International Journal of Engineering and Modern Technology (IJEMT) E-ISSN 2504-8848
P-ISSN 2695-2149 Vol 10. No. 1 2024 www.iiardjournals.org

The Effect of Smart Factory on the Continuous Improvement of the Production Process: A Review

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DOI: 10.56201/ijemt.v10.no1.2024.pg83.107

ABSTRACT

This in-depth exploration uncovers the game-changing effect of smart factories on the continuous improvement of the production process, harnessing the power of advanced technologies. By closely examining key components such as Machine Learning, Virtual Reality, Additive Manufacturing, and Big Data Analysis, this study provides a detailed understanding of how these innovations shape the smart factory landscape. It highlights the adaptability and efficacy of these techniques by showcasing real-world implementations through case studies across several industrial sectors, going beyond the technical aspects. Moreover, the review delves into the practicalities of implementation, discussing strategies like Advanced Sensing, Control, Platform, and Model (ASCPM), and Visualization, Informatics, and Digital Manufacturing (VIDM). A SWOT analysis reveals the internal strengths and weaknesses, recognizing factors like interoperability, decentralization, and modularity, while also addressing challenges such as the need for personnel training and substantial investment. Looking ahead, the paper emphasizes the exciting opportunities presented by smart factories, including sustainable development, cost reduction, and the emergence of new business models. It also addresses potential threats, such as job losses and cybersecurity concerns. Ultimately, the review paints a human picture of smart factories, showcasing their roles or significance in the continuous improvement of the production process through their transformative impact on efficiency, waste reduction, cost savings, and innovation in manufacturing. The future research recommendations underscore the need to focus *on workforce implications and cybersecurity risks, ensuring a human-centric approach to the evolving landscape of smart manufacturing.*

KEYWORDS: *Smart Factory; Continuous Process Improvement; Industry 4.0; Connected Industries; Cyber-Physical System.*

1.0 INTRODUCTION

Traditional factory, its elements, and limitations.

The discourse on traditional factories reveals their historical significance in industrial production, embodying mass manufacturing principles. Characterized by assembly line structures, specialized workstations, and hierarchical organization, these entities prioritize efficiency and economies of scale. Automated processes, operating independently, necessitate frequent human interventions during transitions, highlighting a lack of connectivity within machines and broader business processes. Manual examination of disparate datasets is required for issue identification, limiting monitoring capabilities (He et al., 2016). The limitations of traditional factories encompass insufficient functionality, scalability challenges, complex manufacturing processes, and inadequate connectivity with demand and supply diagnostics Milic & Babic, 2020). The repercussions include factory closures, reduced production, short-time work, and disruptions in supply chains. Lack of adaptability and high maintenance costs for legacy instruments further impede operational efficiency (Chen et al., 2020). Dedicated Manufacturing Systems (DMS), a specific form of traditional manufacturing, prove inadequate in accommodating product varieties and sudden demand increases (Andersen et al., 2017). The inflexibility of assembly line configurations hinders prompt responses to dynamic market demands, especially in adjusting production to align with evolving consumer preferences (ElMaraghy et al., 2013). The formidable initial investment required poses barriers to entry for smaller enterprises. The trade-off between mass production efficiency and limited product customization capacity is a fundamental challenge for traditional factories, particularly in markets where demand for personalized solutions is prevalent. Environmental implications, such as resource-intensive processes, waste generation, energy consumption, and emissions, underscore the importance of sustainable manufacturing practices. Scholarly research advocates finding an equilibrium between efficiency and adaptability. Technological integration, particularly the adoption of the Internet of Things (IoT) and automation, emerges as a pathway to enhance competitiveness. Despite these challenges, traditional factories remain integral to industrial manufacturing. Acknowledging their elements and limitations is crucial for informed decision-making as the industry evolves toward a more adaptive and sustainable future.

The emergence of smart factories, their features, and their acceptance.

Recent technological advancements have ushered in significant progress in the industrial domain, paving the way for the fourth industrial revolution, commonly known as Industry 4.0. This transformation is predominantly characterized by the emergence of smart factories, which involves the application of cutting-edge Information and Digital Technologies (IDT). These technologies encompass the Internet of Things (IoT), supported by both wired and wireless networks, along with cloud computing, big data, and artificial intelligence (AI) (Ghobakhloo, 2020). The integration of these technologies has enabled the convergence of physical and virtual realms through cyber-physical systems (CPS) (Zheng et al., 2018). This convergence aims to enhance efficiency, ensuring higher-quality production at reduced costs. The development of intelligent systems and strategies relies on network and data utilization, facilitating informed decision-making in real time. This involves the collection of physical data at various stages of a product's lifecycle, extracted from interconnected and monitored machines through Industrial Internet of Things (IIOT) devices like sensors. Additionally, identification technologies such as RFID cards or barcodes are employed to track products and production resources, AI technologies play a pivotal role in this paradigm by analyzing and interpreting physical behavior based on the collected data (Wang et al., 2018). Smart factories leverage data collected from sensors embedded in networked equipment to automate production processes (Mohamed et al., 2019). In the realm of Industry 4.0, a diverse array of sensors, including position, pressure, flow, temperature, force, level, electrical, moisture, and heat sensors, are employed (Kalsoom et al., 2020). These sensors find applications across various sectors, spanning motorsport, medical, aerospace, agriculture, and daily life. For instance, in medicine, sensors measure biological functions like blood flow during surgery, while in retail, they detect customer positions and monitor crowd movements (Javaid et al., 2021). In manufacturing, sensors enhance production performance, optimize tasks, and facilitate quality management and equipment tracking (Zhong et al., 2017).

The gathered data serves as a foundation for optimizing production processes and enhancing overall efficiency. Smart factories incorporate collaborative robots, known as cobots, which are equipped with sensors for safe human-robot collaboration within the workspace (Matheson et al., 2023). Unlike traditional industrial robots requiring guarding fences, cobots offer safety advantages. Consequently, sensors play a pivotal role in automating robots and transforming industrial systems into intelligent and efficient entities. This analysis contributes to the control of manufacturing activities, optimization of physical processes, real-time risk alerting and prediction, and ultimately, improved decision-making. According to statistical data, 82% of companies implementing smart manufacturing technologies have witnessed a boost in efficiency, while 45% of these enterprises have reported an enhancement in customer satisfaction (Shrouf et al., 2014). Furthermore, Smart Additive Manufacturing (SAM) integrates 3D printing into smart factories, streamlining Digital Supply Chains. SAM enables adaptable logistics, customized mass production, and rapid prototyping, enhancing flexibility and sustainability across Fletcher's Digital Value Chains (Araújo et al., 2021).

Traditional factory vs smart factory.

Traditional manufacturing facilities typically operate using manual and isolated procedures, lacking integration with various systems and tools. These facilities often depend on outdated systems, leading to frequent machine failures and increased maintenance costs. Decision-making in traditional factories is process-driven, limited by restricted or nonexistent access to data. Limited technology involvement results in poor visibility of operations and productivity data, impeding innovation in product development. Inaccurate asset tracking processes and suboptimal resource utilization are common due to poor interoperability. Manual reconfiguration, necessitating system power down, is required to alter the fixed production line. In contrast, smart factories adopt digitized and integrated processes, seamlessly connecting both existing and new systems and tools. These intelligent systems enhance machine utilization and reduce maintenance costs. Real-time data updates facilitate data-driven decision-making, supported by technologies such as the Internet of Things (IoT), sensors, mobile apps, and radio frequency identification (RFID). Smart factories exhibit increased transparency and visibility in operations, providing essential production data for innovation. They integrate smart and intelligent products, employ accurate asset tracking through IoT and RFID, and optimize resource utilization. High interoperability allows automatic online reconfiguration when transitioning between different product types. Smart factories are characterized by four intelligent features: sensors for self-organization and adaptive decision-making, interoperability for improved device coordination, integration of robots and AI for seamless process integration, and the application of virtual reality (VR) techniques to facilitate collaboration between humans and machines. Emphasizing connectivity, cooperation, and execution, smart factories leverage intelligent production systems and engineering techniques. Through device connectivity, these factories assess situations, exchange information, and integrate the physical and digital realms, making them inherently adaptive.

Table 1.

Key Differences Between Traditional Factories and Smart Factories Across Various Aspects of Operation, Technology, and Adaptability (ElMaraghy et al., 2013; Zheng et al., 2018; Milic & Babic, 2020).

Aspect	Traditional factory	Smart factory
Operational Procedures	Manual and isolated processes	Digitized and integrated processes
System Integration	Lack of integration with various systems and tools	Seamless connection of existing and new systems and tools
Technology Involvement	Limited technology involvement	Utilizes IoT, sensors, mobile apps, RFID for enhanced operations
Machine Utilization and Maintenance	Dependence on outdated systems, frequent failures, high maintenance costs	Enhanced machine utilization, and reduced maintenance costs.

Decision-Making	Process-driven with limited access to data	Data-driven decision-making with real-time updates.
Visibility and innovation	Poor visibility of operations, a hindrance to innovation	Increased transparency, providing essential data for innovation.
Asset Tracking and Resource Utilization	Inaccurate tracking, suboptimal resource utilization	Accurate asset tracking through IoT and RFID, optimized resource utilization
Production Line Flexibility	Manual reconfiguration with system power-down	Automatic online reconfiguration for different product types.
Intelligent Features	Not applicable	Sensors, interoperability, robots, AI, and VR for adaptive processes.
Emphasis	Manual procedures, and isolation	Connectivity, cooperation, and execution through intelligent systems.

This research conducts a comprehensive examination, critically reviewing the latest research and advancements concerning the impact of smart factories on the ongoing enhancement of the production process. The second section delves into the elements comprising the smart factory, elucidating its components. Section 3 outlines the techniques and strategies employed within smart factories. The subsequent section, Section 4, delves into a SWOT analysis of smart factories. Moving forward, Section 5 elucidates how smart factories serve as a pivotal catalyst for continuous process improvement in production. The concluding section, Section 6, succinctly summarizes the primary findings derived from our research.

2.0 Overview of Smart Factories

The concepts of Computer Integrated Manufacturing, Factory Automation, Computer Integrated Enterprise, and Just-in-Time helped in the emergence of Smart Factories, which improved quality while lowering production costs and cycles. Through the horizontal integration of partners, suppliers, and customers and the vertical integration of the entire product lifecycle from development to completion, Smart Factory achieves both horizontal and vertical integration. To create a more integrated system, production configurations are influenced by the preferences of product users as well (Elvis Hozdić, 2015). We achieve a real-time, fully integrated information system where improvement in resource and energy efficiency is achieved by focusing on integrating industry, information technology, and the internet while also connecting people, machines, and products with the environment (Inyang et al., 2023).

According to Elvis Hozdić (2015), smart manufacturing is a manufacturing solution that provides flexible and adaptable production processes to address issues that arise in a production facility with dynamic boundary conditions that change quickly in an increasingly complex world. (Elvis Hozdić, 2015). Achieving a Smart Factory requires utilizing cutting-edge technologies and manufacturing intelligence in real-time for intelligent decision-making, as well as the right people, knowledge, technology, operations, and data at the right time in the manufacturing pipeline (Ogumerem & Pistikopoulos, 2019). Advantages that a smart factory should have include adaptability, reconfigurability, low cost, agility, and slenderness.

A core system used in Smart Factories is called a Cyber-Physical Production System, which converts physical data into digital data by combining computer and physical capabilities with sensors on physical systems and utilizing components like IIoT, Edge Computing, Big Data, RFID, Machine Learning, Sensors, and Artificial Intelligence to create a feedback loop that improves production and decision-making processes (Elvis Hozdić, 2015). Automation, which is a collection of technologies that allow machines and systems to function without requiring a lot of human interaction, is another essential system used in Smart Factories. Technologies like IIoT, Cloud Computing, Robotics, Sensors, Big Data Analysis, ML and AI (Machine Learning and Artificial Intelligence), RFID, and so forth enable Automation in the context of Smart Factories (Shah & Sheth, 2022).

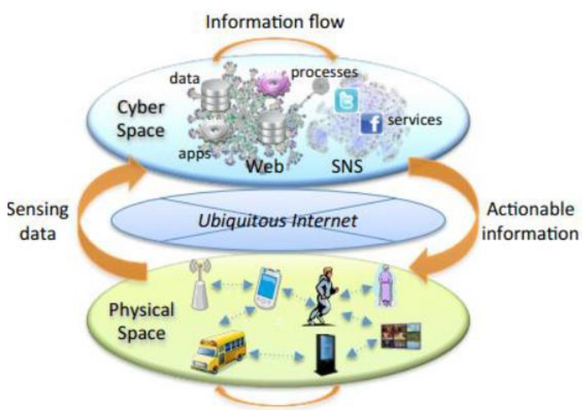

Figure 1. Information exchange between the Physical Space and the Cyber Space (Elvis Hozdić, 2015)

2.1 Components of Smart Factory

These components comprise the technologies that facilitate and allow for the realization of a smart factory. Among other things, they support efficiency, agility, quicker operations, maintenance, and decision-making. These include Machine Learning and Artificial Intelligence, Virtual and Augmented Reality, Additive Manufacturing, Big Data analysis, Cloud Computing, CNC Machining, Manufacturing Design, Edge Computing, IoT and IIoT, Digital Twins and Simulation, Robotics and Sensors.

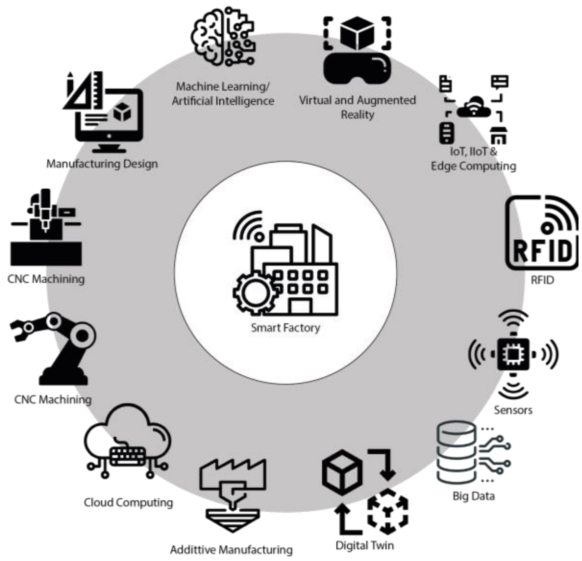

Figure 2. Smart Factory Components (Asset Union, 2023; Circlon Tech, 2023; Design Circle, 2023; Freepik, 2023a, 2023b; Iconjam, 2023; Itim2101, 2023; Kalashnyk, 2023; Orvipixel, 2023; Ppangman, 2023; Rukanicon, 2023; Vector Stall, 2023; Zero_wing, 2023)

Machine Learning and Artificial Intelligence

AI/ML is the ideal technology to support data analysis because it can process large amounts of data and identify patterns rapidly, especially the massive amounts of data generated in smart factories.

Although they are commonly used interchangeably, the terms "machine learning" and "AI" have two distinct meanings. Machine learning enables you to get a better understanding of data's behavior, the root causes, and correlational relationships by aggregating data from different sources. It can assist you in finding the solution to your specific problem by relying on past data for an evaluation of the probability of different options and their likelihood of success. It explains the meaning and provides a degree of certainty for events that are to come. The system in which the recommendations of machine learning are implemented is described by artificial intelligence (Rapp, 2022).

Because machines, sensors, and other sources generate massive amounts of data, Machine Learning and AI have the potential to improve production system efficiency and even help with maintenance (Inyang et al., 2023). They have proven to be remarkably proficient in the analysis and evaluation of large data sets, allowing them to obtain relevant information and patterns that can help inform decision-making and improve Smart Manufacturing (Othman & Yang, 2023). If it has access to real-time data, it can also react autonomously to changes made to production systems, like swapping out tools or turning on and off machinery. It can recognize mistakes and even send out alerts, among other things (Inyang et al., 2023).

Virtual and Augmented Reality

In smart factories, Virtual Reality can be used for a variety of purposes, but the primary use is typically in on-the-job training that helps workers acquire skills faster when they work. Virtual Reality allows you to create computer images and movies that can be used to simulate the physical world. Thanks to technologies that interface communication, location, sound, and video systems in hardware, users will be able to experience the physical world as though they were present.

With the use of mobile phones, tablets, smart glasses, and their cameras, users can overlay computer-generated virtual objects onto real-world environments to create an immersive experience known as Augmented Reality (AR) (Kumar, 2020). Training new hires and conducting product testing in augmented environments both result in more efficient processes and reduced training time. AR technology can be used to assist workers in smart factories by highlighting tools and components needed for a specific task, guiding by indication, and identifying critical areas. When combined with other technologies that facilitate feedback, it can also draw attention to areas of assembly discrepancies or defective parts. As a result, operations and processes become even faster and more efficient, improving quality control (Othman & Yang, 2023).

Additive Manufacturing

The development, creation, and production of new products in the industry have been revolutionized by additive manufacturing, also referred to as 3D printing. Because it is an additive process rather than a subtractive one like milling, it has made it possible to produce lighter, more complex products in the shortest amount of time while using fewer resources and reducing waste (Inyang et al., 2023).

In essence, additive manufacturing (AM) processes involve adding materials to a previously existing surface using various deposition methods, producing parts with varying densities, geometric accuracy, and quality. On the other hand, traditional methods are typically subtractive or, in the case of complex parts, a combination of multiple processes. This is a useful technology for Smart Factory applications because every AM process is computerized, and it allows you to control multiple machines at once from a single computer (Mehrpouya et al., 2019).

Big Data Analysis

Without data, there can be no Smart Factory implementation. The ability to collect data from all assets in a smart factory through sensors and other methods is critical for real-time decision-making, which is required to achieve Smart Manufacturing. These data come from consumer feedback systems, product request systems, businesses, and production units. Big data analysis is used for risk assessment, logistics, costing, quality control, and improvement. It is also used for growth strategies, build-to-order, just-in-time production, and other sales patterns and post-sale services (Elvis Hozdić, 2015). Big data is also used to better serve customers by gathering feedback from them. This information is then used to optimize designs for consumer appeal, pinpoint real-time reasons for product failure, comprehend customer purchase patterns, and comprehend market demands to leverage data for predictive production (Inyang et al., 2023)

Production efficiency will increase with a strong data system, precise records of each product, unique identification, procedure, specification, observational data, quality and product characteristics, safety data sheets, suppliers, etc. (Ogumerem & Pistikopoulos, 2019).

Radio-Frequency Identification (RFID)

Radio waves are used in RFID systems in manufacturing to facilitate communication between RFID readers and tags affixed to physical objects. RFID improves operational efficiency, reduces errors, and allows accurate inventory management by offering unmatched visibility and automation (CYBRA, 2022).

RFID technology is important for big data in Smart Factories because it makes data collection possible while enabling real-time product and equipment monitoring (Tao et al., 2018). It eliminates some limitations that were associated with the use of bar codes. Examples include the reader's requirement for direct visibility, the short distance needed to read it, issues with broken labels, and slowness when reading a large number of barcodes (Elvis Hozdić, 2015).

Cloud Computing

A cloud-based system with distant servers stores and processes data using an AI/ML algorithm. The process of remotely connecting users to scalable, on-demand computer resources via a network is known as cloud computing. By enabling you to use exactly the right amount of resources at the right time, cloud computing seeks to improve the efficiency of computer resource usage (Inyang et al., 2023).

CNC Machining

Computer numerically controlled machine tools are an essential component of manufacturing technology and are used in a variety of operations such as milling, lathing, and drilling. They facilitate automated machining operations and incorporate Internet of Things (IoT) sensors in Smart Factory applications. These features help create an efficient closed-loop system that aids a Smart Factory in achieving its goals. Computer-aided manufacturing software is used to generate the machine codes required to automate CNC machines (Inyang et al., 2023).

Robotics

Robotics is the application of robots, where automation of heavy-duty, repetitive, hazardous, resource-intensive, and eventually jobs requiring human intelligence are the core functions of these robots. ISO 8373:2012 defines an industrial robot as a multipurpose manipulator that may be used in industrial automation applications. It can be mobile or fixed in place, and it can be programmable in three or more axes. The motors and control algorithm combination are the fundamental components of an industrial robot. An industrial robot can reach desired trajectories and complete jobs by following a specific set of executed operations (Arents & Greitans, 2022). The successful deployment of smart factories is largely attributed to robots. They make it possible to carry out operations and duties in a reliable, flexible, safe, and versatile manner while increasing productivity (Gaur & G. S. Virdi, 2018).

Manufacturing Design

Design for Manufacturing and Assembly (DfMA) is a design process in which the manufacturing process and assembly are prioritized in design decisions and guiding principles. This enables the design of a product that is optimized for both manufacturing and assembly. Utilizing CAD and CAM software is essential for accomplishing this, as it enables you to digitally visualize your design (Inyang et al., 2023).

Edge Computing, IoT, and IIoT.

As Smart Factory assets become IoT components and are part of a network where sensors submit data for analysis on the cloud, edge computing—which involves performing local computation on the data before uploading it to the cloud—is made possible by the low-cost CPUs in these assets (Inyang et al., 2023). The term "Smart Assets" refers to the Internet of Things-enabled machinery or equipment that has embedded digital systems that enable data processing, data reception, and task execution, wherein the remote operation of these machines or equipment can also be achieved (Ogumerem & Pistikopoulos, 2019).

Process monitoring, control systems, and physical objects are all connected to the cloud via the Internet of Things. A shared goal can only be accomplished when all parts communicate with each other seamlessly. Improved human-machine interaction, production scheduling, defect localization, preventive maintenance, and resource efficiency are all made possible by IoT. The industrial application of IoT on the production line is known as IIoT (Inyang et al., 2023).

Sensors

Sensors are devices that can gather data and use it for effective performance, allowing for the much-expanded data collection on various devices across manufacturing processes. They are also essential for analyzing behaviors and abilities because they can self-organize, learn, and maintain environmental information. The basic goal of the "smart factory" concept is to establish highly digitalized production processes with little human interaction and information flows between various devices under controlled conditions. The use of sensors makes this possible (Kalsoom et al., 2020). Sensors are important for smart manufacturing processes because they help to track the entire process and contribute to improvements in production performance, quality management, precision in manufacturing machinery, optimizing production tasks through automation and regulation, and of course, detecting and identifying faults (Dodia et al., 2023).

Digital Twins and Simulation

According to FANUC, the world's largest manufacturer of industrial robots, "a digital twin is the concept of creating a digital replica of the physical machines, production processes, or shop floor layouts to generate several competitive advantages" (Aziz et al., 2023).

Digital twins are digital replicas of physical components, processes, and products that can be tested, validated, and optimized virtually before the manufacture or setup of systems. This is accomplished by employing simulation software. It is more efficient and less expensive to simulate plant operations in a virtual setting before setup. The machine settings on the production line can be optimized in the virtual world to validate them before the settings are implemented. Planning and scheduling for production can be done with this virtual model. Calculating expenses and analyzing errors in design, production duration, workforce, and energy consumption throughout the process has become simpler as a result. Before any physical resources are allocated, this even permits for-profit loss analysis and other forms of analysis (Inyang et al., 2023).

3.0 The strategy and techniques used in smart factory

Establishing a Smart Factory requires a strategic pursuit of synchronization goals aimed at seamlessly integrating its components. In this endeavor, diverse strategies come into play, each contributing to the harmonious synchronization of the factory's various elements. The subsequent sections delve into some of the strategies and synchronization properties that are intended to foster the development of a pragmatic Smart Factory.

3.1 The realistic strategy used in establishing a smart factory.

While there are many different strategies to implement a smart factory, we will concentrate on two: VIDM (visualization, informatics, and digital manufacturing) and ASCPM (advanced sensing, control, platform, and model). There is a greater inclination towards ASCPM in the chemical process industry and VIDM in the discrete manufacturing sector. (Ogumerem & Pistikopoulos, 2019).

3.1.1 Advanced Sensing, Control, Platform, and Model (ASCPM)

Advanced Sensing

By monitoring the real-time management of inputs like energy and materials, advanced sensors are used to monitor productivity, efficiency, and assets, thereby increasing the reliability of Smart Factories. These sensors are considered "smart" because they are quick, non-invasive hard sensors or soft sensors (AI type of data-trained computer code). They are also anticipated to be inexpensive and can continuously quantify measurement uncertainties and assess sensor health (Ogumerem & Pistikopoulos, 2019).
A closed-loop feedback system is impossible to achieve in a smart factory without sensors.

Control

This is where theories and algorithms for model-based control and optimization of a Smart Factory are put into action. Automation and control aspects of a smart factory can benefit from the use of AI and CNC (Computer Numerical Control) technologies. The goal of this is to use embedded automated process controls to optimize operations, consume less energy, and increase safety. Additionally, system-wide applications involving several components operating concurrently will be possible thanks to IIoT and cloud computing (Ogumerem & Pistikopoulos, 2019).

Platform

Conventional manufacturing component platforms typically lack interoperability. To address this problem, standardization can be utilized to facilitate interoperability in the pursuit of a Smart Manufacturing goal (Ogumerem & Pistikopoulos, 2019).

Model

Real-time and lifecycle modeling are necessary for the implementation of smart manufacturing. To create models that can be utilized in a Smart Factory to optimize tools, procedures, and techniques, digital twin technology is essential. The ability to simplify and cost-effectively build, deploy, and maintain models across large heterogeneous systems is critical to Smart Manufacturing. Optimizing and controlling models, for instance, should be able to exchange data iteratively, including updated constraints and new control set-points. This requires synchronous interaction and model alignment (Ogumerem & Pistikopoulos, 2019).

3.1.2 Visualization, Informatics, and Digital Manufacturing (VIDM)

Visualization

The information is presented to the user at the appropriate time through visualization. To do this, information must be created that people can visualize and utilize to make decisions. It includes gathering and combining data from multiple sources, displaying it comprehensively in the appropriate context, and presenting it graphically in an understandable way. Turning data into visual information for decision-making. The goals of smart manufacturing will also be greatly advanced by the use of VR/AR technology in visualization (Ogumerem & Pistikopoulos, 2019).

Informatics

Data processing and intelligence extraction are key components of informatics. Utilizing machine learning and artificial intelligence technology effectively allows for the processing of data and the extraction of intelligence, which are two tasks that informatics entails. The extracted data may be processed partially on the smart unit itself (edge computing) or entirely on the cloud (cloud computing) (Ogumerem & Pistikopoulos, 2019).

Digital Manufacturing

The goal of digital manufacturing is to simultaneously define the product and the manufacturing process through the use of integrated, computer-based systems made up of analytics, three-dimensional visualization, simulation, and other collaboration tools. This is achieved with the application of IIoT Technology, Digital Twin Technology, CNC Technology, and other technologies that enhance manufacturing processes. This enables Design Modeling and Analysis for Manufacturing Objects to proceed from concept to manufacturing. Its goal is to achieve better overall manufacturing efficiencies and reduce design and manufacturing life cycles (Ogumerem & Pistikopoulos, 2019).

3.2 The techniques used to synchronize the smart factory components

Optimizing several properties is crucial to synchronizing a Smart Factory effectively. Modularity, heterogeneity, scalability, context awareness, autonomy, interoperability, and networkability play key roles in achieving the Smart Factory's goals. They're fundamental to creating an efficient and interconnected manufacturing system that adapts and operates seamlessly.

Modularity

Through standardized interfaces, the different components can communicate, connect, and exchange resources. Modular systems enable processes, information systems, and products to be packaged as reusable modules that can be (re-)combined with other modules. For modularity, the least amount of interdependence between modules is required. Standardization also makes it possible to synthesize modular networked objects in a standard way with fewer requirements for mutual consent and interoperability. Compositionality is also closely related to modularity, which means that the properties of higher-level systems can be defined by the local properties of individual components. A workable and effective value chain with seamless data transmission and exchange is formed upon the realization of a modular system (Kühnle & Bitsch, 2015).

Heterogeneity

The term "heterogeneity" describes the fact that different components of a smart factory are composed of dissimilar constituents. These various components must be able to work together in a network to create a Smart Factory. Therefore, improving the relationship between these disparate parts is essential to realizing a Smart Factory (Kühnle & Bitsch, 2015).

Scalability

Scalability refers to a smart factory's capacity to smoothly adjust to variations in loads or usage, both as they rise and fall. In other words, it must have the flexibility to increase or decrease its capacity. Without significantly altering the organization or use of technology, this capability must be attained (Kühnle & Bitsch, 2015).

Context Awareness

This is the ability to provide services that fully characterize the execution environment in use as well as any data that can be used to describe an entity—such as a person, place, or object—situation. Smart factory assets possess the ability to self-describe and recognize their current operational and situational conditions. It is useful for decision-making.

External (physical) context dimensions, such as movement, location, alignment parameters, and so on, that aid context awareness can be measured with hardware sensors or captured by unit interactions. Additionally, there are internal (logical) context dimensions that are unique to each unit, such as tasks, goals completed, KPIs, operations, and objectives. The location (i.e., geographic position, proximity, etc.), identity, and status information of Smart Factory assets are also necessary to achieve context awareness (Kühnle & Bitsch, 2015).

Autonomy

Autonomous smart factory units can complete tasks and work toward their goals without the active assistance of other units. It is the ability to self-organize in response to external input and keep a self-fed loop with the environment. This capability could be as straightforward as changing from one state to another or as complicated as modifying unit behavior through decision-making or embedded action plans for self-healing, self-organizing, and self-sustaining. (Kühnle & Bitsch, 2015).

Interoperability

Interoperability refers to the ability of different networks, units, or subunits to collaborate. Interoperability is defined by IEEE as the ability of two or more units or components to exchange information and use the information that has been exchanged. Collaboration is made easier and efficiency is raised when units in a smart factory are interoperable due to their high degree of compatibility (Kühnle & Bitsch, 2015).

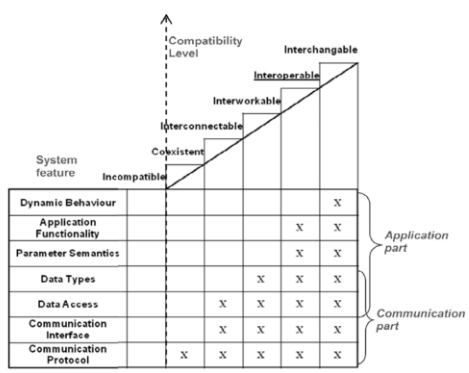

Figure 3. Compatibility Levels Based on IEC TC 65/290/DC Showing Interoperability Compatibility Levels (Kühnle & Bitsch, 2015).

Networkability

The ability of assets in a Smart factory to collaborate across different processes at all layers is referred to as networkability. This is developing the capacity for making decisions and offering all the protocols required to oversee and carry out the tasks required for creating, reorganizing, and establishing new or reorganized processes.

Networkable configurations result in process configurations that are used as descriptive mapping, showing processes that are being run or completed to analyze and extract process parameters; prescriptive mapping, providing expected procedure options for additional analysis and network development; and prospective instrument, displaying expected future simulation configurations (which configurations should be preferred or avoided) (Kühnle & Bitsch, 2015).

4.0 The SWOT Analysis of Smart Factory

A SWOT analysis is employed to pinpoint the internal strengths, weaknesses, opportunities, and threats of a novel undertaking, such as the implementation of a smart factory. Originating in the 1960s and 1970s, this analytical approach was pioneered by Albert Humphrey, a research scholar and leader of the Team Action Model (TAM) at Stanford University. The TAM research team, under Humphrey's guidance, identified crucial areas for examination, utilizing the SWOT analysis tool to delve into each of these identified aspects. They used the categories "What is good in the present is Satisfactory, good in the future is an Opportunity; bad in the present is a Fault, and bad in the future is a Threat." (Thompson et al, 2007).

Figure 4. SWOT Analysis (Alicia Raeburn, 2023)

SWOT analysis is divided into two key components: internal and external assessments. The internal analysis focuses on identifying the organization's inherent resources, capabilities, core competencies, and competitive advantages. In contrast, the external analysis aims to pinpoint market opportunities and threats through an examination of competitors' resources, the industry environment, and the broader environmental factors. The primary goal of SWOT analysis is to leverage insights into both internal and external environments, enabling the formulation of strategic decisions for the organization (Bakhtari et al., 2020).

As the concept of the smart factory emerges, it necessitates a comprehensive analysis to evaluate its utility, shortcomings, and challenges compared to traditional production methods. Bakhtari et al. (2020) conducted a SWOT analysis to assess the features of a smart factory, and the ensuing results are detailed below.

Table 2: *SWOT Analysis of Smart Factories (Bakhtari et al. 2020)*

STRENGTHS ● Interoperability: It facilitates industries in sharing or exchanging their machines and equipment designed to perform similar functions. ● Decentralization: This involves increasing the ability of machines, and operational personnel to make decisions faster and more data-driven without relying on a central decision-maker. ● Increased real-time capability: This increases the response rate and enables the machines to adopt product development as per customer needs. ● Modularity: It enables the production system to be flexible with changes in product design or during seasonal changes, without majorly affecting the process. ● Service orientation: It allows the business, humans, and CPS to interact with each other through the Internet and Internet of services to create much better value for the consumers. ● It leads to the conservation of energy and raw materials, thereby increasing efficiency.	***OPPORTUNITIES*** ● Smart factories can make a big contribution to sustainable development and eco-sustainable production due to an increase in efficiency, productivity, and flexibility of the industries. ● It will increase customer satisfaction with the direct interaction of the customer. ● The product cost will be reduced due to increased efficiency and productivity. ● It will enhance industrial relationships by removing barriers between investors and markets. ● Smart factories will help to have better customization of products and services. ● This will help in waste reduction and reduction of energy consumption due to higher efficiency. ● Shorter lead times due to better connectivity and fast information flow. ● Smart factories have the potential to create new business models. ● Due to high efficiency, the cost of production will decrease
WEAKNESS ● Operation personnel need to be trained and also improve their soft skills to manage modern digital jobs. ● Equipping operators with new skills and workforce transformation to enable them to manage the required task digitally.	***THREATS*** ● There is a danger of job losses as smart factories replace low-skilled and low-wage jobs with computers and digitization. This increases social tensions and pessimistic ideas. ● Data and knowledge will play the most important role, so the security of data

• Data and information sharing among different industries that compete. • High investment is required to make all the industry components smart. • Security of computer data and communication between intelligent systems to avoid leakage of confidential data, which affects the competitiveness of the organization.	and information is a big concern as there is a rise in cyber-terrorism, hacking, and cyber-crimes. These will impede its implementation. • Social beliefs and perceptions against the digitalization and connection of everything through the Internet of Things threaten customer privacy. • Lack of proper and applicable framework to implement Industry 4.0 in the industry. • The development of algorithms to deal with data due to the collection and production of massive data

5.0 Smart Factory the Key Driver of Continuous Process Improvement In The Production Process

Smart factories play a crucial role in continuously improving production processes. The various ways smart factory influences continuous process improvement are discussed below;

5.1 Continuous Process Improvement

Continuous process improvement involves the constant analysis of performance, the identification of opportunities, and the implementation of incremental changes to enhance processes, products, and personnel. W. Edwards Deming was instrumental in popularizing this concept, which originally encompassed a broad philosophy incorporating various approaches to foster a culture of innovation. In contemporary contexts, continuous improvement has become a fundamental principle in project management philosophies such as Agile, Lean Six Sigma, and Total Quality Management (Max, 2022).

According to the American Society for Quality, continuous process improvement entails the ongoing enhancement of products, services, or processes through both incremental and breakthrough improvements. These improvements can be introduced gradually over time or implemented as a single transformative initiative.

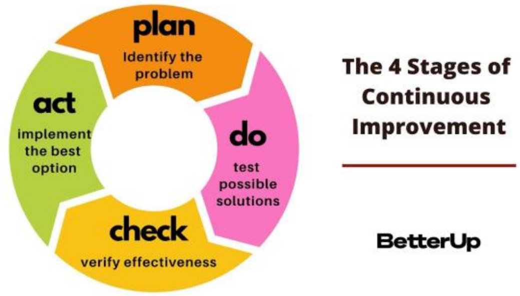

Figure 5. The 4 Stages of Continuous Improvement (Madeline Miles, 2022)

- **Plan**: Identify an opportunity and plan for change.
- **Do**: Implement the change on a small scale.
- **Check**: Use data to analyze the results of the change and determine whether it made a difference.
- **Act**: If the change was successful, implement it on a wider scale and continuously assess your results. If the change does not work, begin the cycle again.

5.2 The significance of smart factories in the continuous improvement of the production processes

The world is currently experiencing a surge in the adoption of the latest technologies, with a particular emphasis on smart technologies by major manufacturing firms. This trend is significantly impacting various domains of human endeavors, particularly the industrial production of goods. Smart manufacturing primarily revolves around methods aimed at enhancing decision-making and processes within industrial manufacturing environments (Gabriel et al., 2020).

According to a report from the McKinsey Global Institute, approximately 60% of all occupations involve activities where at least 30% could be automated. This highlights the potential for boosting production capacities in smart factories through the effective utilization of smart manufacturing technologies (J. Lee et al., 2018). Industries such as food, pharmaceuticals, semiconductors, oil and gas, fine/specialty chemicals, paints and coatings, and additives have leveraged smart manufacturing to optimize their production processes (J.C. Serrano-Ruiz et al., 2021).

The global COVID-19 pandemic since 2020 has had a profound impact on the manufacturing sector, prompting many manufacturers to adopt smart manufacturing practices. With an increased demand for everyday consumable goods and electronic products, the global smart manufacturing market is anticipated to witness significant growth in the coming years. Projections indicate that the market will expand from US$ 249.46 billion in 2021 to US$ 576.21 billion in 2028, with a Compound Annual Growth Rate (CAGR) of 12.7% between 2021 and 2028 (Q. Liu et al., 2021). The surge in investments in automation technologies is a driving force behind the substantial growth in the smart manufacturing sector (Sahoo et al., 2022).

Smart Factory's influence on the Continuous Process Improvement of the production processes (Madeline Miles, 2022)

- It increases efficiency and productivity
- It improves employee engagement and relationships
- It reduces waste
- It reduces costs
- It improves customer satisfaction
- It reduces cycle time
- It increases innovation and staying ahead of the competition
- It allows for agility and adaptation to change.

6. 0 CONCLUSION

The manufacturing industry has undergone a revolutionary change with the emergence of smart factories. These factories have introduced a range of components to achieve flexibility, transparency, interoperability, connectivity, decentralization, and modularity, which have significantly improved production processes. Through continuous process improvement and implementation of the plan, do, check, and act (PDCA) steps, key performance indicators such as increased overall equipment effectiveness, reduced costs, reduced downtime, and waste reduction have been greatly improved. Smart factories have enabled the industry to keep pace with the increasing global demand for goods and products by utilizing automation and CPS technology to boost production capacities. By embracing these advancements, the manufacturing industry has established sustainable and efficient production methods.
In conclusion, smart factories have transformed the manufacturing industry by introducing innovative technologies such as Machine Learning and Artificial Intelligence, Virtual and Augmented Reality, Additive Manufacturing, Big Data analysis, Cloud Computing, CNC Machining, Manufacturing Design, Edge Computing, IoT and IIoT, Digital Twins and Simulation, Robotics and Sensors, and improved methodologies, thus enhancing efficiency, productivity, and sustainability. With the continued use of smart factories for production process improvement, the manufacturing industry is better equipped to meet the ever-increasing demand for products on a global scale.

7.0 RECOMMENDATION

The concerns about smart factories leading to a reduction in the workforce and loss of jobs which pose detrimental consequences on the labor market should be considered in future research. Future research should also consider the potential security risks associated with increased connectivity and data exchanges between man and machine in terms of data privacy and security vulnerabilities. The impact of smart factories on the environment, in terms of waste production, and material consumption, should be a focal point for future research. Future research should ensure that companies prioritize quality and creativity in addition to efficiency.

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