IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 6, April 2024

When Industry meets Trustworthy AI: A Systematic Review of AI for Industry 5.0

Nishant Yadav and Anshika Maurya and Dr.Ashima Mehta
Post Graduate Student, Department of Computer Science Engineering
HOD, Department of Computer Science Engineering
Dronacharya College of Engineering, Gurgaon, India

Abstract*: We are focusing on analyzing the current industrial evolution paradigm, aiming to make it more sustainable and trustworthy. In Industry 5.0, Artificial Intelligence (AI) is one of the key technologies utilized to develop services with a sustainable, human-centric, and resilient approach. Understanding the factors enabling AI adoption in industry, while adhering to trustworthy principles, involves examining its incorporation in early stages, assessing its impact, and identifying emerging trends. Additionally, we aim to grasp the challenges and gaps in transitioning from Industry 4.0 to Industry 5.0,providing insights into the industry's readiness for new technologies. This offers practitioners new avenues to explore for fostering the adoption of trustworthy AI within the sector.*

CCS Concepts: General and reference → Surveys and overviews; Social and professional topics → Government technology policy; • Applied computing → Industry and manufacturing; • Computing methodologies → Artificial intelligence

Keywords: Trustworthy AI, Industry 5.0, Artificial Intelligence, Technology Readiness Level

I. INTRODUCTION

The evolution of industrial processes and factories towards digitalization involves the integration of novel techniques that efficiently automate data computations, thereby enhancing task performance. Industry 4.0 introduced cyber-physical systems into production systems, warehousing, and logistics, facilitating the adoption of new digital assets and their integration into enterprise values. This transition is driven by the decreasing costs of hardware and the proliferation of data, which have spurred the development of techniques for automating, securing, and flexibly adapting factories. Key technologies in this transformation include AI for data analysis andpredictive outcomes, Blockchain for securing and transparently recording and sharing data, Additive Manufacturing for rapid prototyping and product customization, and the Internet of Things (IoT), Edge, and Big Data analyses for enabling real-time data processing and decision-making capabilities. The ongoing evolution of industrial processes and manufacturing facilities toward digitalization represents a transformative shift enabled by the integration of cutting-edge technologies. This transition, often referred to as the fourth Industrial Revolution or Industry 4.0, has ushered in an era where cyber-physical systems are seamlessly integrated into various facets of production, warehousing, and logistics operations. Central to this evolution is the adoption of novel techniques that streamline data computations, optimizing task performance and driving efficiency gains across the industrial landscape. Industry 4.0 has not only facilitated the incorporation of new digital assets but has also entrenched them as integral components of enterprise values, reshaping traditional paradigms of operation.

At the heart of this transition lies a confluence of factors, including the gradual reduction in hardware costs and the exponential growth of data volumes. These factors have catalyzed the development of innovative techniques that automate processes, bolster security measures, and imbue manufacturing facilities with unprecedented flexibility and adaptability.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 6, April 2024

II. BACKGROUND

This section offers a comprehensive overview of both Industry 4.0 and Industry 5.0, aiming to elucidate the prevailing challenges in industrial transformation. Furthermore, it delves into the various domains within industrywhere Artificial Intelligence (AI) finds application.

Industry 4.0 and Industry 5.0

Over the last decade, Industry 4.0 focused on incorporating cyber-physical systems and digital platforms into factories, integrating monitoring processes [127]. By harnessing real- time data, factories are able to gather andanalyze valuable information, thus providing valuable insights for decision-making processes. This has led companies in two directions to enhance their produc-tion capabilities: decision making features and decentralization of production processes from the traditional production control systems [40].

In the scope of decision-making, Industry 4.0 explores the use of technological advancements for training and decision-making using models that replicate real-world situations in controlled and safe environments, such as

Digital Twins and Augmented Reality acting to facilitate (enable) enhanced working environments and experiences in industrial settings, integrating virtual and real systems, both independently and collaboratively with human counterparts. As a consequence, this approach enables a thorough examination of business objective decisions while prioritizing risk mitigation, leading to the minimization of adverse economic consequences on factories and products.

The advent of decentralization has been facilitated by the integration of sensors and actuators across various machines through the Internet of Things (IoT), fostering extensive connectivity with computing systems and leading to the generation of vast streams of data, commonly referred to as Big Data. This data is processed using IoT deviceseither locally or on the Cloud/Edge, which not only reduces costs but also enhances scalability by leveraging virtual

resources in the Cloud or at the network Edge. The increased computational power and cost reduction have significantly improved the efficiency of data processing, enabling the adoption of multiple technologies that align with the objectives of Industry 4.0. However, managing such massive volumes of data necessitates the development of novel methods for intelligent acquisition, collection, and processing. Effective data management and processing techniques not only contribute to improved scalability, security, and efficiency but also lead to a reduction in required resources. For example, Additive Manufacturing optimizes the assembly process by minimizing the number of critical components needed. Although Artificial Intelligence (AI) is not officially considered a fundamental pillar of Industry 4.0, novel techniques supported by AI play a crucial role in driving its advancement.

Numerous companies have developed innovative intelligent systems that enable a certain level of process automation, thereby enhancing overall efficiency and productivity.By utilizing AI, the information from various systems can be efficiently gathered and processed at high speed, enabling the execution of tasks, such as Fault Prediction and Action Selection [7]. AI enables intelligent decision-making and predictive capabilities, allowing for more efficient utilization of the gathered data in Industry 4.0 systems. In summary, AI plays a crucial role in leveraging IoT services and Cloud Computing to enhance the enablers and technologies for industry.

Table 1 shows a list of the most relevant pillars that drive Industry 4.0 as extracted from [106]. Theimpact of the aforementioned technologies extends beyond the industrial sector, encompass-ing homeproducts, business models, clean energy, and broader sustainable aspects that were not fully taken into account in previous industrialrevolutions. Moreover, the industry is recognized to be a catalyst forsystemic transformation towards more sustainable economies [98]. Therefore, it is essential to incorporate various societal and environmental aspects as new driving forces within

the industrial sector.

Table 1. Industry 4.0 Technological Enablers

Category	Description
Additive Manufacturing	Also known as 3D printing, encompasses a range of techniques dedicated to the production of products through layer-by-layer deposition [127]. These methods include vat photo-polymerization, powder bed fusion, binder jetting, material jetting, sheet lamination, material extrusion, contour crafting, cellular fabrication, d-shape, concrete printing, and direct energy deposition [15]. The benefits include reduced costs, reduced supply chain, worker safety, complex forms fabrication, and short turnaround times.
Augmented Reality	By overlaying digital content onto the physical environment, this technology serves as a bridge between the digital and real-world [15]. It offers diverse benefits, including improved product development insights, enhanced maintenance, training, issue resolution, support, quality assurance, and automation [15]. AR utilizes markers, holograms, mobile devices, tracking, and interaction methods to enable real-time information streaming. This facilitates the monitoring and control of virtual representations known as Digital Twins, enhancing the management of industrial processes [15]..
Simulation	Mathematical representations of systems and phenomena offer approaches that enable the evaluation of different alternatives or scenarios within a simulated environment. These approaches find extensive application in investment assessment, production planning, optimization and scheduling, design, capability planning, process improvement, bottleneck analysis, and resource allocation. They serve as powerful tools for decision-making and analysis, providing insights and facilitating informed choices within complex systems and dynamic environments.
Autonomous Systems	These systems exhibit a level of autonomy as they perceive and respond to external information, gathered through various sensors, thus demonstrating a form of intelligence [86]. They are capable of executing repetitive, hazardous, and time-consuming tasks with high accuracy and efficiency, without the need for frequent interruptions [15].
Internet of Things	The interconnection of machinery and sensors through communication channels, such as the internet, provides the foundation for IoT. In the industrial sector, this technology brings various advantages, including cost reduction, mass customization, improved safety, and accelerated time to market. Extensive literature coverage underscores the significance of IoT as a crucial enabler for other Industry 4.0 advancements [59, 74]. It plays a pivotal role in driving the transformation and progress within the Industry 4.0 landscape.
Big Data and Analytics	Aggregated data's significance in the industry became apparent as it emerged as a valuable tool for decision-making processes [15]. Data utilisation is further enhanced by leveraging supporting technologies, such as AI, which can analyze and harness more extensive datasets. The accumulated information is commonly employed for descriptive, exploratory, predictive, and prescriptive tasks [41].
Cloud Computing	The utilization of computational resources through the internet, as facilitated by Cloud Computing, is strongly intertwined with IoT and has significant implications in the manufacturing sector, as evidenced in the literature [8, 83]. Cloud Computing's broad impact drives efficiency, scalability, and digital transformation across various industries.
Cybersecurity	Securing data systems in cyber-physical systems is crucial. This area involves policies and practices to prevent attacks and unauthorized access, meets manufacturer and consumer requirements. It ensures system integrity and protects against threats and vulnerabilities.
Horizontal and Vertical	Protocols and approaches defining machine and customer integration within the production system encompass Horizontal and Vertical Integration. These strategies involve

Integration	acquiring related businesses or controlling production/distribution stages, respectively, to consolidate market position and differentiate from competitors [88]. They expand the traditional perspective of product-to-service integration and contribute to a comprehensive industrial process.

AI, Trustworthy AI and its link to Industry 5.0

AI technologies are extensively utilized across a spectrum of digital services by leading technological giants such as Google, Amazon, Apple, Facebook, and Microsoft. These companies harness AI to drive a myriad of services spanning e-commerce, online advertising, media streaming, smart home systems, self-driving cars, and social networking. The remarkable success of these services can be attributed to the convergence of media and information technology, which propels their exponential growth. It enables the creation of virtual representations of the real world, converts photos into 3D images, generates interactive maps and

Table 3. AI Application Methods in Industrial Environment

Category	Description
Process planning	Research in this field is linked to the scheduling problem in the manufacturing sector. Different approaches such as Q-learning, RF, and decision trees have been applied for this task [72] for cost prediction, energy and resource efficiency, workers localisation, and load forecasting, among other tasks.
Quality control	This research can be seen as the root of product and process quality control (which adds process control and predictive maintenance considerations). Nevertheless, reference settle a distinction by linking quality control to implementations related to the problem of reducing quality assurance costs (e.g. quality detection - CNN, SVM [73]; Root cause analyses [71] and classification [109] - bayesian network,decision tree).
Predictive maintenance	The research conducted in this field is dedicated to estimating the valuable lifetime of parts and components. Literature is broad with using different AI techniques for regression and classification [128].
Logistics	This area of study shares some commonalities with the scheduling problem. Both consider the efficient use, flow, and storage of material (i.e. optimisation). Nevertheless, logistics considers the products from their origin, while schedul- ing refers to the internal transformation of raw materials into products. Based on these, some strategies are employed for system representation in scheduling trends in the field of logistics [19]
Assistance and learning systems	It focuses on supporting and enhancing employees' capabilities. Two key aspects are referenced to consider the assistance; guidance of individual learning processes and the control of competences saturation [76, 113]. Furthermore, this cluster defines research dedicated to training concepts in manufacturing environments.
Robotics	The research is dedicated to incorporating AI within robots. The application of Machine Learning (ML) components for automation and human collaboration is wide and includes motion, object, and human recognition, path planning, and improvement (i.e. optimisation) of automation tasks
Process control and optimisation	It is dedicated to implementing AI in a short-time response to systems monitor-ing and modification by plant-wide and individual unit real-time optimisation, parameter estimation, supervisory control, data reconciliation, alarm manage-ment, emergency shutdown, and sensor and actuator validation, among other tasks. [30, 78]

III. RESEARCH METHODOLOGY

Figure 1 shows a schematic in which the research methodology is described. The processes, on the top row of the Figure, are linked to their primary outcomes, on the bottomrow in the Figure. These are review scope, all papers, bibliometric analysis, relevant papers, classification scheme, and systematic map results. Although the Bibliometric Analysis is not the core of the methodology, it is added to ground a better understanding of the topic trends. These are developed in the subsequent Subsections according to the Figure

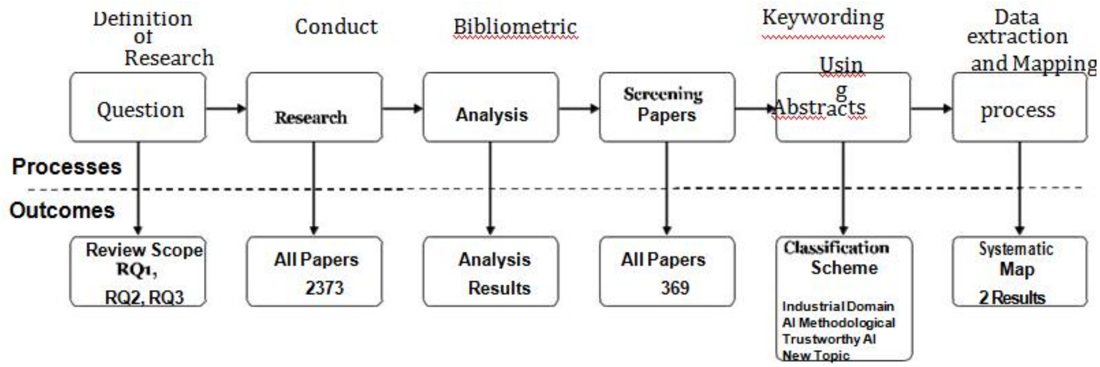

Fig. 1. Systematic Mapping Approach

3.1 Definition of Research Question

The goal is defined as follows:

"To provide an understanding of trends and status on the implementation ofhuman-centric and Trustworthy AI technologies in the industrial sector".

From the goal, the research questions are the following:

RQ1 - What are the key Trustworthy AI requirements prioritized in Industry 4.0 technological enablers and their AI applications, and how can they be further promoted?

IV. SEARCH METHODOLOGY

To evaluate the status of AI in Industry 4.0 and lay the groundwork for Industry 5.0,a comprehensive mapping process and systematic approach were undertaken. Theprocess commenced with the identification of key pillars driving the topic, followedby the utilization of targeted keywords for literature searches. These keywords served as markers, facilitating efficient searches across various platforms.

The methodology utilized to construct queries and define keywords adhered to the PICOC methodology – Population, Intervention, Comparison, Outcomes, and Context. Each of these topics is outlined in detail below:. The methodology applied to construct queries and definition of keywords follow the PICOC methodology – Population, Intervention, Comparison, Outcomes, and Context [53, 90, 91]. Each of these topics is defined next:

Population: It refers to the specific group of individuals or subjects under the interest of the study. In the context of this work, the population is the group of manuscripts from which research questions are formulated.

Intervention: The intervention refers to the approach or technique applied in the empirical study. This study involves software methodologies, tools, technologies, or procedures. Dif-ferent AI techniques that can be applied to specific procedures in the industrial sector are considered. It is represented by the AI Application Methods set, which includes AI applied in Industry 4.0 (Table 3), and the Trustworthy AI set, and thatdefines the requirements from the Trustworthy AI guidelines

V. CONCLUSION

In this study, we conducted a comprehensive analysis to gauge the readiness of Industry 4.0 for the transition to Industry 5.0. We examined the progress made, the challenges encountered, and the emerging trends in the domains of industrial automation and AI. By scrutinizing existing literature, we have acquired invaluable insights into the pivotal technologies and concepts propelling this transition and their potential implications for the future of industrial systems. Industry 4.0 has revolutionized traditional manufacturing processes by leveraging technologies such as IoT, Big Data analytics, Cloud Computing, and cyber-physical systems. These advancements have enabled increased automation, connectivity, and data-driven decision- making, leading to enhanced productivity, efficiency, and competitiveness in industrial sectors. However, as we move towards the era of Industry 5.0, new opportunities and challenges arise, necessitating the integration of AI and intelligent systems into the industrial landscape.

The emergence of AI in Industry 5.0 brings about significant transformations in the way in-dustrial processesare managed and optimized. AI technologies such as ML, Deep Learning, and Natural Language Processing empower industrial systems to autonomously learn, adapt, and make intelligent decisions. This paradigm shifttowards intelligent and Autonomous Systems has the potential to unlock new levels of efficiency, flexibility, and customization in industrial operations. This document sheds light on several Technology Enablers that are driving the transition from Industry 4.0 to Industry 5.0. Blockchain, with its decentralized and transparent nature, offers enhanced security, data integrity, and privacy for industrial systems. Federated Learning, as an AI technique, enables collaborative and privacy-preserving model training across distributed IoT devices, ensuring data privacy and security Big Data processing is a key enabler for Transparency.

In conclusion, the transition from Industry 4.0 to Industry 5.0 represents a significant evolution in industrial automation, driven by the convergence of AI, IoT, and advanced analytics. The study shows that the most developed Trustworthy AI requirements are directly linked to technical components. At the same time, the lowest is not directly dependent on the industrial sector since they require a clear definition of protocols, regulations, and implementation approaches (standards) that facilitate the transition towards Industry 5.0. Finally, attention was driven towards technological approaches such as Blockchain, Federated Learning, MLOps, and ontological approaches to foster different Trustworthy AI requirements. This survey has provided an overview of the current state of the field, highlighting the key technologies, challenges, and potential solutions in the journey towards Industry 5.0. As we navigate this transformative phase, it is crucial for researchers, industry practitioners, and policymakers to collaborate and address the technical, ethical, and societal considerations to ensure the successful and responsible integration of AI in the industrial landscape. By embracing these advancements and leveraging the potential of Industry 5.0, we can unlock unprecedented levels of productivity, sustainability, and innovation in the future of manufacturing and beyond.

VI. ACKNOWLEDGEMENTS

This paper has been partially supported by the European Commission by funding the ASSISTANT project (no. 101000165), AI4Europe project (no 101070000) and the Science Foundation Ireland under Grant No. 12/RC/2289- P2 for funding the Insight Centre of Data Analytics, co-funded under the European Regional Development Fund. We would like to personally thank Mr. Shaun Gavigan for the proofreading of this paper.

Acknowledgement of your topic, "When Industry meets Trustworthy AI: A Systematic Review of AI for Industry 5.0": Exploring the intersection of industry and trustworthy AI is crucial in navigating the rapidly evolving landscape of technological advancements. Your systematic review promises to shed light on the multifaceted dynamics shaping the implementation of AI in Industry 5.0, where trustworthiness stands as a cornerstone for sustainable and ethical progress.

By delving into this subject, you're contributing valuable insights that can guide policymakers, businesses, and researchers towards the responsible integration of AI technologies. Best wishes for your endeavor!

REFERENCES

[1] Ovidiu Vermesan and Joël Bacquest (Eds.). [n. d.]. Next Generation Internet of Things: distributed intelligence at theedge and human machine-to-machine cooperation (Gistrup, Denmark, 2018). River Publishers. OCLC: 1080080699.

[2] Ahmed A. Abdelrahman, Dominykas Strazdas, Aly Khalifa, Jan Hintz, Thorsten Hempel, and AyoubAl-Hamadi.[n. d.]. Multimodal Engagement Prediction in Multiperson Human–Robot Interaction. 10([n. d.]), 61980–61991. https://doi.org/10.1109/ACCESS.2022.3182469

[3] Aidi Ahmi, Hany Elbardan, and Raja Haslinda Raja Mohd Ali. [n. d.]. Bibliometric Analysis of Published Literature on Industry 4.0. In 2019 International Conference on Electronics, Information, and Communication(ICEIC) (Auckland, New Zealand, 2019-01). IEEE, 1–6. https://doi.org/10.23919/ELINFOCOM.2019.8706445

[4] Imran Ali and Huy Minh Phan. [n. d.]. Industry 4.0 technologies and sustainable warehousing: a systematic literature review and future research agenda. 33, 2 ([n. d.]), 644–662. https://doi.org/10.1108/IJLM-05-2021-0277

[5] Luís Alves, Estrela Ferreira Cruz, Sérgio I Lopes, Pedro M Faria, and António Miguel Rosado da Cruz. [n. d.]. Towards circular economy in the textiles and clothing value chain through blockchain technology and IoT: A review. 40, 1 ([n. d.]), 3–23. https://doi.org/10.1177/0734242X211052858

[6] Mohammadhossein Amini, Shing I. Chang, and Prahalada Rao. [n. d.]. A cybermanufacturing and AI framework for laser powder bed fusion (LPBF) additive manufacturing process. 21 ([n. d.]), 41– 44. https://doi.org/10.1016/j.mfglet.2019.08.007

[7] Angelos Angelopoulos, Emmanouel T. Michailidis, Nikolaos Nomikos, Panagiotis Trakadas, Antonis Hatziefremidis, Stamatis Voliotis, and Theodore Zahariadis. [n. d.]. Tackling Faults in the Industry 4.0 Era—ASurvey of Machine-Learning Solutions and Key Aspects. 20, 1 ([n. d.]), 109. https://doi.org/10.3390/s20010109

[8] Zareef Askary and Ravinder Kumar. [n. d.]. Cloud Computing in Industries: A Review. In Recent Advances in MechanicalEngineering (Singapore, 2020) (Lecture Notes in Mechanical Engineering), Harish Kumar and Prashant K. Jain (Eds.).

[9] David Baiden and Oleg Ivlev. [n. d.]. Human-robot-interaction control for orthoses with pneumatic soft- actuators — Concept and initial trails. In 2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR) (Seattle, WA, 2013-06). IEEE, 1–6. https://doi.org/10.1109/ICORR.2013.6650353

[10] Osbert Bastani. [n. d.]. Safe Reinforcement Learning with Nonlinear Dynamics via Model Predictive Shielding.In 2021 American Control Conference (ACC) (New Orleans, LA, USA, 2021-05-25). IEEE, 3488–3494. https://doi.org/10. 23919/ACC50511.2021.9483182