AI-Based Decision Support Systems for Revitalizing American Manufacturing: A Comprehensive Study

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1. Introduction

The development of sustainable, resilient, and efficient manufacturing is essential for an energy-secure, low-carbon future. In American manufacturing, reinvestment in state-of-the-art and state-of-the-practice facilities is critical. Revitalizing advanced low-carbon manufacturing in the United States not only addresses climate change and makes products from sustainable and low-emissions materials, but it is also an opportunity to increase economic productivity. To fully realize this potential, industries must partner with universities and develop advanced decision support for integrating new and higher fidelity materials science and engineering information into computationally enabled manufacturing processes. The use of big data, artificial intelligence (AI), and edge computing are integral to the revitalization process.

The goal of this report is to present a comprehensive study of state-of-the-art artificial intelligence systems for manufacturing. To accomplish this goal, we gathered feedback from domain experts in four town halls and conducted three interviews to understand the front-table challenges for AI in manufacturing. Then, we present a thorough literature review of research that has advanced one or more aspects of these. In Section 2, we discuss the challenges in revitalizing American manufacturing and provide a detailed timeline of our efforts to review the proceedings and to develop this final product. In Section 3, we present work by Holden et al. using the town hall documentation and other reports to catalog use cases and infrastructure specific to efforts to develop and deploy decision support, including their front tables used as a form of design basis accidents for AI applications. In Section 4, we provide a review of the literature, synthesizing domains, approaches, models and tools, methods, and end products enabling a comprehensive review of research. Additionally, we provide a critical review of the national labs' research portfolios and their potential to be used as research building blocks for developed DT&DI DSS. In Section 5, we compile and empirically derive technology readiness levels (TRLs) for AI-based decision support applications.

1.1. Background and Rationale

The seed of American nationhood was revealed in colonial America's oft-cited maxim at the intersection of business and production: "In the abundance of those things, whereof the country affords, every Country-man is generally his own Carver." America's eighteenth-century agricultural ethos imparted the idea that independence, freewill, and self-determination rest on equality of access to resources. Whether this concept was hyped populism designed to energize new arrivals and unite America's diverse colonial worlds or inherent in the social fabric, it has ebbed and flowed through American nationhood and across its most important domain of home and hearth: manufacturing.

AI-based interventions in manufacturing are not new. They have been around for over four decades. We have seen extensive use of machine learning models to both control individual processes and in integrative approaches across manufacturing pipelines for goals such as energy savings, fault detection/diagnosis; part-level fault prediction and real-time measurement and process inputs prediction; maintenance prediction, categorization, and cost estimation; yield loss identification; and fault root cause (deviation) detection. Despite these and other advancements, the renaissance of American manufacturing has been stymied by a number of vexing phenomena including variability encountered in dispersed supply chains, the need to handle complex materials advancements, the constraints of managing physical systems, and the required management of complex relationships in the computing stack. Machine learning models developed in academic settings do not tend to fare well when real-world constraints are taken into account; and critically, organizations lack systematic approaches to solve them based on a comprehensive understanding of challenges and opportunities in manufacturing and associated systems. It is this puzzle that we set out to unravel.

1.2. Research Objectives

The research objectives include the following: - To develop a comprehensive set of decision support systems and methodologies that can be used to optimize the manufacturing design, operations, and business structure within existing and new manufacturing settings. - To address all possible needs of the American manufacturing facility, including supply chain, market, and resource shortages. - To give special attention to equipment support systems designed to help decision makers meet performance requirements by utilizing manufacturing facilities and equipment designed and manufactured in another project (e.g., the Agile, Reconfigurable, Virtual environments Testbed). - To focus on decision supporting systems and methodologies for the creation of a state-of-the-art manufacturing design and feasibility assessment through the rapid construction and assessment of virtual prototypes. - To explore opportunities to utilize existing facilities and manufacture new factories. - To differentiate this project from the few available ones by paying attention to the entire manufacturing process, including multidisciplinary methodologies, and a wide range of supporting aids at the decision-making level.

The main objective for the RFPA Laboratory is to bring several new interrelated design and analysis techniques to the industry, enabled by new II tools built into DSSs for optimizing all factory- and supplier operations, from floorplan design, equipment selection, and control through the allocation of different organizational philosophies.

The objective of the Kennametal work is to develop a software tool, based on multisource performance information, that can offer decision support to shop managers and engineers on a real-time basis.

The main objectives of the various Oak Ridge National Laboratory (ORNL) subprojects are to develop technologies that use real-time or near-real-time sensor data to monitor and control various aspects of workpiece, system, or process conditions. Their primary goal is to use the II interface technology developed in the project for any real-time condition monitoring or controlling of the milling machine.

RFPA is concerned with developing systems for the support of decisions needed to define and subsequently maintain lean factories. The model architecture is expected to be applicable across several markets and factory types.

1.3. Scope and Significance

1.3. Scope and Significance. Recent developments promote the increasing use of AI-based decision support systems for manufacturing operations and service systems. However, the actual use of AI-based decision support systems is mostly supportive of advanced research work carried out for a number of large companies such as Siemens, IBM, Google, etc. Also, with a view to capacity building and revitalizing manufacturing industries in the USA as well as other countries, community colleges and universities provide mainly search query applications based on EV logistics problems, due to the ease of deployment on open-source web-based services. Apart from a few scholarly studies, existing research work predominantly caters for service-oriented operations as opposed to discrete part manufacturing and presents a very limited understanding of the implications when such AI-based applications were used earlier to solve production-related decision-making problems.

The overall objectives of this study were, therefore, twofold. First, the boundary of this study is defined by the parameter settings and scoring functions to be evaluated, based on search queries (posted by prospective employers). Second, the study presents service-oriented problems encountered on educational-based search query applications as compared to manufacturing. We cover many AI approaches including fuzzy logic, data mining, multi-agents, simulation, and machine learning. The scope of the study is also demonstrated by a number of selected published approaches towards AI in decision support systems for spares management alongside other civilian and military-related applications. Thus, the processes and workflow of production and operations management education, practice, and their implications underpin the conceptual analysis of the paper. The major goal of this paper is to broadly disseminate preliminary results before the full-fledged theoretical and empirical assessment in subsequent research stages alongside the experimental setup of web-based e-search scenarios and their corresponding multi-phase assessment in decision-making.

2. The Current State of American Manufacturing

Introduction The decline of manufacturing within the USA has characterized research as an increasingly important societal issue. Manufacturers within the United States are faced with myriad challenges, including limited access to relevant data and technology, organizational factors, social pressures, and globalization irrespective of the geographical location, making trade and the diversification of assets a smart investment strategy. From a microeconomic perspective, new and small firms account for "less than one percent of America's exporters", which is incongruent with their role in job creation. This is not just true for the US; many other organizations fear subsequent "disruption" due to global competition and foreign direct investments. Nevertheless, there are opportunities. From 2004-08, almost 90 percent of the most amazing new goods and services were produced by small firms. Moreover, the US has an estimated 478,000 entities that are, in whole or in part, owned by "foreign multinationals from many countries" (pp. 510-11). Consequently, facilitating competition to the domestic producers is likely to be beneficial for society.

Purpose Although many industrial and academic research and development (R&D) agendas have focused on the potential industrial applications for AI, few have systematically investigated AI's applications within the context of modern American manufacturing and its associated supply chains. Understanding the prevalence of such modes and applications of AI is a necessary first step for business practitioners and some academics who seek to integrate emerging technological IS solutions into developing their own intelligent systems. This research is, therefore, designed to excavate the antecedents, capabilities, and consequences of these systems through a series of three studies. The first study benchmark's AI adoption levels by comparing the results of the 1994 Thor Study to deceased firms from the present, leading to eight recommendations regarding the development of AI. This excellent foundation is extended by presenting various keystone developments and prototypes with the potential of alleviating the cultural, interoperability, and infrastructural issues limiting their scalability and widespread utilization within industry. Furthermore, innovative projects in AI and other intelligent technologies are presented, using concrete examples to elucidate and characterize the architectural and managerial perspectives of these systems. The Current State of American Manufacturing

2.1. Challenges and Opportunities

This project focuses on examining AI-based decision-making in the context of manufacturing. Before doing so, this section details some of the key problems that contemporary manufacturing (with a special focus on American manufacturing) faces. We then provide an overview of the opportunities AI-based management efforts could offer. The data suggest that the activity that occurs within America's manufacturing sector is increasingly being undertaken by an industry grappling with the challenges of a rapidly changing business environment. The rise of digital technologies and automation, concerns associated with the globalization of production systems, an increasingly complicated supply chain regulatory environment, and consumer demand for increasingly complex or configurable goods have created a need for managerial practices that can manage complexity and harness the potential of new technologies.

The MAPI Foundation's 2021 and 2020 Surveys of Manufacturing Frontline Leaders show that leaders in America's industrial production value the potential to improve managerial processes by using AI, Big Data, machine learning, or tech-assisted decision-making systems. More specifically, a 2020 survey report indicated that manufacturing leaders consider algorithmic decision support mechanisms to be a major area of opportunity and place them as the fourth most important future tech tool for managing production—above plant floor collaborative robots but below 3D printing and in-factory drone-based asset management systems. The data indicate, for instance, that some form of "smarter" decision mechanisms such as planning optimization, predictive maintenance, and improved supply chain management modeling are generally viewed favorably both in potential net foreign direct investments and in the enabling potential of relevant technological clusters.

2.2. Technological Trends

Technological Trends encompasses a detailed examination of the current technological landscape in American manufacturing. It analyzes the trends that are shaping the industry and provides insight into the technological context that necessitates the integration of AI-based decision support systems for revitalization. Subsections are as follows:

2.2.1. Industrial Trends 2.2.1.1. Digital Transformation in American Manufacturing 2.2.1.2. Industry 4.0 2.2.1.3. Data-Driven Manufacturing 2.2.1.4. Smart Manufacturing and the Smart Factory 2.2.2. Human-Technological Trends 2.2.2.1. Collaboration of Humans and Machines 2.2.2.2. Augmented Reality 2.2.2.3. IIoT 2.2.2.4. Traditional CAD and New Tools for the Model-Driven Digital Thread Defined by the NIST Digital Thread and Smart Manufacturing Workshop 2.2.2.5. COVID-19 Pandemic: Lessons Learned about Needed Technological Improvements 2.2.3. Integration of Tools and Methods that are Part of Smart Manufacturing (HAZOP, HACCP, RCA, FMEA and Standard Reliability Prediction Models) 2.2.4. Summary of Human-Technological Trends 2.2.5. Technological and Managerial Gaps and the Role of AI 2.2.5.1. Why AI is Needed 2.2.5.2. AI and the Democratic Solution: Decision Support Systems

3. Foundations of AI in Manufacturing

To be able to easily comprehend the body of the literature provided in subsequent sections, it is important to have a good understanding of the foundational concepts associated with the use of artificial intelligence in the manufacturing domain. Therefore, this section shall outline the background, definitions, and technologies underpinning AI and its use within the manufacturing industry.

We hear and read a lot about artificial intelligence (AI) and its positive influences, opportunities, and threats on businesses and societies across the world. In providing a technical scope, the unifying concept behind AI is automation. AI has several forms, which include machine learning, reasoning, simulation, planning, robotics, and natural language processing. Manufacturing can be described as a highly informative context where AI and many associated developments have been put into real use. It is without a doubt that the application of automated solutions is changing manufacturing drastically.

AI has the potential to dramatically boost the performance of individuals by providing decision support. This allows the expert system to adapt to different contexts by using automatic learning. The decision support method may include the following features: expert systems have lagged due to the hurdles of introducing profound knowledge; however, the principle of incorporating AI is alive and has been revived. The first implementation of AI in manufacturing came in the evolutionary planning to Order Entry and Manufacturing (OEM) system. The greatest impact of AI comes from the integration of the three inputs to achieve improved systems. They include the information from the best solutions, the new communication between "The form of representation: AI is not limited to the decision to logic or expert systems. AI includes orchestration and utilization of various techniques.

3.1. Machine Learning

AI is a subfield of science and engineering that allows us to develop and create intelligent agents. There has been rapid growth in AI, which is expected to increase due to recent advances in the amount of available data, the improvement of efficient computing power, reduction in computing cost, and many advances in algorithms to automate intelligence-driven decision-making. An interdisciplinary field like machine learning is concerned with giving machines the ability to learn and make predictions or decisions from that data to automate specific tasks without being explicitly programmed. Machine learning can be broadly divided into three types: supervised learning, unsupervised learning, and reinforcement learning. Predicting strategies based on the past and current data of critical parameters in manufacturing processes are the specific type of problems that are categorized under supervised machine learning, which can be termed as regression analysis.

Why machine learning in the manufacturing sector? The manufacturing sector has gone through many tough times because of globalization and other factors such as labor costs, environmental rules, and new sciences such as 3D printing. However, there are tremendous opportunities to revitalize American manufacturing. New models of manufacturing have come out using prominent features like cloud computing, the internet of things, and a knowledge-driven economy in which learning and innovation will become the main competitive advantage. With machine learning algorithms that can learn from the past and current scenarios of the systems involved without much a priori cause and effect understanding of the system, they can provide useful and insightful strategies to the engineers and business leaders to drive their organization towards innovation. Thus, investment in the development of AI-based decision support tools in the manufacturing sector can bring both the U.S. economy and job markets to a new height.

3.2. Deep Learning

Deep learning is a specialized area in artificial intelligence pertaining to the ability of machines to train themselves to perform tasks using data interpretation and analysis – essentially learning from the given information available. Even though deep learning has wide applications in various sectors, it has not been extensively deployed in manufacturing due to several technological as well as technical challenges. But recent research has shed light on the potential of deep learning in revolutionizing the manufacturing sector if its challenges could be recognized and addressed. It appears that the deployment of deep learning methods in manufacturing can seemingly lead to new tomorrows that would be in sharp contrast to traditional ones. Especially in a country like the United States, deep learning-based decision support systems are anticipated to work as a revolution to facilitate the revitalizing American manufacturing strategies. These are some of the major attractions of a state-of-the-art subfield of artificial intelligence. Deep learning has widely been adopted in diagnosing several diseases such as cardiovascular diseases, diabetes, and cancer. In the education sector, deep learning has shown its face in predictive analytics that assists in early intervention regarding student performance.

When it comes to economic sectors, construction and manufacturing have an astonishingly large potential market for deep learning-based decision support systems. Currently, the focus of the manufacturing sector has shifted from producing a few expensive articles to producing high volumes of low-value products. Today's products and expectations are fundamentally different from yesterday's. Just-in-time (JIT) delivery, customizations, shorter product life cycles, smaller product orders, and high volume low-value products have become the norm. Thus, large-scale advanced analytics tools for manufacturers seem to yield many benefits. Deep learning-based decision systems are aimed at providing vital insights to improve systems' adaptability and sustainability. They do not rely on expert heuristics, predefined analytical rules, or business process or human perception but rather integrate Big Data from automated systems. Overall, the main selling proposition of the deep learning-based decision systems is their remarkable ability to predict the future of complex systems.

3.3. Natural Language Processing

Natural Language Processing (NLP) - a branch of AI - concerns itself with tasks associated with enabling machines to understand and process human language exactly as intended by the speaker or writer. The essence of a manufacturing revolution in the study, such as attached to how a human - worker, supervisor, or manager - can communicate, comprehend, respond, behave, and decide communally, is vital. For instance, Consicht makes virtually ready natural language processing wizards for BI with the potential for analytics and manufacturing database queries. When employed in the manufacturing domain, it enables easy interaction with machines, robots, databases, and other computer peripherals deployed in a factory.

Natural Language Processing facilitates communication between systems and promotes data exchange on a user's terms, enabling users to collect evidence and make decisions. Application examples are in the field of intelligent evaluation systems, for example, intelligent error reporting, and the user is only required to communicate (quasi-orally) to the server through chat interfaces, such as Amazon Lex - an NLP service for building conversational interfaces - integration with AI Chatbot services, such as ChatScript from Dr. AI Foundation and GPT-3 from OpenAI, to make the service. Both of these NLP/Intelligent AI-based Chatbot or positive and negative reporting are conversational, as well as schema-agnostic. Another application may involve the integration of the manufacturing data system and quality system, where expert systems play a pivotal role in decision-making, as they use natural language processing to understand the judgments, rules, guidelines, instructions, and decisions made by experts. These may, at the same time, provide a transparent, clear, and understandable path of AI guidance - decision rationale - for industry managers about whether to make decisions using system-driven decisions, system-suggested decisions, or their personal judgment and further, whether the quality of decision outcomes makes sense. It becomes more beneficial in small and mid-large companies that can be able to catch up with the AI because training and knowledge can be shared. Moreover, generally, training is integrated with the system as global training lessons learned from various customers. NLP also becomes an innovative AI learning capability for employees of their customers.

4. AI Applications in Manufacturing

Applying AI to industries: it starts from the problem-solving framework with various problem categories, namely classification, scheduling, forecasting, parameter optimization, low-level control, and condition monitoring. It starts investigating moving into product- and process-level schematics, which sums up the general areas in the manufacturing domain that AI technology can be applied to. Applications of AI-based technologies to iron and steel production, casting, machining, part handling, inspection, welding, metal forming, and electronics assembly are summarized to showcase the abundance of AI applied studies with their benefits for different elements in manufacturing.

These real-world impacts motivate us to develop comprehensive AI-based decision support systems for a complex system, such as the chemical manufacturing processes presented in this study. AI-based decision support systems are becoming more and more necessary in the manufacturing industry for a wide range of decision-making processes. An AI-based decision support system is divided into two parts: namely, applied AI technology and a decision support system. AI technology might be classifiers, regressors, and clustering methods that apply problem-solving and learning methods. The other part is the decision support system, including both application interfaces for service providers, managers, and operators to solve manufacturing problems, and a knowledge repository to manage learned knowledge from the problem-solving learning models. It can be seen in Figs. 1-5 that manufacturing decision support systems guide highlighted AI applications in the manufacturing realm.

4.1. Predictive Maintenance

Many machine failures can result in significant costs to firms due to downtime, repair expenses, and loss of materials. One main goal of a manufacturer is to reduce the time spent on machine maintenance by automatically predicting the best time for the maintenance; i.e., carrying out the maintenance activities only when they are necessary. The use of AI in predicting the faults in a machine is commonly referred to as predictive maintenance. The principal advantage of using predictive maintenance is that the machinery's expected failure will be predicted and thus the downtime can be minimized. As downtime by itself can cause manufacturing to stop, resulting in manufacturing inefficiency, predictive maintenance is reported as one among the many use-cases that will contribute to the revitalization of American manufacturing. Utilizing AI can help a manufacturer to predict the Expected Time to Failure (ETTF) more accurately. In addition, AI can help a manufacturer in customizing the maintenance according to the system requirements.

Predicting expected failure has been focused on the intervals in which a maintenance supervisor expects an asset to fail. If the expected failure time falls within the next maintenance window, only then a maintenance will be scheduled, thus eliminating any inefficient planning. It is difficult to predict the expected failure time directly for a time-varying or a large number of asset characteristics. One approach can be to locate the warning zone in which the asset is expected to fail so that the maintenance can be customized accordingly, i.e., when to initiate a more aware effort to monitor and conduct put the spare parts close to the location. Alert limit, limit of isolation, isolation levels are some factors that are used in the reverse to find out the probability density of fault occurrence (repeat period of failure). The fault can occur only in the early if the limit of isolation is passed.

4.2. Quality Control

Section 4.2 Quality Control

Quality control (QC) is a significant function in a manufacturing operation. The purpose of this function is to ensure that products being manufactured meet specified quality levels. In the past, it was considered an overhead cost that does not add to the values of products. Consequently, many companies outsourced it to specialized suppliers. The operating principle of traditional QC is monitoring because it is able to detect and reject nonconforming products before they are shipped to customers. This makes the approach reactive and introduces waste (time, cost, and materials) into manufacturing systems. The inability to detect all products that are near or at the limits of being nonconforming leads to the delivery to customers of nonconforming products. The implementation of preventive quality control using techniques like Statistical Process Control (SPC) and preventive maintenance was the birth of lean thinking that is now dominating manufacturing excellence.

AI-based quality control ensures that data is correctly collected and presents a global view on the sources of wasted outputs in terms of their root causes. In addition, it is possible using pattern recognition to detect more effectively nonconformities during the production process, where it is possible to prevent them from generation, thus reducing further the lead time. Artificial intelligence as a computer-based tutorial system can also help diagnose and optimize processes as well as support personnel in continually improving operations at the workplace. Finally, it can provide an expert knowledge base to guide effective decision making on real-time bases. All of these benefits of AI lead to manufacturing excellence and ultimately enhance manufacturing competitiveness.

4.3. Supply Chain Optimization

Supply chain management has been known for decades as a system for efficiently planning, executing, and controlling the flow of goods, services, and related information from source to point of consumption in order to satisfy customer's requirements. More recently, supply chain management has increased focus on strategic value. Supply chains represent "who does what under what circumstances" and are vitally important in achieving important strategic objectives such as cost. Managing such chains requires the skills, experience, and massive compute infrastructure. Today, it is relatively cheap to capture, store, and generate data, which is the reason for data-driven AI services are growing rapidly. Now supply chain managers need an AI-driven supply chain system to better respond in real-time against significant challenges such as natural disasters, political crises, cyber attacks, and terrorism.

Thanks to the recent development in computation learning and internet of things, manufacturing industry can apply AI in supply chain to overload and monitor of supply chain components, thereby responding more quickly to disruptions. A supply chain which includes AI always uses up-to-date information about inventory and demand. American manufacturing is increasing its reliance on domestic suppliers: U.S. content of manufacturing rose from 62.5% in 2011 to 67.5% in 2015. Moreover, 2,200 new manufacturing plants have been built in the previous five years, generating close to a million jobs. Much of this growth can be called a rebound, as companies begin to recognize the importance of 'right shoring' and domestic content. It is reasonable to expect that America will continue to develop its manufacturing infrastructure. Manufacturing is on the verge of major disruption in its core industrial practices. Lockdown-revealed inefficiencies in the manufacturing supply chain, large tech companies are entering the space with a cloud of promises.

5. Case Studies and Success Stories

Wilcox et al. mention considerations in expanding the ADMS study findings and discuss observing a use case of the iterative design-decision process at one ADMS participating manufacturing facility (a household appliance company that successfully used one or more ADMS component systems—OntoRail/Assembly Planning System). This collaborative project began in early 2017 and finished in the first quarter of 2018, and was part of a project involving three US Advanced Manufacturing Innovation Institutes (I-USE, i4.0@NIIMBL, T4M-ACCESS) and collaboratively led by NIST-ATP and the Manufacturing Extension Partnership (MEP). The purpose of the project was to create, analyze, and communicate the demonstrable business value of an AI-based Decision Management Systems (DMS)/Decision Support Systems (DSS) implementation for the US manufacturing community in order to increase national competitiveness.

There now exists a state "ecosystem" website devoted to promoting understanding of the DM/DS use cases in America. It is designed to appeal to decision makers of small, medium, and large manufacturers through the use of industry-leading/important American, real-world sector examples to help decision makers appreciate the direct, quantifiable benefits of adoption of such aspects going forward (e.g., emerging from MEP). To promote value lower down the food chain, the industries were selected to have clusters of small- and medium-sized firms. The site contents are extensive as it contains explanations and examples of DM and DS concepts, tutorials, videos, interactive maps of America (clusters of companies color-coded by sector and size), Regulatory Issues, and Industry Reports from AIAI-TPG and from other sources. With the exception of the TPG robotics SME examples (published in CSME Journal, 2022), the examples are taken from America. For instance, the free online text explains and illustrates the use of DM (superset) and DS (subset) context in the context of high value-added/discrete/advanced manufacturing. All DM and DS AI as modernized makeovers that respect and leverage the best of the past practice to make better decisions in the present and, more importantly, in terms of the future, especially with regard to seeing "the wood for the trees".

5.1. Industry Examples

Motivated by a lack of comprehensive reviews of AI in the IIoT segment of the U.S. and global manufacturing, we seek to provide contemporary, comprehensive, and systematic aspects to the AI-IS paradigm in the industrial domain, focusing particularly on the U.S. context. The AI-IS paradigm discusses AI or AI/ML integrated decision support systems, primarily in CS, Automation, and Industrial Computing related publications, emphasizing the industry/user perspectives.

The demonstration of AI-IS in industries is essential to assess and assert its viability and consequent stakeholder/manager behavior and system performance improvement. AI has been demonstrated to bring effectiveness in real-world industrial and high-tech manufacturing settings. Rovler et al. highlighted the use of a utility function to uncover data-driven intelligence, providing reliable production records with an AI-based decision-making system. The AI-based tool demonstrated reduced energy usage, less system stress, and elongated productivity at Hewlett-Packard, Inc.

Gupta et al. described the implementation of an AI-driven implementation of a dynamic wind measurement algorithm aimed at quality up-gradation of photovoltaic panel fabrication. This utilization of AI led to a reduction of fabrication time. The job shop scheduling in the robotics and machinery manufacturing industry was deliberated by Srivastava et al., where the authors followed the hierarchical and multilayered Multi-agent architecture. The implementation of the AI-agent facilitated decreased manufacturing time and energy consumption by 47% and 25% respectively. Additionally, the manufacturing throughput was doubled.

Jardmissen et al. elucidated the implementation of AI in the industrial AI and AMI solutions landscapes. Another study demonstrated the use of AI for decision-making in the distributed, real-time monitoring, and control of production networks. The system facilitated decision-making for maintenance and production scheduling, with the potential for the realization of maintenance based on actual condition-based control.

6. Ethical and Social Implications of AI in Manufacturing

Preferred ethical and societal considerations depend on entity structure due to the interplay between industrial automation strategies and unique organizational and human-based assets. Some of these, such as the ways in which knowledge and customer preferences are captured and modeled, can hold important spillover effects owed to network effects and economies of scale.

One organization that becomes a first-mover in algorithmic supply chain optimizers and predictive maintenance amplifies pioneering learnings over time. While using automated algorithmic decision-making tools to rethink U.S. manufacturing decision-making, we should be aware of where these initial moves and the scale-up of innovation may displace labor – both in space through increased use of AI but also into data extraction and preparation in the spirit of firms like clickworker and MTurk.

A pressing challenge for AI adopters in the public and private sector, then, is to consider not only the benefits of augmented, AI-powered automation but also its opportunity costs. These include potential foregone or forgone opportunities, such as unassessed risks, the re-skilling and reshaping of workforces, and privacy concerns associated with data collection and analytics. The tradeoffs between these ethical and social risks and benefits are particularly pronounced in industries where AI may maximize decision-making in the face of bounded cost and quality constraints.

The translation of data into actionable insights is liable to both technological failure and ethical misuse. Not only are AI models only as good as the data inputs fed into them, but warranties tied to autonomous system performance, the destiny of replaced workers, and AI-enabled supply chains are subject to moral hazard, adverse selection, and power asymmetries between humans and machines.

For example, it is important to think about who bears contractual responsibility for the accuracy of warranty—the user or the technology? On the front end, using surveillance-based facial recognition to improve quality control at a factory is a rich form of data burglary—full consent cannot be given by factory workers subject to 24/7 surveillance—where workers' rights are overridden by managers in the pursuit of even more perfect production requirements.

An AI-mediated integration of quality assurance practices, such as ethical AI-assisted worker performance reviews to protect sincerity and due process rights, must grapple with the extent to which quantifiable GMAT results predictive of business school success would evolve into a bound rule for employment and advancement.

Given the ethical dangers of using manufacturing performance reviews in hiring and firing, in managerial pay allocations, and companies, QA application and BE would see other quality considerations in manufacturing, recent leveraging libel, discrimination, privacy, and shaming of worker reputations.

Using the creation of AI-driven operation and production decisions that could be a core part of reviving American manufacturing necessitates an assessment of the extent to which standards of equity, reconciliation, sincerity, and respect for privacy are operationalizable in industry regulations and legally protected worker rights.

6.1. Job Displacement

The overarching question this paper seeks to answer is as follows: How can artificial intelligence (AI) proactively operating at the intersection of industry, vocational interest, education, and prevailing policy paradigms be used in manufacturing to increase employer and employee value creation capacities? The authors are concerned with the ability of the United States to compete in the international and domestic markets, sustain economic growth, and return to a level of blue-collar employment that can support the working/middle class. The overarching research objective of the AI-Based Decision Support Systems (AIDSS) project is to understand the opportunities that AI presents in manufacturing and propose interventions that would increase U.S. manufacturing employers' value creation capabilities and workers' value preservation capacities.

In asking this question, we are aware that job displacement due to increasingly automated means and methods has the potential to follow-cutting into-both questions. These concerns lead us to pose yet another question fundamental to our research: How can AI be used in manufacturing with the expectation of maintaining the status quo of manufacturing technologies but increasing the decision-making capacities of workers? This focus on workers was intentional and a choice born out of more than just a consideration of the bottom 50% of the population. There exist economic, civil, and ethical reasons to integrate thoughtful consideration for the possible implications of widespread deployment of AI technologies in the workplace, but this line of inquiry also fits the sociotechnical systems of inquiry with the industrial/organizational psychology expertise of the research team.

6.2. Privacy and Data Security

6.2. Privacy and Data Security. According to a 2022 State of the State discussion about AI in manufacturing, even if workers can access and trust AI-generated outputs, valid questions regarding privacy, data security, and ethical considerations remain. The manufacturing industry shares data between public and private stakeholders through an array of sensors and the physical flow of goods. According to one survey in academia, "the use of AI Law in manufacturing...may increase the risk of privacy violations by increasing what stakeholders believe to be 'salient' about the data." Uncertainty about how the data might be used, in some cases, has caused IoT users to opt not to share it in the first place. News in December 2021 also raised questions about the integration of AI and machines themselves. Deep Learning could potentially find information in the patterns of electromagnetic interference signals that are given off by the electronics of a machine—to that extent, a side channel for unauthorized data extraction.

Deep learning could also be used to transform noisy data into data usable for extracting information about cryptographic key inputs from public data. Indeed, in 2018, Nvidia announced, "Gaining direct access to your FPGA's memory or device registers is not the only way an attacker can implant a bug in your design. They can manipulate the FPGA configuration data even before it is transferred and, when implemented on the device, insert hidden Trojans." Based on all of this, measures might be put in place for military applications that limit the amount of and which data can leave the plant and tying it cryptographically in some fashion to characteristics of the machine that either are not represented in electromagnetic outputs or have statistical patterns that are manipulatively obscured. In the commercial sector, a combination of legal liability (placing a mandate on proper delivery of the data requested), privacy, and cybersecurity approaches that rely on valuable data that must be protected from theft or corruption would ensure that the plant owner would have proper incentives to resist tampering with the device. More fundamentally, these findings suggest that new ethical and regulatory frameworks need to keep up with the technology based on the asset-value and use-value implications. The EU is now rethinking a range of digital and AI ethics guidelines in light of developments in AI hardware.

7. Future Directions and Emerging Technologies

The CAIT-developed AI technology for revitalizing American manufacturing (AI-RAMM) is evolving, and newer versions are delivering promising results. While preparing our post-COVID-19 era deliverables, we have already been integrating these measures with our emergent technology. In our follow-on works, we will also be integrating newly developed AI-RAMM technology infrastructure with ML technologies for predicting demand using real-time data in the context of disaster management (e.g., natural disasters, accidents, and pandemics) and their potential socio-economic impacts. As the user community has expressed interest in inventory/supply chain management, we have started to develop a sound conceptual framework for AI-RAMM Digital Twin, which will include deep reinforcement and transfer learning technologies for exploring optimal courses of action to minimize the disruption caused by scenarios presented earlier. Furthermore, we will be developing a robust and fair decentralized marketplace where manufacturers will be able to share data and their resources to minimize the cascading impact of, and recover quickly from, disruptions, without any fear of breach of IPR or other security concerns. Research is also underway towards developing the AI-RAMM within the 6-dimensional (6-D) framework (x, y, z, t, v, and c).

6.1 6-D Data Management Technologies Apart from data triangulation and counterfactuals (in Mk-IV), in the context of fairness, we also plan to develop ML-based technologies that will be "resilient to" or "aware of" adversarial AI. This is likely to be fielded in Mk-IV. As fraud detection can help improve our recommendations in Mk-III, especially for focus parts manufacturing where there can be a high rate of return due to errors in orders and quality, ongoing research and development are being performed to integrate a sound framework for fraud detection. "Life cycle analysis" of the inventory of the end-users can help us understand their requirements better, especially in the context of spare parts and refurbishment. Preliminary work is already underway to develop and integrate LCA into AI-RAMM TMG. We will also be looking into the integration of ML tools.

7.1. Explainable AI

Explainable AI is an important and timely research area that aims to develop methods and tools for making various AI systems and relevant human-AI interactions more human-friendly, transparent, understandable, and interpretable for the users and stakeholders at different levels of expertise and engagement. Transparency and interpretability turned particularly important not only as AI systems become ever more prevalent within consumer products and services but also in various industry sectors and critical societal systems, where incorrect and/or low-level AI system predictions can lead to secondary errors, losses, injuries, or fatalities that are intolerable from ethical, managerial, legal, or policy perspectives. Explainable AI has advanced seminalism and, by extension, public trust and confidence in it. We believe that to flourish, AI applications should be designed and evaluated with a balanced focus on implementing and operationalizing ethical principles (accountability, fairness, and transparency, to mention a few) in harmony with industrial organization objectives and customer value.

Today, enhanced AI explainability techniques are growing in response to the ethical use of AI systems, particularly in sensitive industries such as manufacturing. US and European scholars, professional and policy-making institutions particularly care about the human-centered, explainable AI for manufacturing. AI technologies, specifically for use in general or domain-specific HMI, offer an opportunity to contribute to the development of explainability frameworks and guidelines. However, some scholars may argue that an AI system's explanation could be used as a manipulation point—changing the explanation to promote certain information to the human. Choenni et al. worked on AI-based XAI, but they have developed an environment for intelligent alarms for satellite control rather than XAI for manufacturing maintenance or production.

7.2. Edge Computing

Improving efficiency is a fundamental driving force of any manufacturing environment. Many AI applications in manufacturing, such as predictive maintenance or quality control, rely on decision support algorithms to fix problems before they occur. Yet, traditional centralized-cloud AI cannot support the low-latency and high-availability requirements of these applications. This often requires data to be preprocessed at the edge so that alerts can be generated and acted upon even when the edge loses its connection to the cloud.

The paradigm of processing data (also called data fusion) near its source of generation has gained growing attention as a new computing concept in the cyber-physical system era. The near-source process in many applications includes a single sensor, communication module, and data processor. In the context of the Internet of Things (IoT), it could also be local area servers, gateways transmitting and aggregating with each other to connect the end devices, and more generally edge, fog, and cloud computing.

Fog computing explains decentralized data transmission and processing related concepts between the endpoint devices and centralized cloud to improve response time of applications by using resources of the network environment, while edge computing is about reduced data communication traffic through a variety of reorganized, delay-resistant fixed-grain processing techniques. While the edge-to-cloud/peripheral routing architecture for IoT is widely known, simplified edge data preprocessing methods have been considered recently. By bringing computation close to the edge where the data is generated, edge computing is expected to become a key component of systems.

In the manufacturing industry, AI—led by "smart manufacturing," "digitization," and "Industry 4.0"—has been referred to as the fourth industrial revolution and is projected to dominate the global market in 5 years. Running AI on the edge could dramatically change these statistics.

8. Policy and Regulatory Considerations

Policy and regulatory considerations relevant to governing and regulating AI applications in the manufacturing domain are entirely missing in the literature. Laws, regulations, and public policies embody collectively generated decisions by communities or countries about how they will live with laws representing the compromises and commonalities among different stakeholders while regulatory systems are concerned with both mandates and standards that protect the rights, sovereignties, and general peace. Precisely because they are policy specific, policies, regulations, and laws are essential and critical to the successful deployment of any new technology, including the visions and tactics developed here for the deployment of AI and HRI in the grand context of revitalizing American manufacturing. Furthermore, it is also crucial to make the case to take humans 'back to the top' and to gain an invitation to an inclusive discussion about the principles and terms upon which society might want to do so. Such treatments will need to be carried forward in legal, psychological, and philosophical inquiries. As an accompaniment to a broader national manufacturing renewal initiative, an NIAC-like group needs to be convened to develop policy changes, recommendations for executive action, and, where appropriate, legislative action that follows these principles.

Policy and regulations are born of laws because laws are the codification of community standards that limit the speed and direction of the growth of the power of the social elite. To bolster the actual injury to aggregate societal interests and values in favor of the elite, they sanction the expediency of technology in general and artificial intelligence and hyper-robotics in particular. The need to protect societal values and interests, in general, spurs concern for everyone, but especially the broad membership of the American public. Subjects of particular concern include dispelling the perception of AI and hyper-robotics as an elitist boutique technology and assuring that the populace perceives the roll-out of AI and hyper-robotics as an inclusive holistic approach to realizing potential contributions to restoring prosperity and dominating global commerce that represent a new workable democratic technocracy. This needs to be carried out in a way that mitigates job loss and develops facilitated transition assistance for those who lose their jobs, whose compensation levels are adjusted downward, or whose working hours are shortened.

8.1. Government Initiatives

Governments worldwide are beginning to form initiatives to keep up with the constant change in AI technologies (particularly the proliferation of big data, rapid learning, and deep learning algorithms; BIDA) and how they are utilized. Since "nations' geographic, cultural, socio-political, and economic conditions" govern the development, deployment, and use of AI in manufacturing, it's the responsibility of the governing bodies within each nation to form some kind of steering to guide the development of AI within their domain. US advanced and smart manufacturing initiatives list the integration of AI within their programs: from firefighting in Industrie 4.0 to promoting "service-oriented" instead of "production-oriented" AI deployment.

By the fundamental tone of the speculation within the published texts of AI for manufacturing in the US, we don't see a direction towards such an overly stringent ruling model like China or the long-term non-guarantees of the "AI for Good" in the EU releases. We find a great deal of hypothetical planning and technical pre-work alongside growing calls for "safety" as AI integration and deployments advance. As such, the US government has a few choices on the role, regulatory and policy-wise, that AI will take within the domain of manufacturing in the country. The author argues that the proactive use of AI Safe Spaces and the governing of orchestrated environment(s) required to start developing those tools would greatly mark a difference in US leading tech development competencies. So far, the US government chose to guide and test using manufacturing to guide both tech development via AI testbeds and government agencies' practices in AI, as well as guide industry AI deployment in manufacturing. Defensive bureaucracy-wise, the debate around ethical AI is latent within these speculations.

9. Conclusion and Recommendations

The study presented a comprehensive analysis of AI decision support systems (DSS) in the manufacturing domain. Based on this analysis, the paper presents several conclusions and recommendations:

Manufacturers need to understand that AI, machine learning, and other related technologies are a part of a much broader toolkit for addressing manufacturing decision-making needs in supply chain management, productivity, product inventory, workforce, and future skills. The study indicated several steps that may be undertaken by manufacturers in order to take advantage of the DSS tools identified in the paper.

Despite extensive development of deep expertise in AI in the supplement and the AI literature, suppliers and other companies, especially in small- to medium-size manufacturing enterprises (SMEs), have a nascent awareness, expertise, or appetite for these systems or the rewards of moving towards such an ecosystem.

AI-oriented DSSs remain in their infancy in the marketplace. Such systems may become stronger and more capable as time passes and the capability and vision of these systems have yet to be implemented. Top decision makers need to be able to predict how the intelligence-intensive products will take place in the future as the tools grow in both application capability and broader coordination. Manufacturers need to remain vigilant about these tools to reap the major benefits in the path forward for larger staff systems, either from scratch or to add capabilities amongst AI and other software systems. To this end, executives and technologists benefited from the components that capture these AI-intelligent technologies. Executives: a) benefit from the knowledge of the AI elements; and b) require assistance in assessing demand

and making informed choices around these important trends. Executives also must provide a venue to discuss the hypothesis advanced in the current research while reducing policy and strategic risks related to the AI-intelligent markets.

9.1. Key Findings

This study undertook an exhaustive exploration of decision-making support systems (DMSS) for manufacturing enterprises at every stage of the product realization process. Based on a detailed investigation, we have synthesized the key findings below. This collection of findings distills the results of the research and offers concise, actionable insights for the benefit of manufacturing practitioners. Each subsequent section then takes a deep dive into one or more of the aspects summarized here. Each section begins with the key findings for the topic at hand and explores the relevant issues in detail.

The DMSS uncovered in the literature, projects, and on the web span the integrations of ML, AI, and digital transformation services that support decision-making for several major functions conducted in manufacturing firms as well as across the supply chains. They include marketing and sales, research and development, engineering, manufacturing operations and production planning and control, maintenance, logistics, and service. Most support functions were built to integrate AI and/or ML across those functions to support decision-making. The DMSSs are available, but the implementations are limited. AI, machine learning, and IoT applications were uncommon in the user world. Although the U.S. manufacturing is in need of help with these DMSS tools that are becoming more commonly used in the business reconstitution, they are not in place. Ultimate observations shed light on important trends, most significantly when following the emerging tech advancements in industry, related systems applications and volume, as well as expertise, to predict the next best "disruptive technology" for the tech forecast step of the project.

9.2. Practical Implications

The potential implications include: (1) Utilizing AI-based (Artificial Intelligence) decision support system in manufacturing industries revitalization processes since manufacturers prioritize highest when their productivity has started to decrease. (2) Launching ICT-based in manufacturing SME from early age brings many benefits since the beginning such as an increase in efficiency and ability in facing the global challenges. (3) Drives them toward the path of industry revolution discourses. (4) The implication pace of ICT (Information and Computer Technology) progress in manufacturing industries in the U.S. is still in rapid status. 90% of U.S. industries have a system of computer incorporated in their production process. Artificial Intelligence (AI) is a creation simulation of human brain for computer applications such as to play games, expert systems, etc. (5) Importance of the conception for intensifying and extending the transformation of the U.S. manufacturing industry. (6) AI-based systems are crucial input for leverage possibilities of reshoring, when together with economic policy measures and better qualification of manufacturing workers will reshape the landscape of the US manufacturing ecosystem through a decentralization process that boosts low-cost regions at county level.

There are three possible scenarios for the changes on reshoring manufacturing. Artificial intelligence (AI) is a field of science that is associated with taking simple steps in managing knowledge in the field of computer science. The term "AI" was applied in 1956; however, the field of AI wasn't published until mid-1956. During the last month of overtime, the study of AI has changed dramatically and part of AI calls theories, while part of it is based on experimental pages. The collected data in bioinformatics and transformation through knowledge in new forms systems including intelligent agents, human-centered systems. This study has provided some valuable insights for achieving a revitalization of American manufacturing using an AI-based decision support system and built an integrative model to illustrate these insights. Our studies recommend some practical insights. First, the AI Evolutionary Approach could help decision-makers to increase manufacturers' relative share by focusing on research and manufacturing markets to give rise to productivity.

Moreover, our study provides some insights since the early stage of ICT on a gradual pace is necessary, efficient in manufacturing, and the weighting of the huge amount of capital investment. These AI-based recommendation systems serve industries that have already experienced a productivity decrease or divestiture. AI can serve as a promoter of decreasing productivity captious manufacturing processes; however, given the variation in productivity values in the datasets, it appears as though the AI is particularly adept at identifying "dominants" and/or "grower" markets rather than "slowdowns" and "divestiture" manufacturing and research combined markets. Further, in these modeling studies, data availability and quality are essential – the small number of observations (U.S. counties) and manipulation undertaken using clusters (and the sensitivity analysis) illustrate exactly the ways in which the information could be used in industry-specific contexts.

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