Achievement of Sustainable Manufacturing From Industry 4.0 Technologies – Future Perspective

Irina Badurashvili
Public Management and Policy, Hochschulstrasse 4, 3012 Bern, Switzerland.
irinabad@hotmail.com

Correspondence should be addressed to Irina Badurashvili : irinabad@hotmail.com.

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Abstract – Throughout history, manufacturing has consistently been at the forefront of technical progress, seeing the evolution from steam engines through cyber-physical systems, electricity, IoT, microprocessors, AI, automation, computers, and now. In the context of promoting growth of economy and generating lasting value in industries, sustainable manufacturing comprises the three essential components of manufacturing, namely processes, products, and systems. In order for manufacturing to be deemed sustainable, it is essential that these three components, when examined individually, illustrate the advantages in terms of environmental, economic, and social aspects. The primary objective of sustainable manufacturing is to produce things of superior quality while minimizing resource consumption and ensuring the safety of customers, employees, and local communities. This article explores the future direction of research in the domains of Industry 4.0 and sustainable manufacturing technology. Upon reviewing the extant literature, six key areas emerge as important subjects for further inquiry. These focal points are elucidated, along with the identified gaps in knowledge that need more exploration. Relevant papers for this research were identified using keywords such as "Sustainability," "Industry 4.0," "sustainable manufacturing," "manufacturing sustainability," or "smart manufacturing."

Keywords – Smart Manufacturing, Industry 4.0, Manufacturing Sustainability.

I. INTRODUCTION

Manufacturing companies' business models have undergone substantial changes as a result of the introduction of Industry 4.0. Edwards, Kuhn-Sherlock, Dela Rue, and Eastwood [1] claim that a variety of new intelligence, information, and communication technologies may increase industrial flexibility, efficiency, and output. Additive manufacturing, AI, big data analytics, cloud computing, blockchain, simulation, and industrial IoT are among the technological initiatives included under Industry 4.0. Applying Industry 4.0 technology has the potential to result in major improvements in competitiveness and innovation while also boosting the sustainability of current industrial systems.

The use of Industry 4.0 in companies has been more significant and prominent in recent years. However, it is crucial to provide more consideration and assessment to the impact of new technologies on society's sustainability goals. Traditional agricultural methods have gained a reputation for generating significant ecological imbalances. Mulk [2] argue that conventional industrial techniques and technologies may be attributed to a range of issues, including increased resource consumption, global warming, environmental degradation, and greater levels of pollution. In addition, our society is confronted with a multitude of social issues and obstacles, including but not limited to poverty, inequality, prosperity, as well as concerns pertaining to peace and justice.

According to [3], the idea of legitimacy posits that achieving sustainability objectives that are important to key stakeholders, such as decreasing the emissions of carbon, may lead to enhanced performance of organization. The fourth Industrial Revolution has the ability to solve the social and ecological limits associated with conventional industrial practices and technology, hence offering the prospect of a more sustainable future. In the final analysis, these efforts have the potential to result in sustained organizational competitiveness. Based on a study conducted by Liang and Yu [4], including 130 participants from several sectors in China, it is evident that Chinese manufacturing businesses exhibit significant excitement and anticipation towards the implementation of Industry 4.0. However, the survey findings indicate that just 57% of Chinese organizations have achieved comprehensive readiness in terms of adopting technologies of Industry 4.0. According to worldwide research conducted in 2016, the percentage mentioned is much lower compared to that of the United States (71%) and Germany (68%). One significant factor contributing to this issue is the lack of comprehension among industrial enterprises about the significance of these technologies.

The integration of manufacturing and information technology in Industry 4.0 technologies is characterized by a sophisticated and integrated architecture. Assessing the effect of these technologies by conventional assessment methods may present challenges; however, including supplementary evaluation criteria to gauge sustainability advantages might enhance their strategic adoption, while further complicating the process. Therefore, the assessment of Industry 4.0 remains a significant and ongoing area of study, as highlighted by Ashadi, Priyana, Basikin, Triastuti, and Putro [5]. In general, the use of efficient and resilient assessment methodologies and decision support systems may facilitate the successful integration and comprehension of Industry 4.0 technologies inside manufacturing enterprises, particularly when considering their wider economic ramifications. In addition to social and environmental considerations, these larger implications include the enhancement of enterprises' and countries' competitiveness.

This study examines the prospective avenues for future research in order to attain industrial sustainability via the use of Industry 4.0 technology. The literature evaluation reveals the presence of six prominent study topics that need further exploration in future studies, accompanied by a discussion of the existing research gaps. The inquiry presented in this study is as follows: What are the primary constraints associated with Industry 4.0 technologies pertaining to the sustainability of production, and what are the key research topics that need further exploration? The subsequent sections of the study have been structured in the following manner: Section II provides a comprehensive review of the research, including key aspects and relevant information. On the other hand, Section III delves into the methodology used in this particular study, outlining the approach and techniques utilized. Section IV provides an overview of the assumptions made in earlier literature that are relevant to the scope of the investigation. Section V of the paper focuses on the primary discussions pertaining to various aspects of lean production systems in the context of industry 4.0 environmental management. This section explores the connection between sustainable practices and the fourth industrial revolution, while also identifying shared elements between sustainability and industry 4.0. Additionally, it delves into topics such as big data analytics and its impact on sustainability, the influence of machine learning and artificial intelligence on sustainability, integrated process scheduling and planning for the sustainability of the shop floor, and non-destructive quality control methods for ensuring manufacturing sustainability. Finally, Section VI provides a summary of the key findings and offers closing observations on the study conducted.

II. OVERVIEW OF RESEARCH

The current research used the SLR (systematic literature review) methodology, which offers a more complete and lucid examination of the literature compared to a descriptive literature review. Aagaard, Lund, and Juhl [6] have asserted that systematic literature review is a viable methodology for identifying novel research prospects within a certain field by comprehensively examining and amalgamating previously published publications. Mortoja, Yigitcanlar, and Mayere [7] provided a definition of a systematic literature review as a methodological approach that serves as an effective means for hypothesis testing, summarizing the findings of prior research, and evaluating the coherence and agreement among these studies. It is important to note that these specific tasks are distinctively relevant to the field of medicine.

In recent years, other study domains have used SLR methodologies, using diverse datasets. Nevertheless, several investigations have documented the use of systematic literature review (SLR) methodologies using a solitary scientific database. In their study, [8] examined the benefits associated with the use of numerous databases in the context of SLR (systematic literature review) methodologies. Industry 4.0 is a burgeoning area of investigation that has garnered significant attention from both practitioners and scholars. According to [9], practitioners have limited access to literature that offers information on new breakthroughs and research possibilities in industry. Simple Linear Regression (SLR) may be used as a valuable tool for identifying and analyzing research patterns and emerging prospects within a certain field of study.

RQ: What are the primary areas of study that have yet to be explored in relation to technologies of Industry 4.0 for the purpose of enhancing manufacturing sustainability, and what specific research concerns should be prioritized in future investigations?

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III. METHODOLOGY

The process of indexing academic articles and conference proceedings began in April 2021, with the objective of gathering relevant material pertaining to the domains of green manufacturing and Industry 4.0 The following search terms that were judged pertinent to the study were used to find the publications. ("Smart manufacturing" OR "Industry 4.0") "Sustainable manufacturing," "sustainable manufacturing," OR "Sustainability" AND "Manufacturing" TITLE-ABS-KEY AND TITLE-ABS-KEY. The research used the following conditions as inclusion criteria. In order to be considered acceptable, articles must satisfy all of the below criteria: The selected articles must meet the following criteria: (1) they should be written in the English language; (2) their publication date should be before to May 2021; (3) they should be sourced from reputable conference proceedings or academic journals; (4) their primary emphasis should be on the convergence of manufacturing sustainability and Industry 4.0 technologies; and (5) they should fall into either the concise or extensive category, excluding editorial pieces or abstracts.

IV. LITERATURE REVIEW

Sustainability and digitization are two pervasive considerations that impact all facets of the manufacturing process. There exists a convergence of practices between the two perspectives, encompassing design for disassembly, remanufacturing, and recycling as integral components of life cycle management. Additionally, reverse logistics is employed to facilitate a circular economy, while lean and green management strategies are implemented to optimize resource utilization. Furthermore, sustainable design principles are adopted to mitigate potential hazards for both consumers and employees. The elimination of dangerous substances from both the final product and the production procedure has been highlighted by Drogaris [10].

Lean manufacturing is a production method that aims to minimize the duration of waiting periods for both inputs and outputs. The concept of just-in-time (JIT) manufacturing is closely associated with this notion. With a primary emphasis on operational efficiency, productivity, and a commitment to ongoing improvement, the concept of "just-in-time" manufacturing endeavors to synchronize production with demand by only delivering goods that have been specifically requested, hence minimizing waste for both manufacturers and suppliers. Lean manufacturing is a production approach that utilizes the just-in-time technique, with the objective of reducing cycle, flow, and throughput times by eliminating inefficient operations. The integral role of the marketing and customer service departments, together with the individuals directly engaged in production, is crucial for the achievement of lean manufacturing.

Following World War II, the Japanese automobile manufacturer Toyota implemented a novel operational framework referred to as the Toyota Production System (TPS), alternatively recognized as "The Toyota Way" inside the United States. This technique has a strong correlation with lean manufacturing principles. According to the second source. There is nothing in the user's writing that might be used to guide an academic rewrite. Toyota's strategy is built upon the principles of just-in-time (JIT) inventory management and automated quality control (AQC). The seven "wastes" (known as muda in Japanese) were initially conceptualized by Shigeo Shingo, a Toyota engineer. These wastes encompass various inefficiencies in manufacturing processes, including surplus inventory of both raw materials and finished goods, overproduction, excessive processing or production of parts beyond customer requirements, unnecessary transportation, superfluous motion, and the automation of tasks that could be performed by human labor. The user did not provide any text to rewrite.

The word "Lean" was first introduced by John Krafcik, an esteemed American entrepreneur, in his seminal paper titled "Triumph of the Lean Production System" in the year 1988 [11]. In 1996, Womack and Jones, American researchers, provided a definition of Lean that encompasses five fundamental principles. These principles include the precise specification of value for a particular product, the identification of the value stream associated with each product, the establishment of uninterrupted flow of value, the facilitation of customer-driven value retrieval from the producer, and the relentless pursuit of perfection. There is nothing in the user's writing that might be used to guide an academic rewrite. The methodology is used by enterprises with the aim of enhancing productivity. The implementation of just-in-time delivery enables firms to get resources in accordance with their immediate requirements, therefore minimizing waste and achieving cost savings. The potential benefits may be reduced by minor disruptions in the supply chain, emphasizing the need of accurate demand prediction by producers. The potential consequences of heightened pressure and less flexibility may have a negative impact on personnel. In order to achieve success, it is essential for businesses to maintain consistent outputs, use high-quality methods, and establish reliable relationships with suppliers.

The implementation of Industry 4.0 is anticipated to yield various benefits, including enhanced productivity, flexibility, and resource efficiency. These improvements can be achieved through the utilization of technologies such as big data for fast production systems reconfiguration and predictive maintenance. Additionally, the adoption of Industry 4.0 can lead to a reduction in overproduction, energy consumption, and waste. For instance, surplus renewable energy can be shared with other plants, contributing to a more sustainable approach. Furthermore, the concept of servitization, along with increased stakeholder engagement and collaboration, can be facilitated through the implementation of closed-loop production systems that connect information systems, production processes, machines, and stakeholders.

According to Zairul and Zaremohzzabieh [12], Industry 4.0 has the potential to facilitate value creation across various dimensions of sustainability. Galati and Bigliardi [13] suggest that in this context, there are several avenues for industry development. Firstly, they propose the exploration of business models that leverage smart data, enabling the provision of novel product-services. Secondly, they highlight the significance of industry symbiosis and closed-loop product life cycles in establishing value networks. Lastly, they emphasize the utilization of cyber-physical systems (CPS) equipment to retrofit SMEs (small and medium-sized enterprises) and digitize their operational processes.

Xu, Hou, and Zhang [14] suggest that each dimension of sustainability encompasses a unique system centered on a digital value-creation solution. Consequently, the implementation of a solitary solution may yield both direct and indirect consequences across several sustainability dimensions. There exist three distinct categories of interactions within sustainability systems. These include causal relations, which pertain to the effects observed between a given solution and its direct as well as indirect effects. Additionally, scale and magnitude drivers play a significant role, as the extent to which a solution is implemented directly influences its direct and indirect impacts. Lastly, latency and timely duration dependencies are also crucial factors to consider in understanding the dynamics of sustainability systems. Our examination of the papers will just consider causal links.

Lean approaches are often seen as enablers for the deployment of Industry 4.0 (I4.0), which, in turn, is perceived as a means to achieve the realization of the extended lean enterprise. Consequently, there has been a significant research focus on examining the interaction between these two paradigms in recent years. Sanders, Elangeswaran, and Wulfsberg [15] argue that the prevailing perception of Lean and Industry 4.0 as compatible is rooted in their shared conceptual characteristics, including their same objectives such as complexity reduction, holistic approach, and emphasis on the important role of employees, among other factors. In the realm of tool combinations, a plethora of papers exist that advocate for the synergistic use of I4.0 and lean tools to enhance the efficiency of industrial processes. According to Blake [16], one example of a technological solution for ordering and managing inventory levels is the use of e-Kanbans. These e-Kanbans utilize real-time data provided by CPS (Cyber-Physical Systems) to automate the process. Furthermore, the use of RFID technology plays a crucial role in enabling a CPS-based production system to effectively acquire data pertaining to inventory, location, networking, and the interaction between humans and machines. Additionally, it supports the seamless flow of digital information between the floor of the shop and other departments of business. Clear and effective changes of communication in technical drawings and components not only contributes to the reduction of errors, enhancement of capacity, and improvement of customers' experiences, but also facilitates the attainment of a leaner and more streamlined process.

Furthermore, it is worth noting that operators have the capability to receive real-time mistake alerts and promptly address them by using CPS-based intelligent devices such as smart watches. Furthermore, it has been suggested by Bagula, Ajayi, and Maluleke [17] that the implementation of appropriate sensors in CPS may enable the diagnosis of problems and the initiation of fault-repair operations in other CPS, all without the need for human participation. Furthermore, Park [18] proposed a standardized and integrated approach for the design and implementation of a CPS (cyber-physical system) based smart system. This approach leverages cloud and IoT (Internet of Things) technologies to ensure the system's flexibility in terms of configuration, deployment, and performance. Furthermore, Liu, Sun, Zhao, Zhao, Wang, and Liao [19] put up a system backed by Cyber-Physical Systems (CPS) whereby intelligent agents autonomously make decisions on their paths. This proposal highlights the advantages of such an approach in terms of decreasing time of throughput and facilitating the optimal allocation and efficient production capacity. In their study, Şişman [20] propose a logistics model that integrates IoT/IIoT technology and adds elements of Lean Six Sigma. This model aims to provide a global supply chain that is fully autonomous that achieves optimum flow and total efficiency within the context of Internet of Things and Cloud computing. This IIoT-enabled architecture enhances operational performance, cost savings, and resource efficiency by enabling seamless communication between supply chain and production via the use of actual-time data.

Furthermore, Park, Gofman, Wu, and Choi [21] proposed an Internet of Things (IoT) framework that facilitates seamless integration between machines and enables efficient transmission of sensor data to end-users in production settings. Nalluri, Ramasubbareddy, and Kannayaram [22] have developed a cloud-based application that exhibits the capability to process actual-time inputs from systems that are computational inside an organization, hence facilitating the automated generation of electronic work instructions and standard tasks. In their study, Pech and Vaněček [23] put out a research endeavor that explores the integration of mindful computing with lean techniques as a means to ensure organizational prosperity. Cognizant computing provides databases that are enabled by the IoT and operate in real-time, using cloud-based infrastructure. The reported benefits include significant cost savings and profit increases, shorter lead times and inventory levels, diminished process wastes, and less need for rework. Additionally, according to Deng and Thoben [24], the use of cloud technology plays a crucial role in minimizing the generation of waste caused by users who are not connected or by the dissemination of inaccurate information during the product development phase. Moreover, Mohamaddiah, Abdullah, Subramaniam, and Hussin [25] highlight the significance of using machine learning and cloud computing for condition monitoring in order to enhance quality of a product and Total Productive Maintenance (TPM). This approach effectively reduces machine downtime, rework, and scrap.

Cloud computing also enables the efficient scheduling of dynamic maintenance activities and the seamless distribution of maintenance data among personnel. Furthermore, there is much documentation about the use of big data in facilitating lean applications. In his work, Mathieu, Puech, and Yahia [26] suggests a novel approach to enhance data processing efficiency within project teams. This approach involves the integration of cloud technologies and data analytics, with the objective of generating real-time key performance indicators (KPIs). By including the most current information, this technique aims to enhance overall efficiency and project team motivation. Furthermore, Shalihin [27] introduce the VSM (Value Stream Mapping) 4.0 as an innovative approach that focuses on the acquisition, retention, organization, and utilization of data to facilitate the development of key performance indicators (KPIs). The primary objective of this strategy is to optimize waste reduction and enhance comprehension of data flow within logistical operations. Hayashi and Ohsawa [28] concurred that the use of Big Data has the potential to augment the Vector Space Model (VSM). The enhancement of the value stream was achieved via the use of key technologies such as data analytics, simulation, and a user interface backed by RFID technology, which facilitated the real-time presentation of results and enabled staff participation.

V. FUTURE RESEARCH DIRECTIONS

This section examines the potential areas for future study in order to attain industrial sustainability via the use of Industry 4.0 technology. Based on the comprehensive analysis of existing literature, six prominent study domains have been identified that need further investigation. These topics will be further elaborated upon, highlighting the gaps in current research.

Systems of Lean Production for Industry 4.0's Environmental Management

Upon the implementation of the lean manufacturing concept, the shop floor exhibits enhanced discipline, cleanliness, effective time management, and improved productivity. The effective use of lean manufacturing leads to a reduction in changeover or set-up time. The application of lean tools yields several advantages. These include enhanced profitability and competitiveness for the company, reduced occurrences of shortages and stock-outs, improved cash flow and inventory turnover, decreased indirect costs, enhanced customer service, reduced queue times, increased equipment uptime, improved machine efficiency, leveled production, more effective utilization of labor, and increased manufacturing flexibility and capacity. The implementation and sustainability of lean practices provide significant hurdles due to their inherent complexities related to time, cost, interest, and engagement. These ideas together contribute to the successful adoption of lean principles, fostering organizational growth and improvement.

The scholarly literature on lean manufacturing highlights the advantages of using techniques of lean production in the context of mass production. These studies elucidate the ways in which lean manufacturing may effectively meet consumer demands. In their study, Basu and Dan [29] examine the practical consequences of incorporating enabled practices of lean within the industry 4.0 context. They also identify many research areas that are relevant to the implementation of lean-enabled practices in both large- and small-scale companies. In their study, Maria Aslam and Siddiqui [30] examined the correlation between Industry 4.0 technologies and lean practices. Their findings indicate a significant association between sustainability pillars and Industry 4.0. The literature on how lean concepts may be applied to Industry 4.0 is still in its infancy. The academic community would benefit more from studying the results of combining lean manufacturing methods with Industry 4.0 machinery. Future studies might benefit from presenting a unified framework that takes lean principles and industry 4.0 ideas and brings them together. This framework aims to optimize performance and reduce inefficiencies in manufacturing processes.

Linking Sustainable Practices with the Fourth Industrial Revolution

The majority of research conducted on Industry 4.0 mostly originates from industrialized nations, indicating a greater emphasis on this subject within these countries. Nevertheless, the implementation and acceptance of Industry 4.0 in poor countries is hindered by limited technology breakthroughs and insufficient resources necessary for its adoption. Several studies undertaken by Fathi and Ghobakhloo [31] have explored the potential research possibilities linked with technologies of Industry 4.0 in the achieving sustainability context. These studies have focused on identifying the various elements that influence the technologies of Industry 4.0 integration for sustainable outcomes. There is a scarcity of scholarly research that examines the correlation between sustainability and the variables associated with Industry 4.0 in the context of business operations.

Moreover, it is essential to integrate the elements pertaining to risk-related and political variables. The impact of these aspects on the concept of sustainability is examined by Luo [32]. Industry 4.0 theories must include these factors if they are to successfully incorporate sustainable practices into their manufacturing procedures. This will be a helpful tool for setting standards in emerging industries. The impact and interconnections among the variables pertaining to sustainability and Industry 4.0 can be ascertained through the use of hybrid multi-criteria decision-making methodologies, as well as decision-making techniques in the face of statistical and uncertainty tools, in future research endeavors.

Identifying Common Sustainability and Industry 4.0 Elements

The advent of technologies of Industry 4.0 has resulted in significant disruptions within supply chains, hence compelling industrial sectors to reassess and reconfigure their supply chain architecture. Over the recent years, a number of novel technologies have surfaced, hence causing significant modifications to conventional supply chain methods. Currently, several sectors are through a process of business model transformation as they embrace modern models of supply chain. New technologies are making it easier to digitalize the supply chain, which has the potential to upend established norms. Blockchain, machine learning, the internet of things, big data analytics, artificial intelligence, and automation are all examples.

According to Torres and Mahmoodi [33], the implementation of digitalization in supply chains has been shown to result in significant reductions in operating costs, inventory needs, and missed sale chances. Specifically, these studies have revealed decreases of 30% in operational costs, 70% in inventory requirements, and 60% in lost sale opportunities. The successful implementation of digital supply chain techniques requires substantial dedicated efforts and long-term investments. This approach will contribute to the attainment of cost reduction and operational efficiency within SCM (supply chain management).

Future research may investigate the effects of implementing a sustainable supply chain on many aspects of smart manufacturing, such as product recycling, reverse logistics, and remanufacturing. Nevertheless, there is a scarcity of research papers that have specifically examined environmental concerns within supply chains that are facilitated by blockchain technology. The study concerns and difficulties pertaining to sustainable supply chains for sustainability of manufacturing are presented in **Table 1**.

Big Data Analytics and Sustainability

Numerous academic papers on the usage analytics of big-data in the field of manufacturing have been published recently. This finding underlines the issue's importance and demonstrates the high degree of attention among academics. Big-data analytics research and application in the industrial industry may be divided into two basic categories. First, theoretical research is being done with an eye toward creating universal models for incorporating big-data analytics into industrial processes. This entails analyzing the existing state of the industry and putting forward theoretical answers. Second, there is applied research and development geared on developing unique products made especially for industrial needs. These research projects have a common trait: the use of basic concepts, such as the identification of new and potentially significant data sources, the integration of data, and the creative application of data to improve the performance of the system under study. The information utilized in these projects, as well as the information intended for use with the existing data-analytics solutions, comes from the manufacturing habitat as well as numerous other sources, including the internet and sensor networks set up at public event venues. Many research projects and efforts have made use of common big-data technologies, such the Hadoop software architecture and NoSQL databases.

Table 1. Research Challenges of Creating Industry 4.0 Sustainable Supply Chain Procedures

Category	Research Issue	Literature
Industry 4.0 Supply Chain Planning	What challenges are being presented to traditional manufacturing by the advent of digital technologies? How do strategies of supply chain relate to Industry 4.0 innovations? How does digitalizing the supply chain affect the value of the resulting network?	Danese, Romano, and Vinelli [34]
The Importance of the Supply Chain to Industry 4.0	To what extent is the advent of digital technology causing the industrial sector to reevaluate its core business practices? Can you explain the connection between supply chain tactics and Industry 4.0 tools? Where does digitization of the supply chain fit into the equation of network value?	Eng [35]
Adding Value for the Customer	In the era of Industry 4.0, what outcomes can we expect from data-driven SSCM approaches? With the advent of Industry 4.0 technology, how can manufacturers better adopt SSCM?	Tran and Vu [36]
SSCM and Human-Centered Design	In a fully digitalized supply chain, what function do humans still play? How can supply chain management (SCM) benefit from AI-based and machine learning technologies to make it more environmentally friendly?	Calvert, Heikoop, Mecacci, and van Arem [37]; Parker and Russell [38]

The requirement for efficiency and automation often dictates the use of clever heuristic approaches and data analysis techniques, such as machine learning. In fault-diagnosis scenarios involving complex industrial processes, where the process states are defined by elaborate patterns involving a large number of factors, the efficiency of these methodologies is often shown. Intelligent heuristic analysis approaches enable a high degree of automation and the detection of complex patterns that are beyond the reach of humans. In [39], deep learning has shown exceptional performance in this particular domain. Nevertheless, the use of these technologies in practical applications remains infrequent. The rationale for this is the dearth of scholarly investigations pertaining to holistic referencing. This study aims to explore data analytics solutions that effectively depict the outcomes of analyses and their practical implementation inside a genuine industrial setting. Additionally, these solutions should instill a satisfactory level of confidence in the end user.

As tools to make it easier to employ data analytics in industrial processes, many conceptual models have been developed. The application of predictive analytics in the manufacturing industry is proposed by Schmidt, Gandhi, Wang, and Galar [40] as a domain-specific paradigm. Civerchia, Bocchino, Salvadori, Rossi, Maggiani, and Petracca [41] have provided thorough system specifications and a collection of information that are necessary for the deployment of equipment-maintenance applications in industrial settings. Additionally, they have proposed a model data system that provides a fault-tolerant and scalable big-data pipeline. This model facilitates the seamless integration, processing, and analysis of equipment data of an industry. Fazil Ahmad [42] provide a framework that outlines the planning, conception, and execution of big-data initiatives within corporate settings.

Christefa, Mawengkang, and Zarlis [43] provide a comprehensive framework for the analysis of large-scale data in order to enhance decision-making in product-lifecycle-management and cleaner-production domains, leveraging the potential of big data. Sakao and Nordholm [44] provide a theoretical framework aimed at enhancing product-lifecycle management via the use of big data. This framework is designed to tackle many issues, including the scarcity of valuable information and dependable data that can be leveraged to facilitate informed making of decision in management of product-lifecycle. In their study, Lee, Ryu, and Cho [45] put out a smart-manufacturing framework that is based on data analysis. This framework has four distinct modules, namely the problem-processing module, the manufacturing module, the real-time monitor module, and the data-driven module. In their publication, Win, Tianfield, and Mair [46] put out a proposition for a cloud-based big-data analytics platform specifically designed for the sector of manufacturing.

In addition to manufacturing-specific models, the integration of analytics of big-data into systems of manufacturing can benefit from the utilization of broader reference concepts and models from various domains. Well-established reference models of data-analytics like KDD, CRISP-DM, and SEMMA, are also applicable in this context. The current body of literature on big data analytics in manufacturing lacks comprehensive coverage because the concepts and solutions suggested are either limited in their applicability to particular manufacturing issues or detailed descriptions of data-analysis procedures and do not have the necessary specificity and essential elements required for the development of specific data-analysis solutions in manufacturing systems. The usage of analytics of big data within the sector of manufacturing has several prospects for sectors of manufacturing in relation to the production monitoring processes and the real-time optimization thereof, therefore contributing to the promotion of sustainability.

Both the big data analytics and IoT (Internet of Things) play a crucial role in the Industry 4.0 development. The methodologies used in big data analytics are founded upon the three dimensions of volume, variety, and velocity, often referred to as the 3V framework. These techniques are capable of effectively managing and processing vast quantities of data, and may be categorized depending on various phases during their life cycle. According to the findings of Zhu, Zhou, Vogel-Heuser, and Kurfess [47], the use of analytics of big data has been identified as a valuable approach in addressing forthcoming issues associated with smart manufacturing. In recent years, there has been a notable increase in the interest and use of big data methodologies among professionals. Currently, several industries use these methodologies to enhance their service provision and maintenance procedures. According to the research conducted by Kumar and Kirthika [48], the use of big data analytics has been identified as an effective approach for addressing the industrial issues associated with Industry 4.0. This is primarily attributed to its capacity to effectively manage and process vast quantities of data.

Further research might be undertaken to explore novel methodologies in big data analytics with the aim of attaining sustainability within the industrial sector. There is a must to assess and scrutinize a substantial volume of data that is created during the diverse phases of manufacturing operations. In prospective research endeavors, the amalgamation of simulation and optimization methodologies with data analytics holds promise for enhancing comprehension of models pertaining to shop floor management. There is a scarcity of research pertaining to the advancement of enabled analytics of IT big data. The investigation of these designs' function in achieving sustainability in manufacturing may be explored in future research. There is a limited body of research that has addressed the potential of big data analytics (BDA) in the context of sustainable manufacturing, specifically focusing on condition-based predictive maintenance concerns. Future research studies in this field might be done by taking into account the limitations associated with multicomponent-based systems, as shown in a majority of previous studies. The topics of research and obstacles for enabled strategies of big data for sustainability of manufacturing are presented in **Table 2**.

Table 2. Research Concerns Pertaining to analytics of big data in the context of Industry 4.0 related to Promoting Sustainability within the Manufacturing Sector.

Research challenge	Literature
Innovations in SSM architecture for long-term sustainability	Holovashchenko [49]
SSM data acquisition problems	Janakiraman [50]
Integration and aggregation of data problems	Helman [51]
Modeling and algorithm development for BDA-enabled SSM techniques	Ali, Qadir, Rasool, Sathiaseelan, Zwitter, and Crowcroft [52]
Problems in managing data quality for SSM	Savage [53]
The function of cloud computing in SSM	Yousif [54]
Energy consumption and optimization-related issues	Jackson and Brodal [55]

The Effects of AI and Machine Learning on Sustainability

The rise of AI and machine learning technologies is altering organization fields and is projected to effect world environmental and global productivity results.

In an attempt to address the uncertainties, present in the extensive body of literature concerning sustainable development, [56] undertook a comprehensive analysis of existing studies on the subject. Mensah contends that the fundamental concept of sustainable development revolves around the principles of fairness and justice, both within and between generations. These principles are primarily based on three interrelated dimensions, namely the environment, economy, and society. The World Commission on Environment and Development defined sustainable development, which had its origins in economics, as "improvement that impactively addresses the current needs while safeguarding the capacity of future generations to fulfill their own needs." Sustainable development encompasses the inherent conflict between fostering innovation and ensuring the fair allocation of resources across society over successive generations.

Additionally, sustainable development may be described as a paradigm for growth that places an emphasis on raising living standards while also preserving the health of the planet's ecosystems and addressing environmental problems like air pollution, water pollution, and deforestation. According to the widely accepted definition, sustainable development is seen as a system that facilitates the interaction between society and the environment. Therefore, it may be seen not just as an abstract notion, but also as a kind of social mobilization. Sustainable development has been characterized as a forward-thinking and visionary paradigm, including three fundamental pillars: environmental, social, and economic sustainabilities. Sustainable development encompasses the inherent conflict between fostering innovation and ensuring fair allocation of resources, as well as the conflict between addressing the demands of the environment, economy, and society.

Considering the aforementioned discourse on sustainable development and the verbatim interpretation of sustainability as "the ability to uphold a particular entity, outcome, or process over a period of time," one may ponder the implications of sustainable artificial intelligence (AI). In [57] propose that the concept of "Sustainable AI" should include the intricacies of sustainable development in the context of artificial intelligence (AI). Therefore, it is essential for sustainable artificial intelligence (AI) to include the inherent conflict between advancing AI for sustainable development objectives and specifically addressing the sustainability aspects of AI training and use. In addition, it is recommended that the ongoing international discourse on artificial intelligence (AI) include not only the examination of human rights and ethical concerns, but also the examination of the inherent conflict between meeting the demands of the environment, economy, and society.

In summary, the planned implementation of AI in our society must not contribute to the unsustainability of our societal systems throughout its growth and use. This notion should prompt us to recognize that the use of artificial intelligence in society is a deliberate decision. The development and use of AI are not inherently preset, but rather contingent upon the choices made by many societal stakeholders, including developers, industry leaders, customers, citizens, and policy officials. The aforementioned argument, which opposes technological determinism, underscores the need for societies to make deliberate and thoughtful decisions about the preservation of their desired values, such as privacy, dignity, fairness, and justice. It is essential to actively strive towards the development of artificial intelligence in a manner that does not compromise the sustainability of these values.

The use of AI and machine learning has been shown to have both good and negative implications for sustainable development. According to the study conducted by Frutos-Pascual and Zapirain [58], the use of AI and machine learning techniques has been seen to contribute significantly to the attainment of sustainability in the industrial sector, as well as the Industry 4.0 implementation successfulness. The use of machine learning methodologies has shown potential advantages in the optimization of production processes, development of recovery plans, and implementation of condition monitoring strategies. The research issues pertaining to the integration of ML (machine learning) and AI (artificial intelligence) in manufacturing sustainability are outlined in **Table 3**.

Table 3. Issues in Machine Learning-Enabled Industrial Sustainability and Artificial Intelligence (AI)

Future research challenge	Literature
Integrated SM layout development using machine learning techniques	Alruwais and Zakariah [59]
What impact does sustainability have on Industry 4.0 in terms of AI and machine learning techniques?	Hamdoun and Rguibi [60]
Concerns with condition-based monitoring and prediction modeling	Çalış and Fidan [61]
Machine learning and AI -based intelligent making of decisions	Torra, Narukawa, Yin, and Long [62]
Quality prediction issues	Khoshkangini et al. [63]

Integrated Process Scheduling and Planning for Sustainability of Shop Floor

The segregation of process manufacturing scheduling and planning is often seen in manufacturing operations. The process of manufacturing process planning involves the determination of the specific methods and procedures that will be used in the production of a certain product. The process of manufacturing process selection and sequencing involves the deliberate choice and arrangement of manufacturing processes and their corresponding parameters in order to accomplish certain objectives, such as cost reduction and shorter processing time. Additionally, this decision-making process must adhere to a set of domain-specific restrictions. Manufacturing scheduling, conversely, refers to the procedure of allocating resources of manufacturing chronologically to the collection of processes of manufacturing outlined in the plan process. The scheduling algorithm establishes the optimal timing for executing each operation, considering the temporal dependencies between manufacturing processes and the constraints of capacity of the production resources shared. The assignments also affect a schedule's suitability in light of factors like price, tardiness, or throughput. In essence, scheduling refers to the process of optimizing the allocation of finite resources throughout time, including both parallel and sequential activities. The optimization process is of growing significance for manufacturing firms as they seek to enhance productivity and profitability by improving shop floor agility. This is crucial for their survival in a highly competitive global market.

At the shop floor level, Industry 4.0 employs sophisticated technology and comprehensive automation, facilitating the seamless movement of data across internet networks. Industry 4.0 encompasses key enabling technologies, notably cyber-physical systems capable of autonomous operation and network-wide self-optimization. The optimization of sub-components within the production process does not guarantee the optimization of the whole manufacturing process. The achievement of synergy in the whole production system necessitates the use of global optimization strategies. The responsibility for determining what, when, and where to manufacture goods within businesses lies within the realm of planning and scheduling. The realization of the whole advantages of Industry 4.0 processes in manufacturing sectors necessitates the capacity to make judgments from a global perspective. Currently, contemporary global supply chain processes need an elevated degree of complexity in planning and scheduling, sometimes referred to as "Scheduling and Planning 4.0". The advent of technologies of Industry 4.0 has brought about important transformations in the manufacturing sector, necessitating the implementation of scheduling systems and integrated planning that can effectively provide enhanced integration, automation, and transparency. The Opessa MLS V7+ software might be seen as a potential solution for the challenges associated with scheduling and planning in the context of Industry 4.0.

Further investigation may be undertaken to explore the potential impact of process scheduling and planning in the Industry 4.0 context on the sustainability dimensions, including habitat and economic aspects, as well as resource efficiency.

Within the realm of manufacturing sustainability, two primary components may be identified: (1) input elements including raw materials, inventories, and the interaction between human labor and machinery; and (2) elements of output consisting of waste, scrap, pollution, and potential risks. In the context of calculating plans of scheduling in a predictive or reactive way, these aspects might be regarded as decision variables. The scheduling implementation in the Industry 4.0 context necessitates the use of decision techniques that are dynamic, efficient, and decentralized. In prospective research endeavors, the integration of intelligent algorithms holds promise for examining the autonomous behavior of industrial systems in real-time. In order to create schedule plans that are both efficient and successful in terms of sustainability, it is possible to use innovative methodologies and ideas like cyber physical systems, intelligent products, and product service systems.

Non-Destructive Quality Control for Manufacturing Sustainability

The use of technologies of Industry 4.0 is significantly augmenting non-destructive techniques utilized for control of quality in the industrial sector, so exerting a profound influence on sustainability, safety, and the overall quality of products. The use of non-destructive testing within the context of Industry 4.0 encompasses a comprehensive range of activities, spanning from the examination of raw materials through the last stages of product delivery. In spite of the advancements made in non-destructive quality control within recent years, certain restrictions persist in the form of skilled labor requirements, intricate user interfaces, sluggish data exchange procedures, inspection speed constraints, and intricate data interpretation challenges. These limitations provide opportunities for future research to solve. Several significant research concerns in the field of quality control that is non-destructive for industrial sustainability may be identified. What are the main barriers to testing non-destructive in the context of Industry 4.0, as well as its requirements? In the framework of Industry 4.0, the modern connectivity standardization for testing methods which are non-destructive is a matter of interest. The current research looks at the difficulties with non-destructive testing's cost and skill development within the context of Industry 4.0.

VI. CONCLUSION

This article examines the potential avenues for future research in order to attain industrial sustainability via the use of Industry 4.0 technology. The literature evaluation reveals the presence of six prominent research topics that need further investigation. These areas are reviewed in relation to existing research gaps. The process of retrieving articles was carried out by using certain keywords pertaining to the study domain, including Industry 4.0, Manufacturing, smart manufacturing, sustainable manufacturing, manufacturing sustainability, and Sustainability. The interrelation between digitalization and sustainability is evident inside the production chain, since it encompasses several techniques like disassembly, remanufacturing, recycling, reverse logistics, and sustainable design. Lean manufacturing is a production methodology that seeks to minimize the duration of processes inside the system, as well as the time it takes to get responses from suppliers and consumers. The concept under consideration has a tight relationship with just-in-time production, a methodology that places emphasis on optimizing efficiency and productivity. Lean manufacturing is a production methodology that draws its principles from the Toyota Production System. Its primary objective is to minimize waste, energy use, and excessive output. Industry 4.0 has the potential to facilitate the generation of value across several aspects of sustainability. This encompasses the development of business models that are propelled by intelligent data, the establishment of closed-loop product life cycles, the use of communication and information technology to enhance training and motivation, the cultivation of organizations with a focus on sustainability, and the implementation of sustainable process design via the adoption of novel technologies. The connections of sustainability systems may be categorized into three types: causal relationships, drivers of size and scale, and dependencies based on latency and timely length.

There has been a notable increase in academic attention towards the convergence of Lean and I4.0 paradigms. Lean methodologies are being recognized as facilitators for the deployment of I4.0, while I4.0 is seen as a mechanism for achieving the expanded lean business. The existing body of research indicates that the integration of Industry 4.0 technologies with lean methodologies has the potential to enhance operational efficiency within the industrial sector. Illustrative instances include the use of real-time data provided by Cyber-Physical Systems (CPS) for electronic Kanban systems, the application of Radio Frequency Identification (RFID) technology for efficient inventory management, and the integration of CPS-based smart watches as intelligent gadgets. The use of IoT and cloud technologies has been suggested as a means to enhance operational efficiency, save expenses, and mitigate resource utilization. Potential avenues for future study include the incorporation of lean production systems into the realm of environmental management in the context of Industry 4.0. This entails a specific emphasis on the tangible ramifications of lean practices, as well as an exploration of the influence exerted by lean practices on the technologies associated with Industry 4.0.

Furthermore, the use of lean principles with Internet of Things (IoT) technology has the potential to optimize operational efficiency and reduce inefficiencies in industrial processes. The variables associated with Industry 4.0 have an influence that is substantial on the concept of sustainability, with a considerable body of research mostly concentrating on industrialized countries. Nevertheless, the rate of adoption in poor countries is hindered by the lack of technology developments and the insufficient resources necessary for its implementation. In order to attain sustainability, it is essential to take into account political and risk-related concerns, alongside the influence of sustainable supply chains within the Industry 4.0 context. The use of digitalization inside supply chains has the capability to decrease operating costs, inventory demands, and instances of missed sales opportunities. Further research is required to investigate the potential effects of sustainable supply chains on the domains of product cycle, smart manufacturing, reverse logistics, and remanufacturing. The usage of analytics of big data has the potential to contribute to the attainment of sustainability goals in supply chain management. However, the existing body of literature lacks comprehensive investigations into holistic reference data-analytics solutions that provide pragmatic approaches for presenting findings and their practical implementation within a genuine manufacturing setting.

A range of conceptual models have been devised to facilitate the integration of data analytics into manufacturing systems. These models include domain-specific frameworks, information system models, and cloud-based big-data analytics platforms. The objective of these models is to enhance the management of product lifecycles and facilitate decision-making towards cleaner manufacturing via the use of big data. However, the current body of literature pertaining to big-data analytics in the industrial sector often lacks clarity and comprehensive descriptions of data-analysis methodologies. The use of big data analytics plays a pivotal role in the Industry 4.0 context, as it has the capability to effectively manage and process vast quantities of data, hence enhancing the quality of services and maintenance operations. Future research should prioritize the advancement of novel methodologies in big data analytics with the aim of attaining sustainability in the manufacturing sector. This entails the examination and interpretation of data derived from diverse phases of manufacturing operations, as well as an exploration of the significance of information technology-enabled big data analytics. The anticipated effect of AI and machine learning methodologies on worldwide productivity and environmental results is noteworthy. The concept of sustainable development encompasses the inherent conflict between fostering innovation and ensuring fair allocation of resources, while also addressing the demands of the society, economy, and environment.

The achievement of sustainable development objectives necessitates a careful equilibrium between the pursuit of innovation in the field of artificial intelligence and the sustainable practices associated with the training and use of AI systems. The worldwide discourse around artificial intelligence (AI) necessitates a comprehensive examination of human rights, ethical concerns, and the intricate interplay between environmental preservation, economic considerations, and societal well-being. Machine learning and artificial intelligence have both advantageous and detrimental effects on the progress of sustainable development. Machine learning (ML) and AI have the capability to contribute importantly to the attainment of sustainability goals in the industrial sector and the implementation that is successful of Industry 4.0. The optimization of resources and enhancement of productivity are vital for achieving industrial sustainability, making integrated process planning and scheduling crucial in this regard. The advent of technologies of Industry 4.0 has brought about significant transformations in the industrial field, hence necessitating the implementation of integrated planning and scheduling systems. Further investigation is required to examine the extent to which these processes contribute to the promotion of sustainability and resource efficiency. The use of non-destructive quality control methods is crucial for ensuring the sustainability of manufacturing processes. However, it is important to acknowledge that there are some limitations associated with this approach. These constraints include the need for specialized personnel, the complexity of user interfaces, and the sluggishness of data exchange procedures.

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The author(s) declare(s) that they have no conflicts of interest.

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