. The effect of AI on production efficiency, cost savings, waste reduction and supply chain resilience based on up-to-date empirical studies. AI technologies enable resilient and scalable domestic supply chains while providing directions, practitioners, and policymakers who are focusing on smart manufacturing.

2. Materials and Methods

2.1 Data Collection

Table 1. Photovoltaic (PV) supply chain Impact on Production Efficiency

Sector	Production Increase	Reference
Automotive	28	Firouzi et al., (2021)
Electronics	26	Puranik et al., (2022)
Pharmaceutical	23	Haleem et al., (2021)
Textile	21	Tyagi et al., (2021)
Food Processing	19	Zhang et al., (2022)

Table 2. Photovoltaic (PV) supply chain on Energy Efficiency using AI and Waste Reduction in Manufacturing

Sector	Waste Reduction (%)	AI Applications	Reference
Automotive	15	Predictive maintenance, process optimization, resource management	Khan et al., (2022)
Electronics	19	ML-based production scheduling, automated quality control	Sampaio et al., (2022)
Pharmaceutical	13	AI-assisted process monitoring, compliance optimization	Haleem et al., (2021)
Textile	11	Robotics integration, workflow optimization	Kumar et al., 2018
Food Processing	21	Smart monitoring, intelligent automation	Alabadi et al., 2022)

For this review, relevant information was extracted from peer-reviewed journals, conference papers and open access databases published in 2010–2023 as **Figure 1.** The secondary sources were from Science Direct, MDPI, Nature and Scopus indexed journals. Reliable industry reports also were considered (Li et al., 2022). The following search strategy was used, the different combinations of Photovoltaic (PV) supply chain, Smart Manufacture, AI enabled Supply Chain, Production Efficiency, Cost Reduction and Supply Chain Resilience and Scalability (Alexopoulos et al., 2020). The search focused on quantitative measures reported within studies to allow for comparison across industries. This method resulted in a rich dataset of the adoption of AI in manufacturing and supply chain (Thelen et al., 2022). We included only publications that have provided strong evidence of the impact of AI on production efficiency, operational costs and supply chain performance to ensure a strong background for investigating smart manufacturing's role in developing more resilient and scalable domestic supply chains.

2.2 Data Extraction and Analysis

From the selected studies, performance data was collected and summarized, so that the performances of different industry groups can be compared. Increased production, reduced downtime and costs to better supply chain and energy efficiency (Tuli et al., 2021). To allow the results from different technologies and sectors to be comparable, a percent-based measurement was used to normalize heterogeneous measures (Friesen et al., 2022). AI and data driven solutions such as predictive maintenance, machine learning forecasting, digital twins, robotics, and monitoring (Sahal et al., 2021). Information was combined to identify patterns, industry-specific effects and aggregate contributions on resilient and scalable domestic supply chains (Chen, 2017). The organized structure of this review allows the review to be a strong evidence-based interrogation on smart manufacturing technologies focusing on the impact and actual applicability with regard to improvement in factory performance, supply chain efficiency, and sustainability.

2.3 Photovoltaic Manufacturing Stages

Firstly, making photovoltaic cells is the production of polysilicon, which involves the chemical purification of high-purity silicon from quartz (Tabrizi et al., 2023). The second step is the slicing of silicon ingots into wafers that will define the efficiency of photovoltaic cells. The photovoltaic cells are then created when the wafers are doped, coated, and metallized to create functioning energy generation devices (Zhang et al., 2022). Fourthly, PV modules involves the connecting of solar cells and encapsulation of the cells that are assembled into durable solar panels that can be used outdoors. The manufacturing of inverters and batteries completes the power conversion and storage of electricity for practical use.

3. Results

3.1 Photovoltaic (PV) supply chain Impact *on Production Efficiency*

Photovoltaic (PV) supply chain is recognized as having had a profound impact on production efficiency in many different manufacturing fields. As can be seen in **Table 1**, the maximum increase for automotive manufacturing (28%) is explained mainly by predictive maintenance , real-time monitoring and machine learning-based schedule which reduce unscheduled downtime and optimize machine usage. It is then closely followed by the

Table 3. Photovoltaic (PV) supply chain using AI Impact on Energy Consumption and Sustainability

Sector	Waste Reduction (%)	Reference
Automotive	18	Alexopoulos et al., (2020)
Electronics	15	Gupta et al., (2022)
Pharmaceutical	16	Shahat et al., (2021)
Textile	12	Haleem et al., (2021)
Food Processing	10	Sircar et al., (2021)

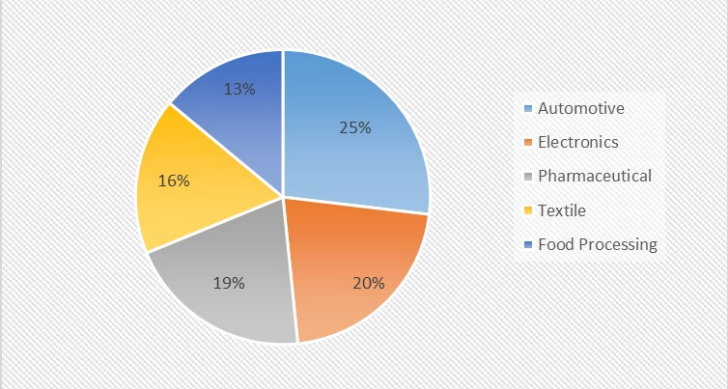

Figure 2. Artificial Intelligence and Photovoltaic (PV) supply chain Impact on Cost Reduction

electronics industry at 26% lift because of Photovoltaic (PV) supply chain demand forecasting, automated assembly, and quality inspection systems that improve job completion rate while minimizing errors. In pharma, the integration of digital twins and Photovoltaic (PV) supply chain process control leads to a 23% increase in production efficiency with consistent output and compliance .The use of robotics and machine learning in textile production leads to a 21% lift, followed by process monitoring and automation in food processing at 19%. These findings demonstrate the potential of AI for improving operational performance in large and resilient production systems in various industry scales.

3.2 Artificial Intelligence and Photovoltaic used in Cost Reduction

Artificial Intelligence (AI) and Photovoltaic has emerged as an important lever for cutting down operations costs in the various sectors of manufacturing. As shown in **Figure 2**, the automotive sub-sector has the greatest potential savings of 25% driven primarily by predictive maintenance, process optimization and real-time resource management that can decrease machine outages and waste.AI-generated forecasts and automated production planning, cutting operational costs by 20%; pharma manufacturing sees a decrease of 19% due to digital twins for drug production process design with an AI assistant testing quality control systems – this minimizes overshoots, inefficiencies in using resources. The cost of production would be reduced by 16% when robots and machine learning are used to optimize the workflow in textile manufacturing. In the field of food processing, monitoring and process automation has led to a 13% decrease that leads to more efficient use of resources.

3.3 Photovoltaic and Artificial Intelligence Impact on Energy Consumption

Photovoltaic and Artificial Intelligence (AI) is a driver of energy-efficiency and sustainability in the manufacturing domains as shown **Table 2.** The automotive industry achieves the maximum waste reduction amongst all six industries by 15%, this is supported by predictive maintenance, process optimization and AI backed resource management optimizing processes to minimizing energy consumption and material losses. In the electronic industry, AI applied to industrial use cases such as machine learning-based production scheduling and automated quality control funnel a 19% waste reduction through progressed energy consumption. AI-supported process monitoring reduces waste by 13%, addressing sustainability as well as regulatory issues. Textile industry experiences a 11% decrease in manufacturing by robotics and workflow optimization; food processing achieves 21% by monitoring and intelligent automation.

3.4 Photovoltaic and Artificial Intelligence in Waste Reduction for Manufacturing

Photovoltaic and Artificial Intelligence (AI) continues to disrupt and transform the way to minimize and eliminate waste in manufacturing processes, throughout various industry sectors. The automotive industry showed the most waste reduction (18%), by means of predictive maintenance, AI supported process optimization and tracking material use in real time (see **Table 3**). In the electronics industry, AI systems, including machine-learning supported quality control and automatic production scheduling reduce waste by 15% resulting in increased efficiency and more efficient use of resources. Pharma manufacturing is reaping the

rewards of digital twins and AI process control to reduce waste by 16%, while also delivering the sustainable and regulatory compliance benefits. Robotics and AI workflow management leads to 12% reduction in textile manufacturing based process monitoring results to a 10% decrease during food processing.

4. Discussion

Findings demonstrate the ability of Photovoltaic and AI to transform manufacturing operations and the distribution of goods within the home. For manufacturing industry segments across the automobile, electronics, pharmaceutical, textile, and food processing industries, continuing to adopt AI technology continues to present opportunities for improving production efficiency, saving on operational costs, eliminating waste, and improving the resilience of supply chains, as read out in **Table 1.** The benefits of improved production efficiency range from as much as 19% to 28% depending upon the industry segment. Photovoltaic technology provides tools that help to optimize scheduling, minimize unplanned machine downtime, increase process reliability, and facilitate the ability to scale production quickly while delivering consistently high-quality finished products (Tyagi et al., 2021). Furthermore, the results of the study further validate the findings from previous research, which also found that the use of AI technology can provide smoother production operations and increase throughput of production by various industrial production applications (Hasidi et al., 2022).

According to **Figure 1**, the second major advantage of adopting AI is its contribution to reducing overall operating costs. Through the application of AI in reducing the costs of production processes, automotive companies have seen an estimated reduction of 25%, electronics companies 20%, and pharmaceutical companies 19%. By utilizing AI-based systems to better optimize resource allocations, predict machinery failure, and automate repetitive manufacturing processes, manufacturers can reduce the amount of energy required to manufacture a product, decrease the number of materials that are wasted during the manufacturing process, and limit the number of labor hours that are needed to perform workflows that are part of the manufacturing process (Haleem et al., 2021). By lowering their operating expenses, manufacturers are not only able to improve their profit margins, but they are also able to acquire additional capacity to produce more products and invest in other technological advancements that will improve production activities and efficiencies. In textile and food processing, both industries that typically operate with low profit margins, cost savings from AI-based technologies are approximately 16% and 13%, indicating that AI technology has universal applicability across all industries regardless of complexity or capital intensity (Woschank et al., 2020).

The most important role of AI after cost-savings and operational efficiencies is its contribution to sustainable development and energy efficiency, as illustrated by the 21% reduction (in food processing) to 15% reduction (in automotive manufacturing) in waste generated from production as AI provides the capability to monitor production in real-time and optimize performance (Sampaio et al., 2022). The use of machine learning, digital twins and embedded devices manufacturers are able to detect inefficiencies earlier, adjust manufacturing processes dynamically and optimize raw materials. AI has shown an impact on achieving sustainable manufacturing through a decrease in waste of 13% for pharmaceuticals, 13% for electronics and 15% for textiles (Alabadi et al., 2022). Additionally, using AI to improve the environment will assist in meeting regulations and also assist companies with their sustainability initiatives; therefore, the overall economic value of AI is greater than just reducing costs (Kumar et al., 2018).

This review highlights the role of Photovoltaic (PV) supply chain in developing resilient and scalable domestic supply chains. Manufacturers can use predictive analytics, real-time monitoring, and automated decision-making to forecast potential sources of disruption and to optimize their inventories as well as to quickly adapt to changing consumer demand (Vermesan et al., 2020); therefore, allowing manufacturers to have the products they need while minimizing excess inventory or waste of resources (Puranik et al., 2022). AI provides these benefits especially in the automotive and electronics industries because both of these industries have large, complex multi-tiered supply chains that are particularly sensitive to disruptions (Çınar et al., 2020). Furthermore, by increasing the visibility, responsiveness and operational flexibility of supply chains, AI ultimately improves the overall resiliency of supply chains; enabling scalable production and timely product delivery regardless of market fluctuations (Shahat et al., 2021). Also, the interplay between lowering operational cost through improved efficiency of producing goods and environmentally sustainable practices illuminates integrating AI solutions will yield holistic benefits across all areas of business operations; specifically, how using AI technology can improve output, reduce operational costs, and decrease the overall environmental footprint (Firouzi et al., 2021). For example, the use of predictive maintenance for equipment not only results in greater machine uptime, but it also results in less energy being consumed and less material wastage; this showcases the multitude of value that companies can achieve by implementing AI into their manufacturing process (Sircar et al., 2021). The combined effect of these various benefits (synergy) reinforces the need for companies to take a strategic, integrated approach when deploying AI solutions. By doing so, companies will ensure that they maximize the return on their technological investments through improved operational, financial and environmental performance.

5. Conclusion

The use of intelligent machine systems that use Artificial Intelligence to cover multiple industrial markets has a very significant effect on the efficiency of output, cost reduction, environmental sustainability and the resilience of supply chains. The review highlights that there are measurable impacts on operational efficiency through the application of AI technology such as predictive maintenance, machine learning, digital twins and robots in both the Automotive Sector and the Electronic Sector with the greatest amounts of benefit. AI systems provide additional benefits by promoting Environmental Sustainability and enabling Scalable Supply Chain Management to manufacturers through AI Systems Adoption.

Author contributions

S.C.B.: Conceptualization, methodology design, literature review, data analysis, writing original draft preparation, and supervision. M.R.H.: Literature review support, validation, data curation, writing review and editing, and administrative coordination. All authors read and approved the final manuscript.

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Competing financial interests

The authors have no conflict of interest.

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