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Research Article

Lights-Out Factory : Advancements, Challenges, and Prospects for Fully Autonomous Manufacturing

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Abstract: Lights-out factories, or fully autonomous factories, integrate robotics, artificial intelligence (AI), and the Internet of Things (IoT) to enable continuous, human-free production. Initially conceptualized in the 1980s, early implementations faced technological and economic barriers. However, advancements in AI-driven predictive maintenance, real-time analytics, and IoT connectivity have enhanced feasibility. This study paper employs a qualitative comparative analysis framework to examine the evolution, key technologies, and challenges of lights-out factories, particularly through Fuji Automatic Numerical Control (FANUC) and Tesla case studies. The concept of lights-out factories is evolving rapidly, driven by advances in artificial intelligence (AI), Internet of Things (IoT), robotics, and cyber-physical systems (CPS). Predictive maintenance algorithms, for instance, reduce downtime by 30%, while smart sensors boost production efficiency by 20%. Fully autonomous factories have shown labour cost savings of over 35%, especially in high-volume operations. These trends highlight the shift toward data-driven, self-regulating manufacturing with minimal human involvement. While lights-out factory increases efficiency, lowers labour costs, and enhances product quality, challenges such as cybersecurity risks, high capital investment, and adaptability to production variability remain. Workforce displacement further necessitates reskilling initiatives to sustain employment. AI-driven decision-making, collaborative robotics, and blockchain-secured IoT networks will improve flexibility and security in the future. Industry 5.0 emphasizes human-machine collaboration, shifting from full automation to synergy between AI and human oversight. Addressing integration challenges through strategic investments, innovation, and regulatory frameworks will determine the long-term success of autonomous manufacturing. This study provides a comprehensive analysis of the opportunities and challenges associated with lights-out factories, offering insights into their viability in modern industrial landscapes.

Keywords: Advanced manufacturing; Dark-manufacturing; Fully autonomous manufacturing; Internet of thing (IoT); Lights-out factory; Robotics manufacturing

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1. Introduction

Lights-out factories, also known as dark manufacturing, are highly automated manufacturing facilities designed to operate with minimal to no human intervention. The term ”lights-out” stems from the fact that these factories do not require continuous lighting because human operators are not present (Boeck et al., 2017). This manufacturing approach leverages advanced technologies, such as robotics, artificial intelligence (AI), and the Internet of Things (IoT), to maintain uninterrupted production (Javaid et al., 2022). In the context of increasing global competition, rising labour costs, and supply chain disruptions, industries are rapidly adopting lights-out manufacturing to achieve greater efficiency, cost reduction, and sustainability. The lights-out manufacturing concept dates back to the 1980s, when Fuji Automatic Numerical Control (FANUC) pioneered its implementation in Japan (CB Insights, 2018). However, early adoption was limited due to technological constraints, high capital investment, and reliability issues in automation. With advancements in AI-driven predictive maintenance, real-time data analytics, and industrial IoT networks, fully automated production lines are becoming more feasible and scalable (Atieh et al., 2023).

The integration of AI and IoT within the automated factory environment ensures continuous and optimized production with minimal human intervention. As data are collected from the sensors in real-time, the predictive maintenance algorithms assess the condition of machinery, predicting potential failures before they occur. This proactive approach minimizes downtime, ensuring a more efficient and reliable production process. Augmented Reality (AR) and Android Studio (APK development) are also incorporated to provide operators with real-time visual feedback and maintenance instructions, enhancing the user experience and enabling remote troubleshooting. The use of these advanced technologies promotes a highly flexible, scalable, and autonomous manufacturing ecosystem, where machines adapt to production changes and optimize their own operations, driving the next generation of Industry 4.0 solutions in autonomous manufacturing (Erdoğan, 2019; Pop et al., 2022).

Figure 1 illustrates the schematic of key technologies integrated into autonomous manufacturing systems, showcasing how robotics, artificial intelligence (AI), Internet of Things (IoT), and predictive maintenance tools work together to optimize production. The diagram highlights the data flow from various sources, such as sensors and industrial robots, to AI-driven systems that enable real-time decision-making. These systems are tightly connected through both proprietary and non-proprietary protocols, allowing seamless communication across different machines and devices within the factory. The use of additive manufacturing and CNC systems further enhances flexibility in production, allowing for on-demand customization and increased precision in product manufacturing.

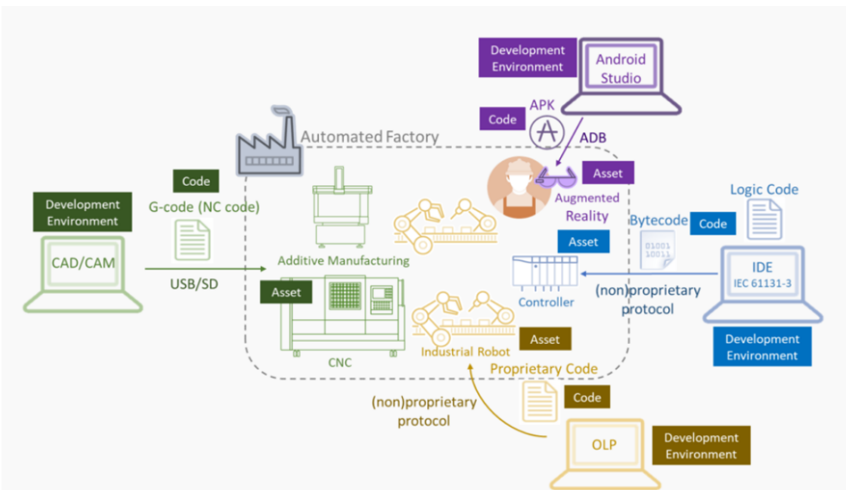

Figure 1 Schematic of the integrated system architecture in a factory with lights out (Adapted from TXOne Networks, 2023)

Despite these developments, several challenges persist, including integration difficulties with existing production systems, cybersecurity risks, high initial costs, and the need for continuous optimization to prevent costly downtimes (Ghodsian et al., 2023).

A key enabler of lights-out factories is the seamless integration of robotics, AI, and IoT to create a self-sustaining production ecosystem. Robotics perform repetitive precision tasks, while AI-driven algorithms monitor equipment health, detect anomalies, and optimize efficiency in real-time (B. Zhang et al., 2023). IoT-enabled smart sensors ensure that all machines and systems communicate seamlessly, allowing remote diagnostics and predictive maintenance (Kang and Chung, 2020; Kurniawati et al., 2023). However, fully autonomous manufacturing remains challenging, as issues such as system malfunctions, data security concerns, and limited adaptability to unexpected disruptions continue to hinder widespread adoption.

In addition to technological challenges, there are economic and workforce implications. The transition to fully automated factories requires significant investment in infrastructure, software, and skilled personnel to develop, maintain, and troubleshoot AI-powered systems (Erdoğan, 2019). The transition to fully automated factories presents significant challenges for small and medium enterprises (SMEs), especially in terms of high initial costs, limited access to advanced technologies, and scalability. Unlike large corporations with substantial financial resources, SMEs often struggle to absorb the costs associated with implementing AI, robotics, and automation systems. The current technologies available are typically designed for large-scale production, making it difficult for SMEs to customize or scale down, which often rely on more flexible, smaller-scale operations. As a result, SMEs face the added financial burden of adapting these systems to fit their specific needs, hindering their ability to compete with larger companies that can easily implement such technologies (Olivier and Craig, 2017).

Moreover, SMEs face a skills gap because advanced automation systems require highly specialized knowledge for installation, maintenance, and troubleshooting. Recruiting and retaining skilled workers is becoming a major hurdle, as these talents are often in high demand by larger firms that offer better compensation. To bridge this gap, SMEs must invest in training programs to upskill their existing workforce, which further increases costs. Additionally, automation systems raise concerns about job displacement, particularly for lower-skilled workers, and require a shift in job roles. This necessitates a focus on reskilling and workforce adaptation, ensuring that employees are equipped to work with new technologies and take on new roles, thus mitigating the risks of displacement while improving long-term operational effectiveness (C. S. Silva et al., 2022).

As industries are advancing Industry 4.0 and moving beyond, lights-out factories are expected to play a pivotal role in next-generation manufacturing. Emerging innovations such as collaborative robots, AI-enhanced decision-making, and self-learning automation systems, are anticipated to enhance the efficiency and reliability of fully automated production environments (Zou et al., 2024). However, realizing the full potential of lights-out factories will depend on addressing current limitations through continuous innovation, strategic investments, and robust cybersecurity measures to ensure long-term operational stability and sustainability (Ibrahim and Kumar, 2024). The digital twin, a real-time digital replica of physical assets, is valuable for production optimization but are often too expensive for SMEs due to the need for advanced sensors and data analytics. Similarly, predictive maintenance algorithms that prevent equipment failures require robust data infrastructure and machine learning capabilities, which many SMEs lack. Additionally, cobots that work alongside human workers need specialized programming to ensure safety and efficiency, and the shortage of skilled workers who can manage these systems exacerbates the problem. To bridge this gap, SMEs should shift their focus to workforce training programs to equip employees with the skills to oversee, program, and maintain automation systems. Furthermore, the shift toward automation raises concerns about job displacement, especially for lower-skilled workers, which necessitates a focus on reskilling and adapting the workforce to new roles. These challenges make it difficult for SMEs to fully leverage the potential of automation, despite its theoretical advantages, and highlight the need for more affordable, scalable solutions tailored to their specific needs. This paper explores the challenges of current technology and predicts the future of AI-driven, fully automated factories that can operate without human intervention, offering a fresh perspective on their long-term viability.

2. Historical Evolution and Related Works of Lights-out Factory

The roadmap evolution of the lights-out factory began with the introduction of basic automation in the mid-20th century. Early advancements in programmable logic controllers (PLCs) and robotic automation laid the foundation for further development in manufacturing technology. By the late 20th century, automation had expanded to integrated robotic systems and AI-driven manufacturing, setting the stage for the modern lights-out factory concept (Scaria et al., 2019). Figure 2 shows the technological advancements over time, from the introduction of programmable logic controllers (PLCs) in the 1960s–1970s to the adoption of Industry 4.0 and AI-driven autonomous decision-making systems projected for 2030, highlighting the evolution from early automation to smart factories. Since the 1960s–1970s, the use of programmable logic controllers (PLCs) has improved production efficiency by 40% by reducing setup times and enhancing process control. In the 1980s–1990s, the rise of industrial robots increased production speed by 15% and reduced labour costs by 35%. In the 2000s, the integration of CNC and PLC technologies led to a 25% reduction in machine downtime. In the 2010s, the implementation of AI and IoT introduced predictive maintenance algorithms that reduced downtime by 30%, with AI predicting component failures with 85% accuracy, thereby reducing equipment downtime by 40%. In the 2020s, digital twins are projected to optimize production processes by 25%, and quantum computing is expected to accelerate data processing by 10 times. By 2030, AI is expected to reduce the need for human labour by 50%, while robots will enable more flexible, collaborative production. 3D printing is expected to reduce material usage by 30% and production time by 50%, and AI-enhanced supply chain management is strongly expected to forecast demand with 95% accuracy and adjust production accordingly (Ivanova and Ivanov, 2024; Rudigkeit and Gebhard, 2019).

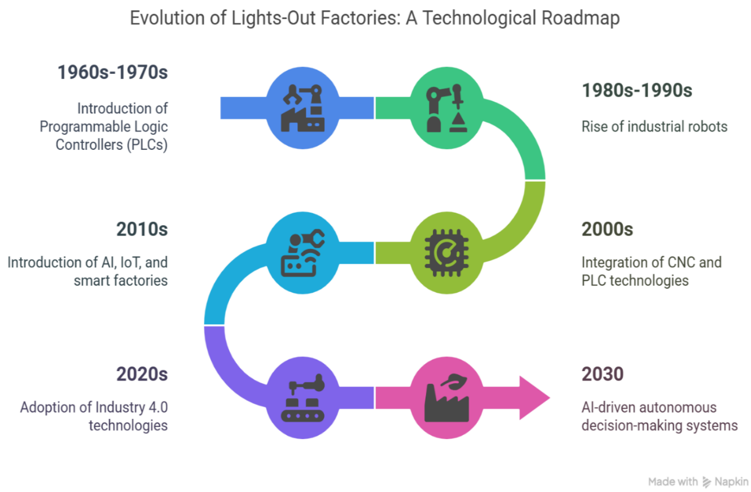

Figure 2 Evolution of factory lights-out technologies

In the decades that followed, the automation landscape continued to evolve with significant technological advancements. The introduction of industrial robots revolutionized manufacturing by enabling precise and efficient execution of repetitive tasks. Companies like General Motors and Toyota were among the early adopters of robotic automation, integrating robots into their production lines to enhance efficiency and reduce labour costs (Pop et al., 2022). These early developments laid the foundation for the concept of lights-out manufacturing, highlighting the potential of robotics to transform the manufacturing industry. As manufacturing industries began integrating AI and IoT into their production models in the late 20th century, some companies took the next step by developing fully autonomous, human-free manufacturing facilities. One of the most successful examples of this transformation was FANUC's lights-out factory in Japan, which pioneered the integration of robotics and AI for extended autonomous operation.

A conceptual framework is introduced that classifies these elements into three main categories: levels of automation, deployment models, and industry verticals. This framework provides a structured approach to understanding how lights-out technologies are implemented and utilized across different sectors and automation levels. The levels of automation include fully autonomous systems where no human intervention is needed, semi-automated systems that combine human oversight with automation, and collaborative systems in which humans and robots work together in real time. Deployment models refer to how automation is introduced, with greenfield implementations involving new factories built with full automation, brownfield models retrofitting existing facilities, and hybrid models mixing human-driven and automated processes for greater flexibility. Industry verticals exhibit varied applications of lights-out factories, with the automotive industry adopting fully autonomous systems for high-volume production, the electronics industry using semi-automated systems for customization, and the pharmaceutical industry favoring hybrid models to meet regulatory requirements. Figure 3 shows the conceptual framework for lights-out manufacturing.

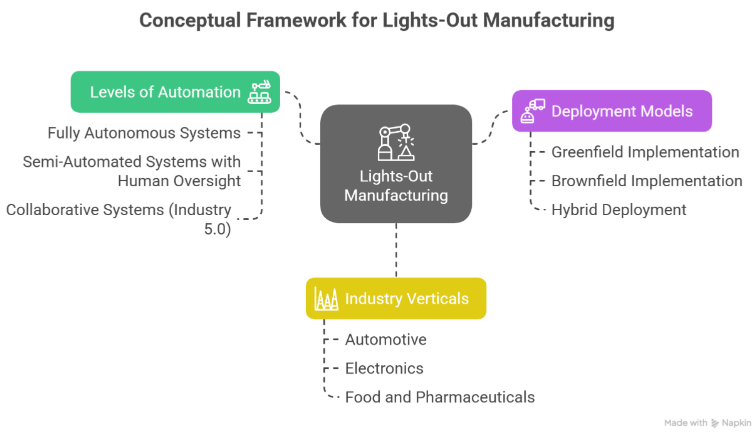

Figure 3 Conceptual framework for manufacturing of lights-out

This review is based on an extensive search of peer-reviewed literature, industry reports, and case studies on autonomous manufacturing and Industry 4.0 technologies. Data were gathered from academic databases such as Scopus, Web of Science, and IEEE Xplore, with search terms including "lights-out manufacturing," "fully autonomous manufacturing," "Industry 4.0," and "smart factories." Sources were filtered based on their relevance to the study's focus on technological advancements, challenges, and applications. The review synthesizes findings from over 100 publications spanning from 2000 to 2025, categorizing them into key themes: technological milestones, industry case studies, challenges, and future trends. This synthesis formed the structure for the paper, which led to the discussion of real-world case studies such as FANUC's lights-out factory.

2.1 Case Study: FANUC's Lights-out Factory

FANUC's factory represents one of the earliest successful implementations of a fully automated lights-out factory model. Developed in Japan in the 1980s, this facility was capable of running for extended periods without human intervention and was a pioneer in integrating AI-driven robotics into manufacturing. Unlike traditional factories, FANUC relied on parallel robotic networks, allowing redundancy in operations to prevent failures from disrupting production. However, FANUC's success was not without its challenges. The use of redundant robotic networks is a key factor in its stability. If one robotic system fails, another can seamlessly take over operations. Additionally, FANUC has optimized predictive maintenance through AI-powered fault detection, allowing the system to address issues before they lead to downtime (Cholewa et al., 2016). This case study offers three universal lessons for industries aiming to transition to lights-out factories as shown in Table 1. As shown in the table, the gradual scaling of automation was crucial to success, allowing FANUC to implement automation in stages. AI-driven predictive maintenance played a pivotal role in detecting failures early, which helped prevent costly downtimes. Additionally, redundant robots ensured system stability, allowing continuous operation without unexpected faults, proving essential for maximizing uptime in a fully autonomous factory.

Table 1 Universal lessons for industries transitioning to lights-out factory

#	Lesson	Description
1	Gradual Scaling	Rather than immediate full automation, FANUC first implemented partial automation in key areas before achieving complete independence.
2	AI-driven Predictive Maintenance	Utilising AI algorithms to detect anomalies early prevents costly system failures.
3	Redundant Robotics for Stability	FANUC's use of parallel robotic systems ensures that failures in one unit do not halt the entire operation.

Key Takeaways:

- Gradual automation scaling is key to transitioning to a fully autonomous factory.
- AI-driven predictive maintenance is essential for identifying and addressing potential failures early to avoid, costly downtime.
- Redundant robotics ensureensures continuous production without system failures by minimizingminimising downtime.

These lessons highlighted that lights-out manufacturing success depends not only on robotic efficiency but also on strategic risk mitigation and phased implementation.

One of the key factors contributing to FANUC's success is the extensive use of robotics. The factory is equipped with various robotic systems, each designed to perform specific tasks with high precision and consistency. From assembling components to packaging finished products, these robots work seamlessly together to ensure a smooth production flow. Additionally, FANUC employs AI algorithms to monitor and optimize the performance of these robots, identifying potential issues before they escalate and adjusting processes to maximize efficiency (Lin et al., 2018; She et al., 2018).

Another important aspect of FANUC's lights-out factory is the integration of IoT devices. These devices collect data from various machines and systems, providing real-time insights into factory operations. This data is then analyzed using AI and machine learning techniques to identify patterns and trends, enabling predictive maintenance and process optimization. By leveraging IoT and AI, FANUC can maintain high levels of efficiency and minimize downtime, ensuring that the factory operates continuously without human intervention (Jiang and Wu, 2022; Resende et al., 2021).

The lessons from FANUC's implementation demonstrate how technology, strategy, and resilience must work together to achieve successful lights-out operations (J. Li et al., 2016). While the company benefited from cutting-edge automation, its journey also highlights several risks that must be managed, such as presented in Table 2. The high initial costs of AI-powered systems and robotic solutions were a significant barrier, especially for smaller manufacturers. Furthermore, the complexity of IoT integration meant that achieving a fully autonomous system took years of iteration, underlining the importance of gradual optimization rather than expecting immediate results. Finally, the limited flexibility of the automated systems for custom production remains a challenge, highlighting that while mass production benefits are clear, customization remains difficult to achieve with the current automation models.

Table 2 Risk challenges in FANUC's automation implementation

#	Risk	Description
1	High Initial Costs	FANUC's early investments in AI-powered predictive maintenance and redundant robotics were capital-intensive and may not be feasible for all manufacturers (Lal et al., 2023).
2	Complexity of IoT Integration	FANUC required years of iterative optimization before achieving a fully autonomous system, demonstrating that full-scale automation is not an overnight success.
3	Limited Flexibility for Customization	While FANUC excels in mass production, its automated processes are less adaptable to small-batch, high-customization manufacturing.

Key Takeaways:

- When implementing advanced automation technologies, high initial costs can be a barrier for smaller manufacturers.
- Iterative optimization must reach full automation—it is not a quick transition
- Limited customization flexibility can be a challenge for certain production processes, particularly in low-volume, highly custom manufacturing.

Companies considering lights-out manufacturing can adopt a balanced approach by examining these lessons, ensuring that automation aligns with long-term goals rather than being implemented solely for efficiency gains. FANUC's model provides a roadmap for factories transitioning to LOA. Manufacturers can reduce failure risks and optimize production efficiency by prioritizing scalable automation, predictive AI-driven maintenance, and robust robotic networks.

2.2 Significance of the Lights-out Factory

Lights-out factories emerged as a strategic solution to modern production challenges as manufacturing technologies evolved from early automation to fully autonomous operations. The significance of these factories lies in their ability to enhance operational efficiency, reduce labor costs, and minimize human error. Adopting lights-out manufacturing offers a competitive advantage with global manufacturing facing increasing production demands and cost pressures. Lights-out manufacturing addresses these needs by enabling continuous production without the limitations of human work hours. This results in higher output and reduced lead times, giving companies a competitive edge in the market (Erdoğan, 2019; C. S. Silva et al., 2022).

Moreover, lights-out factories are particularly relevant in today's industry, driven by the need for higher productivity, and the integration of Industry 4.0 principles emphasizes the digital transformation of manufacturing through the adoption of smart technologies, data analytics, and automation (Kadne et al., 2024; Verevka and Gao, 2025). Lights-out manufacturing embodies these principles by leveraging advanced robotics, AI, and IoT to create intelligent and adaptive production environments. This not only enhances productivity but also improves product quality and consistency, as automated systems are less prone to errors compared to human workers (Zou et al., 2024).

Lights-out manufacturing also offers environmental benefits by optimizing energy use and reducing waste, aligning with sustainability goals (Ibrahim and Kumar, 2024). Automated systems can be programmed to operate at optimal efficiency, minimizing energy consumption and reducing the manufacturing process's environmental footprint. Additionally, the precision and consistency of robotic systems result in fewer defects and less material waste, contributing to more sustainable production practices (Dodampegama et al., 2024). In an era where environmental sustainability is a critical concern, lights-out factories present a viable solution for achieving greener manufacturing (Linke et al., 2012).

2.3 Automation and Robotics

The foundation of a lights-out factory is built on three key elements: AI-powered decision-making, IoT-driven connectivity, and robotic automation. Robotics perform precision tasks such as assembly, quality inspection, and material handling, whereas AI monitors real-time production efficiency and predicts maintenance needs (Akkaladevi et al., 2019). IoT sensors act as the communication bridge between machines, enabling real-time adjustments and reducing downtime. The versatility and reliability of modern robotics make them indispensable in lights-out manufacturing, where uninterrupted production is essential (Ren et al., 2023).

In a lights-out factory, the interaction between these technologies forms a self-sustaining ecosystem where data flows seamlessly from the sensors to the AI algorithms and back to the robots, ensuring continuous, uninterrupted production. With the use of predictive analytics and AI-driven decision-making, the factory can optimize every aspect of its operation, from machinery health to production processes, without human intervention. Thus, the integration of IoT, AI, robotics, and cloud-based monitoring ensures that the factory can maintain optimal performance, high productivity, and flexibility all while minimizing the need for human oversight and intervention. This model of automation provides significant cost-saving benefits, improves product quality, and enhances overall operational efficiency (Zou et al., 2024).

Figure 4 effectively illustrates the technical framework of a lights-out factory, a fully automated production facility connected to the internet via a network of sensors. This diagram highlights the intricate interconnectivity between key technologies, including AI, IoT, robotics, and cloud-based monitoring systems, all of which collaborate to drive factory automation.

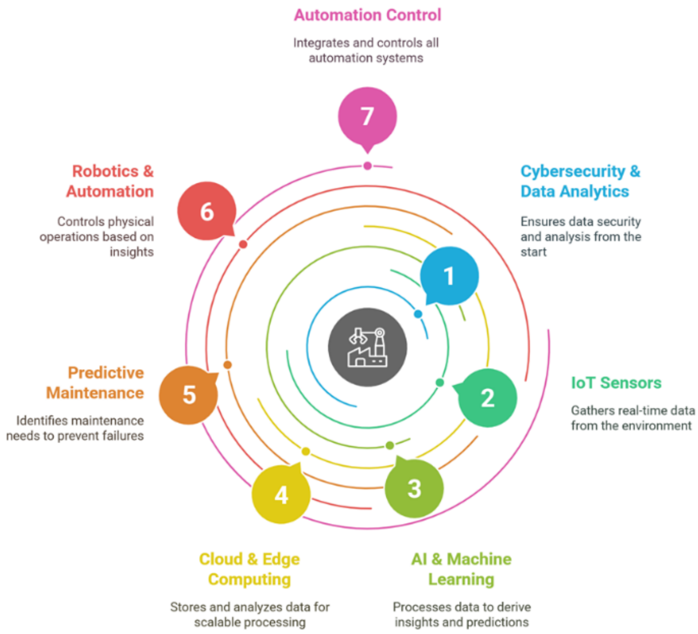

Figure 4 Technical framework of a lights-out factory, showing the connection of key technologies such as automation control, robotics, maintenance, cloud computing, artificial intelligence (AI), Internet of Things (IoT) sensors, and cybersecurity

Robotic systems used in lights-out factories are equipped with advanced sensors and actuators, allowing them to perform tasks with high accuracy. These sensors provide real-time feedback on the robot's position, orientation, and force applied, ensuring precise execution of tasks. For instance, robotic arms can assemble intricate components with micron-level precision, resulting in high-quality products (Polishchuk and Tkach, 2020; Wieland et al., 2009). Moreover, robots can work tirelessly around the clock, maintaining a consistent pace of production without the need for breaks, thereby increasing overall productivity. Figure 5 illustrates the robotic arms in a lights-out factory performing a critical job in an assembly line.

Figure 5 Robot with automated arms in an assembly line lights-out factory (Double Row Forming with Omni Metalcraft, 2019)

One of the key advantages of using robotics in lights-out factories is their ability to handle hazardous or repetitive tasks that are unsuitable for human workers. For example, robots can operate in environments with extreme temperatures or harmful chemicals, reducing the risk to human health and safety. In addition, robots excel at performing repetitive tasks with unwavering consistency, eliminating the variability and errors associated with human labor. This leads to higher product quality and fewer defects, which is critical in industries where precision and reliability are paramount (Sithole et al., 2023).

Empirical studies indicate that fully automated robotic assembly lines can improve efficiency by 30-50%, as demonstrated in a comparative study between manually operated and robotic assembly lines in the automotive sector (Ivanova and Ivanov, 2024). However, challenges persist as Tesla's Model 3 production line revealed over-reliance on automation as a critical failure factor, leading to bottlenecks and unplanned downtime (Rodríguez Aguilar et al., 2024). Moreover, while robotic systems enhance speed, their ability to adapt to real-time production variability remains limited, necessitating further advancements in AI-driven decision-making for greater operational flexibility (Lal et al., 2023).

2.4 Artificial Intelligence and Machine Learning (ML)

AI and machine learning (ML) are the decision-making core of lights-out factories, enabling autonomous real-time adjustments across all manufacturing operations (Tripathy et al., 2022; Whulanza et al., 2024). AI interprets sensor data from IoT devices embedded in robotic systems to identify inefficiencies and predict maintenance needs. By continuously analyzing machine learning models trained on historical production data, AI optimizes factory operations by adjusting robotic workflows, scheduling preventive maintenance, and ensuring energy-efficient machine utilization. The relationship between AI and IoT is particularly crucial, as IoT feeds live operational data to AI systems, allowing them to predict failures before they occur and dynamically adjust machine settings to prevent production slowdowns (Cui et al., 2022). Studies show that AI-based predictive maintenance reduces downtime by up to 40%, significantly lowering operational costs (Thakkar and Kumar, 2024). Despite these advantages, the adoption of AI in manufacturing faces three major challenges, as shown in Table 3. One of the most prominent challenges is the high computational requirements, with real-time AI processing demanding robust edge computing systems, resulting in increased hardware costs. Additionally, data integration issues present a barrier, as legacy systems often cannot seamlessly integrate with new AI models. Finally, the limited adaptability of AI to handle unforeseen production anomalies necessitates continuous algorithm training, indicating the need for ongoing updates and fine-tuning to adapt to new challenges in production environments.

Table 3 Challenges in implementing AI for lights-out factories

#	Challenge	Description
1	High Computational Requirements	Real-time AI processing requires robust edge computing systems, leading to increased hardware costs (Jain et al., 2023).
2	Data Integration Issues	AI models rely on massive datasets, but integrating legacy system data remains a barrier for older factories (B. Silva et al., 2021).
3	Limited Adaptability	Unlike humans, AI struggles with unforeseen production anomalies, requiring continuous algorithm training for better decision-making (Suryadevara et al., 2023).

Key Takeaways:

- High computational requirements drive up the cost of edge computing systems, posing challenges for smaller factories.
- Data integration issues remain a major challenge in adopting AI, especially for older factories with legacy systems.
- Limited adaptability of AI requires ongoing training to improve decision-making, particularly in the face of unexpected anomalies.

Machine learning algorithms play a vital role in optimizing manufacturing processes by continuously learning and adapting to new data. These algorithms can analyze production data to identify inefficiencies and suggest improvements, leading to higher productivity and reduced costs (Ma'ruf et al., 2024; Vilela De Souza et al., 2022). For example, AI can optimize the scheduling of production tasks to minimize idle time and maximize resource utilization. The utilization of resources is also enhanced by machine learning, which helps to predict equipment failures and schedule maintenance activities.

Another significant application of AI in lights-out factories is autonomous decision-making. AI systems can make real-time decisions based on data from various sensors and IoT devices, ensuring the factory's optimal performance (Rudra Kumar et al., 2023). For example, AI can adjust the speed and parameters of robotic systems to adapt to changing production demands. This level of autonomy allows lights-out factories to operate with minimal human oversight, thereby enhancing their efficiency and reliability (Ezenkwu and Starkey, 2019).

2.5 Internet of Things (IoT) and Connectivity

IoT serves as the central nervous system of lights-out factories by enabling real-time connectivity between AI, robotics, and predictive maintenance systems (Zou et al., 2018). IoT sensors embedded in machinery continuously collect operational data on variables such as temperature, vibration, and energy consumption. This data is relayed to AI-driven analytics platforms, which interpret patterns and issue commands to adjust robotic performance or schedule preventive maintenance. Additionally, IoT allows inter-machine coordination, where autonomous systems dynamically adjust workflow speed, resource allocation, and energy consumption based on demand fluctuations. Without IoT-enabled communication, AI-driven optimizations would lack real-time input, and robotics would be unable to operate autonomously in a fully synchronized manner (Qu et al., 2016).

IoT devices in lights-out factories are equipped with advanced sensors that monitor various parameters, such as temperature, humidity, vibration, and energy consumption. This data is transmitted in real-time to central control systems, where it is analyzed using AI and machine learning techniques (Kondratenko et al., 2022). By continuously monitoring these parameters, IoT devices can detect anomalies and trigger alerts or corrective actions, thereby preventing potential issues from escalating. For example, if a sensor detects an increase in vibration in a machine, it can indicate a potential mechanical failure, prompting maintenance before the machine breaks down (Mohd Ghazali and Rahiman, 2021).

The connectivity provided by IoT also enables seamless communication and coordination between different machines and systems in the factory. This is particularly important in lights-out factories, where multiple robotic systems and automated processes must work together efficiently (Gunasekaran et al., 2023). IoT ensures that data flows smoothly between these systems, enabling coordinated actions and real-time adjustments. For instance, if one part of the production line experiences a delay, IoT can adjust the speed and operations of other parts to maintain overall efficiency.

3. Success Stories and Best Practices

Among the companies that have successfully implemented lights-out manufacturing are Philips and FANUC. These contrasting strategies for achieving automation excellence. Philips' factory in the Netherlands relies on a centralized AI monitoring system that continuously analyzes various metrics to optimize production efficiency, whereas FANUC employs a modular approach where each robot unit operates independently, reducing the impact of system-wide failures. A comparative analysis of these two strategies suggests that hybrid models combining centralized AI oversight with decentralized robotic autonomy may offer the best path forward for lights-out manufacturing (Jauregui-Becker and Wits, 2013). The best practices identified from these successes include thorough planning, robust technological infrastructure, and continuous monitoring and improvement (Ungan, 2007).

Philips' lights-out factory in the Netherlands stands as a testament to the potential of fully automated manufacturing (Blau, 2007). The factory produces electric razors with minimal human intervention and relies on advanced robotics and AI to maintain production. The success of this factory is attributed to meticulous planning and investment in state-of-the-art technologies (Zhong et al., 2017). Philips ensured that all aspects of the production process, from assembly to packaging, were automated, ensuring high levels of performance and reliability. However, despite these advancements, there remains room for further improvement, particularly in areas such as energy efficiency and sustainability.

Tesla's highly automated production lines offer another example of lights-out manufacturing, but their experience highlights critical challenges in achieving full automation. Overreliance on robotics and AI without adequate fallback mechanisms led to frequent malfunctions, resulting in a 20% increase in unplanned downtime. Precision of robotic arms was reduced by 15% due to calibration errors, and AI misinterpretation of quality control led to a 6% defect rate increase in the initial trial production runs. These issues ultimately resulted in a delay of 10 days per month in production, costing Tesla an additional $10 million per month. Compared to FANUC's implementation, Tesla's automation struggles are evident in the higher AI latency and downtime, which directly impacts production efficiency and increased costs. FANUC's use of redundant robotic systems and AI-driven predictive maintenance enabled a 25% reduction in downtime and a 20% increase in energy savings, while Tesla faced difficulties with the calibration errors and AI misinterpretations, which led to significant production delays and quality issues. These failures illustrate the importance of balancing automation with adequate human oversight and system adaptability. Table 4 illustrates key performance metrics from FANUC's and Tesla's production lines, showcasing the impact of ARO and AI integration on operational efficiency. The table highlights the superior robot precision and lower AI latency at FANUC, demonstrating the effectiveness of their systems in maintaining higher production accuracy. It also contrasts the success of FANUC in reducing downtime and energy consumption, which is an indicator of the effectiveness of their predictive maintenance and energy optimization strategies compared to Tesla's experience.

Table 4 Performance metrics of robotic systems in lights-out manufacturing

Performance Metrics	FANUC Factory	Tesla Model 3 Production	Average Industry Benchmark
Robot Precision (mm)	0.05	0.15	0.10
AI Latency (ms)	50	80	70
Downtime Reduction (%)	25	10	15
Energy Savings (%)	20	15	18

The company's Gigafactories are equipped with advanced robotics and AI systems that handle various aspects of production, including battery assembly and vehicle manufacturing (Sharma and Kumar Tiwari, 2023). Tesla's approach emphasizes the importance of integrating automation with innovative design and engineering. The company has invested heavily in developing proprietary automation technologies that enhance the efficiency and quality of its production processes. By leveraging AI and machine learning, Tesla can optimize its manufacturing operations and respond quickly to changing production demands (Cioffi et al., 2020).

3.1 Challenges and Limitations

Technical failures in lights-out manufacturing, such as Tesla's Model 3 automation difficulties and Philips' initial production inconsistencies, highlight the necessity of integrating adaptive AI systems that can self-correct in real time. Future automation strategies should focus on developing robotics capable of autonomously detecting and resolving operational anomalies. Additionally, implementing blockchain-based quality assurance tracking can enhance supply chain visibility and prevent disruptions in fully automated facilities. Addressing these technological gaps will be critical for ensuring the sustainable evolution of lights-out manufacturing (García and Alvarado, 2013). Additionally, the high initial investment required to set up a fully automated factory can be a significant barrier for many companies.

One of the primary challenges in lights-out factories is ensuring the reliability and robustness of automated systems. Even minor malfunctions in robotic systems or AI algorithms can lead to significant disruptions in production. For example, a sensor failure or a software glitch can halt the entire production line, causing delays and potential financial losses. To mitigate these risks, companies must invest in high-quality components and implement rigorous testing and maintenance protocols. Additionally, the complexity of integrating various technologies, such as robotics, AI, and IoT, requires a high level of expertise and careful planning (Lins and Givigi, 2021; Zhao et al., 2021).

Another significant challenge is the high initial investment required for lights-out manufacturing. Setting up a fully automated factory involves substantial costs, including purchasing advanced robotics, developing AI algorithms, and installing IoT devices. For many companies, especially small and medium-sized enterprises (SMEs), these costs can be prohibitive. To address this issue, companies need to conduct a thorough cost-benefit analysis to determine the long-term benefits of automation (Hu et al., 2019). Additionally, exploring financing options, such as government grants or partnerships with technology providers, can help alleviate the financial burden.

4. Case Studies of Failures and Lessons Learned

Tesla's early attempt to fully automate its Model 3 production line offers critical insights into the technological and operational limitations of lights-out manufacturing. The failure was largely due to the over-reliance on robotics and AI without robust fallback mechanisms for manual intervention. Tesla encountered calibration errors in robotic systems, AI misinterpretations in quality control, and incompatibility between different automation software layers (Müller et al., 2019). Furthermore, the excessive complexity of Tesla's automated material handling system resulted in bottlenecks rather than efficiency gains. This failure underscores the importance of gradual automation scaling, redundancy planning, and the integration of adaptive AI models that can learn from unexpected anomalies. Table 5 presents a comprehensive analysis of the challenges faced by Tesla in integrating autonomous manufacturing technologies, specifically focusing on robotics, AI-driven predictive maintenance, production line flexibility, and cybersecurity. The table identifies several key categories that highlight the unique difficulties Tesla encountered while adopting these advanced systems in its production lines.

Table 5 Overview of lights-out factories challenges with Tesla case study

Category	Description	Tesla-Specific Challenges
Autonomous Technology Integration	Adoption of fully autonomous systems for vehicle assembly, logistics, and quality control using AI and robotics.	Early over-automation led to production bottlenecks and delayed deliveries.
Production Line Flexibility	Challenges in quickly adapting production lines for new models due to rigid automation infrastructure.	Difficulty in customizing automation tools across model variants without extensive reprogramming.
AI-driven Predictive Maintenance	Use of machine learning for forecasting equipment failure and scheduling maintenance, reducing downtime.	Initial AI systems lacked sufficient historical data, reducing the accuracy of maintenance predictions.
Skilled Workforce Requirement	Requirement for high-tech training programs to upskill workers for supervisory and system oversight roles.	Limited pool of automation-literate engineers slowed the transition to the new manufacturing model.
Cybersecurity and Data Management	Implementation of secure data protocols and cloud-based infrastructure to manage real-time factory data.	Increased attack surfaces due to IoT expansion raised cybersecurity concerns.
Capital Investment Needs	High upfront costs for hardware, software integration, and facility redesign to enable lights-out operations.	High CapEx strained budgets and limited flexibility during rapid scaling phases.

Tesla's attempt to fully automate the Model 3 production line encountered several issues that highlighted the challenges of lights-out manufacturing. One of the main problems was the overreliance on automation without adequate backup plans for manual intervention (Kahan et al., 2009). When robotic systems malfunctioned or encountered unexpected scenarios, there were insufficient human workers available to address the issues promptly (Honig and Oron-Gilad, 2018). This led to significant production delays and quality control problems. Tesla's experience demonstrates the importance of maintaining a balance between automation and human oversight, especially during the initial phases of implementing lights-out manufacturing.

Another lesson learned from Tesla's experience is the need for thorough testing and validation of automated systems before full-scale implementation (Kahan et al., 2009). The company faced challenges in integrating various robotic systems and ensuring their interoperability. This complexity was compounded by the ambitious production targets set by Tesla, which added pressure to the already challenging task of automating the production line. To avoid similar pitfalls, companies should adopt a phased approach to automation, starting with smaller-scale implementations and gradually scaling up as the systems are validated and optimized.

5. Impact on the Workforce and Society

The advent of lights-out factories brings significant changes to the workforce. While automation reduces the need for manual labour, it also creates new opportunities for skilled workers in areas such as robotics maintenance, AI programming, and data analysis. This shift requires workers to acquire new skills and adapt to the changing landscape of manufacturing (Srinivasan et al., 2020; Sutarman et al., 2024). The increasing demand for technical skills and expertise characterizes the transformation of the workforce in the context of lights-out factories.

Traditional manufacturing jobs that involve manual tasks are being replaced by roles that require knowledge of robotics, AI, and IoT. For example, workers who previously operated machinery may now be responsible for programming and maintaining robotic systems (Nixdorf et al., 2021). This shift necessitates a comprehensive training and upskilling program to equip workers with the necessary skills to thrive in an AM environment. Figure 6 shows the transformation skills of the workforce.

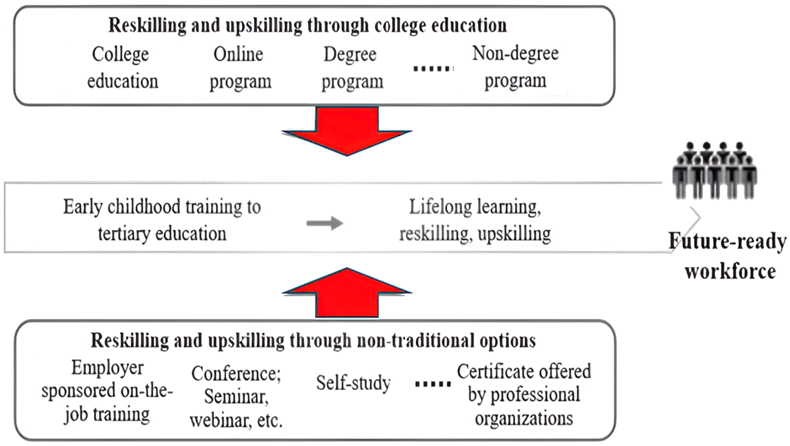

Figure 6 Transformation of workforce skills (L. Li, 2022)

One of the key strategies for workforce transformation is investing in education and training programs that focus on advanced manufacturing technologies (Sizwe, 2022). Companies can collaborate with educational institutions and training providers to develop courses and certifications that cover topics such as robotics programming, AI algorithms, and IoT integration. Additionally, on-the-job training and apprenticeships can provide workers with hands-on experience and practical knowledge. By investing in workforce development, companies can ensure a smooth transition to lights-out manufacturing and create a pool of skilled workers who can support the ongoing operation and maintenance of automated systems (Rumsey et al., 2019).

6. Societal Implications

The societal implications of lights-out manufacturing are significant. On one hand, automation can lead to job displacement and economic disruption, particularly in regions heavily dependent on manufacturing employment. On the other hand, it can drive economic growth by increasing productivity and creating new high-skilled jobs (Fang et al., 2023).

Job displacement is one of the primary concerns associated with the rise of lights-out factories. As automation replaces manual labor, workers in traditional manufacturing roles may face unemployment or need to transition into new careers. This can have significant social and economic impacts, particularly in communities where manufacturing is a major source of employment (Schwabe and Castellacci, 2020). To mitigate these effects, it is essential to implement policies and programs that support displaced workers, such as retraining initiatives, job placement services, and social safety nets.

Simultaneously, lights-out manufacturing can drive economic growth and create new opportunities. The increased efficiency and productivity resulting from automation can lead to cost savings and higher output, boosting manufacturing companies' competitiveness. Additionally, the demand for skilled workers in areas such as robotics, artificial intelligence (AI), and data analysis can create new high-paying jobs. Light-out manufacturing can contribute to the overall economic development and prosperity of society by fostering innovation and technological advancement (Arjun Santhosh et al., 2023; Murray, 2018).

7. Environmental and Economic Impact

Lights-out manufacturing offers significant environmental benefits by optimizing energy use and reducing waste. Automated systems can be programmed to operate at optimal efficiency, minimizing energy consumption and reducing the manufacturing process's environmental footprint. Additionally, the precision and consistency of robotic systems result in fewer defects and less material waste, contributing to more sustainable production practices (Carabin et al., 2017; Uhlmann, 2023).

The optimization of energy use is a key environmental benefit of lights-out factories (Mohamed et al., 2019). Automated systems can be designed to operate only when necessary, thereby reducing unnecessary energy consumption during idle periods. For example, robots can enter a low-power mode when not in use, and lighting and climate control systems can be adjusted based on real-time occupancy data.

Additionally, the integration of renewable energy sources, such as solar or wind power, can further enhance the sustainability of lights-out factories. By reducing energy consumption and utilizing clean energy, lights-out manufacturing can significantly lower greenhouse gas emissions and contribute to climate change mitigation (Worrell et al., 2009). Figure 7 shows the overall strategic sustainability performance plan.

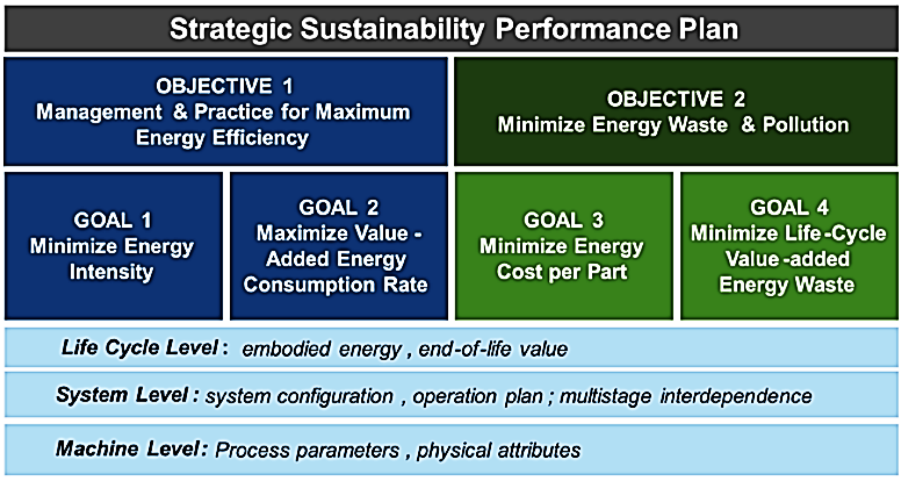

Figure 7 Overall strategic sustainability performance plan (Xia et al., 2023)

Another important aspect of sustainability in lights-out manufacturing is the reduction of material waste. The precision and accuracy of robotic systems minimize errors and defects, resulting in fewer discarded materials and products (Liu et al., 2020). Additionally, automated systems can be programmed to optimize material usage, ensuring that raw materials are used efficiently and reducing the overall waste generated during production. This not only benefits the environment but also reduces costs associated with material waste and disposal, contributing to the circular economy (Huysveld et al., 2019).

8. Economic Advantages

The economic advantages of the lights-out factory are significant. Cost savings and efficiency improvements are among the primary benefits of automation (Fang et al., 2023). By reducing labour costs and increasing productivity, lights-out factories can achieve substantial financial gains (Lee et al., 2015). Additionally, the ability to operate continuously without the limitations of human work hours allows for higher output and faster turnaround times, further enhancing the economic benefits of automation.

One of the primary economic advantages of lights-out manufacturing is the reduction in labour costs. Automated systems can perform tasks that would otherwise require human workers, eliminating the need for salaries, benefits, and other labour-related expenses (Javaid et al., 2022). This can result in significant cost savings, particularly in industries where labour costs represent a substantial portion of the overall expenses (Chobanov and Hardalov, 2022). Additionally, the ability to operate 24/7 without breaks or shift changes maximizes the utilization of equipment and facilities, further reducing costs and increasing efficiency (Sowmya and Chetan, 2016).

Another economic benefit of lights-out manufacturing is the potential for increased productivity and output. Automated systems can operate at a consistent pace, maintaining high levels of productivity without the variability and interruptions associated with human labour (Patic et al., 2014). This results in higher output and faster production cycles, allowing companies to meet customer demands more effectively. Additionally, the precision and accuracy of automated systems can improve product quality, reducing the costs associated with defects and rework (Chaudhari et al., 2017). By enhancing productivity and quality, lights-out manufacturing can drive revenue growth and profitability (Irshad Ali et al., 2011).

9. Future Trends and Innovations

The future of lights-out manufacturing is closely tied to the development of emerging technologies. Innovations in robotics, AI, IoT, and additive manufacturing (3D printing) are poised to further enhance the capabilities of lights-out factories. These technologies offer new possibilities for automation, enabling more complex and flexible production processes (Meng et al., 2020). The next evolution of lights-out manufacturing will depend not only on advanced robotics and AI but also on the seamless fusion of AI-driven real-time process optimization, blockchain-secured IoT data exchange, and decentralized autonomous decision-making systems. Future lights-out factories will require self-adaptive AI models capable of real-time anomaly detection and autonomous corrective measures, thereby reducing factory downtime without human intervention. Additionally, Industry 5.0 will shift focus toward collaborative AI-human systems, ensuring that AI complements human oversight rather than replaces it. However, cybersecurity risks, ethical AI concerns, and unpredictable supply chain disruptions remain major obstacles to achieving truly autonomous factories. Addressing these challenges will be key to the next phase of AI-powered, resilient, and sustainable factories of the future. For example, advancements in collaborative robots allow for safer and more efficient interactions between humans and robots, while AI-driven process optimization can continuously improve manufacturing efficiency (R. Zhang et al., 2022).

Robotics technology is expected to continue advancing with the development of more sophisticated and capable robotic systems. Collaborative robots represent one of the most promising areas of innovation (M. D. Silva et al., 2023). Unlike traditional industrial robots, collaborative robots are designed to work alongside humans, enhancing productivity while ensuring safety. These robots are equipped with advanced sensors and AI algorithms that enable them to adapt to dynamic environments and perform complex tasks (Wang et al., 2021). As robotics technology matures, it is likely to play a significant role in the future of lights-out manufacturing.

AI and machine learning are also expected to drive significant advancements in lights-out manufacturing. Future AI systems will be able to analyze vast amounts of data in real-time, making autonomous decisions and optimizing production processes with unprecedented accuracy and efficiency (Tercan and Meisen, 2023). For example, AI can be used to develop predictive models that anticipate equipment failures and enable proactive maintenance, thereby minimizing downtime and maximizing productivity (Bouyahrouzi et al., 2023). Additionally, machine learning algorithms can continuously learn from data and improve manufacturing processes, leading to higher quality and efficiency.

Advancements in AI, IoT, and robotics will shape the future of lights-out manufacturing. Foresight methodologies such as scenario planning and the Delphi method will be used to better predict these developments. Scenario planning helps explore different potential outcomes, such as rapid technology adoption leading to full autonomy or a slower, more gradual transition, particularly for SMEs facing high costs. The Delphi method involves gathering expert opinions to identify key success factors and challenges for adopting these technologies. The implementation roadmap will involve a phased approach to technology adoption, workforce training, and regulatory compliance. As automation technologies improve and become more affordable, industries such as automotive manufacturing will be able to scale automation more effectively. The integration of technologies, such as blockchain and quantum computing, will enhance security and flexibility, driving the next wave of autonomous manufacturing innovation.

10. Industry 4.0 and Beyond

The integration of Industry 4.0 principles with lights-out manufacturing represents a significant trend in the future of the manufacturing industry. Industry 4.0 emphasizes the digital transformation of manufacturing through the adoption of smart technologies, data analytics, and automation (Solanki, 2023). Lights-out manufacturing embodies these principles by leveraging advanced robotics, AI, and IoT to create intelligent and adaptive production environments. This not only enhances productivity but also improves product quality and consistency, as automated systems are less prone to errors than human workers (Atalay et al., 2020).

Industry 4.0 enables the interconnectedness of machines, systems, and processes, facilitating seamless communication and coordination (Devesh et al., 2020). This interconnectedness in lights-out factories is facilitated by IoT devices that collect and transmit data in real time. This data is then analyzed using AI and machine learning algorithms to optimize production processes and ensure efficient operation (Chen, 2020). The integration of Industry 4.0 principles enhances the flexibility and adaptability of lights-out factories, allowing them to respond quickly to changing market demands and production requirements.

Looking beyond Industry 4.0, the future of the lights-out factory may be shaped by the development of Industry 5.0 (Maddikunta et al., 2022). While Industry 4.0 focuses on automation and data exchange, Industry 5.0 emphasizes collaboration between humans and machines. This involves the use of advanced technologies such as AI, robotics, and virtual reality, to create synergistic interactions between human workers and automated systems. In the context of lights-out factories, Industry 5.0 could enable more efficient and intuitive collaboration between humans and robots, enhancing productivity and innovation (Raffik et al., 2023). The parameters used to differentiate Industry 4.0 and Industry 5.0 in this study are core focus, key technologies, human role, production model, sustainability, resilience, and end goal. Table 6 compares the differences between Industry 4.0 and Industry 5.0.

Table 6 Key differences between Industry 4.0 and Industry 5.0

Feature	Industry 4.0	Industry 5.0
Core Focus	Automation, connectivity, and data-driven optimisation	Human-machine collaboration, sustainability, and societal value
Key Technologies	IoT, AI, cyber-physical systems, cloud computing, digital twins	Cobots, AI-human collaboration, blockchain, sustainable manufacturing technologies
Human Role	Minimal direct involvement; humans supervise and monitor	Active collaboration with machines; humans provide creativity and decision-making
Production Model	Mass production and high efficiency	Mass personalisation with adaptive manufacturing
Sustainability	Secondary consideration	Core design principle (low carbon, resource efficiency, and circular economy)
Resilience	Primarily efficiency-driven systems	Robust systems that are adaptable to disruptions and global challenges
End Goal	Fully automated and optimised manufacturing	Balanced, human-centred manufacturing with integrated environmental and societal processes

A manufacturing system can be considered Fully Autonomous when it achieves 95%-100% automation of production tasks, with AI-driven decision-making handling over 90% of scheduling, quality control, and optimization. Predictive maintenance must prevent at least 30% of unplanned downtime, while human intervention is limited to 5% of operations. Full IoT-enabled integration across machines, ERP systems, and supply chains is essential, alongside sustainability measures that reduce energy use by 20% and material waste by 30%.

The adoption of fully autonomous systems in manufacturing has a profound impact on several key areas. In terms of operational efficiency, automation allows for 24/7 production without the need for breaks, leading to significant productivity gains and a reduction in downtime. AI-driven predictive maintenance, for example, can reduce unplanned downtime by up to 40%. Regarding cost, although the initial investment in autonomous systems can be substantial, long-term savings in labor costs and reduced waste typically outweigh these upfront expenses. Quality control is also enhanced, as machines can perform tasks with precision and consistency, thereby reducing human error and leading to higher-quality products. In terms of the workforce, while the introduction of fully autonomous systems can reduce the demand for manual labor, it also creates new job opportunities in areas such as system maintenance, monitoring, and AI model training. Finally, from a sustainability perspective, autonomous systems can optimize energy consumption, leading to reductions in both material waste and energy use, with potential savings of 20-30% in energy costs. These advancements not only drive operational improvements but also contribute to the creation of a more sustainable, eco-friendly production environment.

11. Roadmap for the Implementation

Implementing a lights-out factory requires a strategic approach that involves careful planning, investment in advanced technologies, and ongoing monitoring and optimization (de Mendonça Santos et al., 2024). The first step is to conduct a thorough assessment of the existing manufacturing processes and identify areas where automation can be most beneficial. This involves analyzing production data, assessing the feasibility of automation, and developing a detailed implementation plan.

One of the key considerations in the implementation of a lights-out factory is the selection of appropriate technologies (Khorram Niaki and Nonino, 2018). The proposed roadmap for a lights-out factory begins with short-term (2025–2027) milestones focusing on upgrading legacy systems with IoT-enabled sensors and deploying basic AI for predictive maintenance, targeting a 20% reduction in unplanned downtime. The mid-term (2028–2030) phase involves the integration of robotics, digital twins, and AI decision-support systems, with the goal of achieving 40% productivity gains and 30% cost savings through process automation. The long-term phase (2031–2035) envisions achieving complete autonomous operations with minimal human oversight, leveraging quantum computing for real-time supply chain optimization and advanced 3D printing for customized production. The final target is a fully self-sustaining, carbon-neutral factory by 2035, with a 50% reduction in energy consumption and near-zero waste output. Companies need to invest in advanced robotics, AI algorithms, and IoT devices that are capable of performing the required tasks with high precision and reliability. Additionally, it is essential to establish a robust IT infrastructure that can support the seamless integration of these technologies. This includes implementing data analytics platforms, cloud computing solutions, and cybersecurity measures to ensure automated systems' secure and efficient operation. Figure 8 illustrates the roadmap phases of the lightlight-out factory.

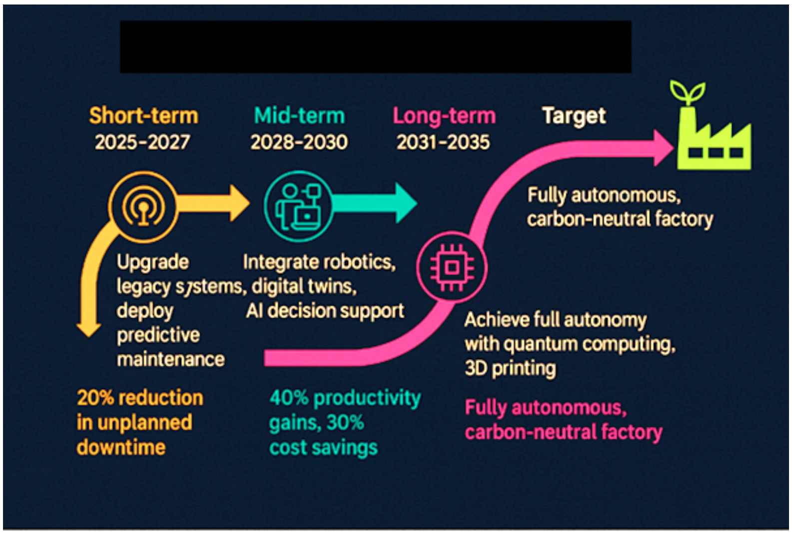

Figure 8 presents the phases of the roadmap for the lights-out factory

Ongoing monitoring and optimization are crucial for maintaining the performance of lights-out factories (Fera et al., 2020). Companies should implement real-time monitoring systems that provide continuous insights into the operation of automated systems. This involves collecting data from various sensors and IoT devices, analyzing it using AI algorithms, and taking corrective actions as needed. Additionally, companies should adopt a continuous improvement approach, regularly reviewing and optimizing their manufacturing processes to enhance efficiency and productivity (Cordova et al., 2023).

12. Policy and Regulatory Support

The successful implementation and adoption of a lights-out factory requires supportive policies and regulatory frameworks. Governments and regulatory bodies play a crucial role in fostering innovation and ensuring the safe and ethical use of automation technologies (Katz, 2021). This involves developing policies that incentivize investment in advanced manufacturing technologies, providing financial support for research and development, and establishing standards and guidelines for the use of robotics and AI in manufacturing.

One of the key policy considerations is the provision of financial incentives and support for companies adopting lights-out factories. This can include grants, tax credits, and subsidies for investment in automation technologies (Busom et al., 2014). For instance, Malaysia's Industry4WDR policy encourages SMEs to adopt Industry 4.0 technologies by providing subsidies, grants, and tax incentives for the implementation of robotics, AI, and IoT systems. Similarly, the European Union's Industry 5.0 framework emphasizes human-centric, sustainable manufacturing and advocates for policies that balance automation with workforce adaptation and environmental sustainability. These policies play a crucial role in reducing the financial burden of high upfront investments in autonomous technologies, especially for SMEs, and in ensuring that the workforce is reskilled to operate in increasingly automated environments. Additionally, governments can support research and development initiatives that focus on advancing automation technologies and addressing the challenges associated with lights-out factories (Borowiecki et al., 2019). By providing financial support and incentives, governments can encourage companies to invest in and adopt advanced manufacturing technologies.

Regulatory frameworks are also essential for ensuring the safe and ethical use of automation technologies (Ludlow et al., 2015). This involves establishing standards and guidelines for the design, implementation, and operation of robotic systems, AI algorithms, and IoT devices. Additionally, regulations should address issues related to data privacy, cybersecurity, and the ethical implications of automation (Naik et al., 2022). By establishing clear and comprehensive regulatory frameworks, governments can ensure that lights-out factories are implemented in a safe, secure, and ethical manner.

13. Conclusion

Light-out factories, characterized by advanced automation, artificial intelligence (AI)-driven decision-making, and Internet of Things (IoT)-enhanced connectivity, are revolutionizing modern manufacturing. This review examines their historical development, core technologies, successful implementation case studies, and the challenges they face. Key findings reveal that lights-out factories depend on robotics, artificial intelligence (AI), and Internet of Things (IoT) to create fully autonomous production lines, offering benefits such as predictive maintenance, real-time optimization, and improved quality control. Case studies from FANUC and Tesla illustrate both the successes and challenges of such systems, with FANUC achieving significant labor reduction and efficiency gains, while Tesla faced early integration difficulties. The economic and environmental impacts are notable, with substantial cost savings, increased productivity, and reduced environmental footprints. However, high initial investments, system malfunctions, and the complexity of integrating multiple technologies pose significant barriers to broader adoption. While the review provides valuable insights, it also highlights the need for further research to address the gaps in AI adaptability, cybersecurity, and cost-effective automation strategies, particularly for SMEs. Future advancements in industrial automation will likely enhance efficiency, sustainability, and technological breakthroughs.

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Author Contributions

Sivarao Subramonian contributed to conceptualization, methodology, supervision, original draft preparation, and project administration. Kumaran Kadirgama contributed to conceptualization, validation, formal analysis, supervision, and manuscript review and editing, and served as the corresponding author. Zuhair Khalim and Shukor Salleh contributed to data curation, investigation, and original draft writing. Abdulkareem Al-Obaidi and Umesh Vates contributed to formal analysis, visualization, and manuscript review and editing. Satish Pujari contributed to literature review, data curation, and original draft preparation. Rakesh Phanden contributed to investigation, resources, and manuscript review and editing. Anuar Kassim contributed to methodology development, validation, and visualization. Amran Ali contributed to supervision, funding acquisition, project administration, and manuscript review and editing. All authors have read and agreed to the published version of the manuscript.

Declaration for AI

The advantage of AI was taken to generate images to represent advanced manufacturing scenario for this paper. Thus, Figure 2, Figure 3, Figure 4 and Figure 8 are generated using AI for this paper.

Conflict of Interest

The Author(s) declare that there are no conflicts of interest.

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