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# INDUSTRY 4.0 TECHNOLOGIES' EFFECTS ON ENVIRONMENTAL SUSTAINABILITY - A SYSTEMATIC LITERATURE REVIEW

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## ABSTRACT

In the existing literature, Industry 4.0 and its potential impact on environmental sustainability have been studied from different perspectives. However, Industry 4.0 is a concept that gathers different technologies that are not necessarily combined. It is clear that the combination of different technologies is the core value of Industry 4.0. However, the examination of each technology separately is crucial for determining the right combination of technologies for each specific case. Therefore, the following research provides a systematic literature review (SLR) of each technology included in Industry 4.0 and its effects on environmental sustainability aspects based on 107 research papers. 417 articles from the SCOPUS database, which contain the word Industry 4.0 in the title, abstract, and/or in the indexed keywords, were scanned by the command-line program Astrogrep to find the most common Industry 4.0 technologies. The results revealed that the Internet of Things (IoT) was mentioned 252 times, Artificial Intelligence/Machine Learning (AI/ML) 81 times, Simulation 38 times, Blockchain 30 times, Augmented Reality (AG) 27 times, and Additive Manufacturing (3D printers) 23 times. First, the study reviews the potential effects of the six technologies on different aspects of environmental sustainability. Later on, the challenges faced by organizations when applying these technologies for environmental purposes were reviewed, and new research scopes and future research directions were highlighted.

**Keywords:** *environmental sustainability, industry 4.0, Digital transformation, IoT and CPS*

## 1. Introduction

Industry 4.0 is no longer a fictional hype that presents repackaged concepts. It is instead a new revolution in manufacturing that researchers, governments, and industrialists acknowledge. In May 2022, more than 24.000 papers were available in the SCOPUS database that contained the word Industry 4.0 either in the title, abstract, and/or indexed key words. Since the first industrial revolution in the 18th century, the globe has faced the difficulty of creating more products from limited and decreasing natural resources to fulfil the ever-increasing demand for consumption while minimizing negative environmental and social implications (Müller et al., 2018). The significance of Industry 4.0 is broad, ranging from mass production to satisfying customers through product customization. The adoption rate of Industry 4.0 in the last couple of years has been extremely high (Dev et al., 2020). There is a trend toward using Industry 4.0 for economic purposes only, despite the high potential that the technological facilities have for environmental aspects. Industry 4.0 can play a significant role in balancing the cost/reward of environmental sustainability commitment if presented in the "right way" (El Merroun, 2022). The primary goal of environmental sustainability is to preserve the earth's environmental systems' equilibrium, the balance of natural resource use and replenishment, and ecological integrity (Glavič & Lukman, 2007). Since previous industrial revolutions resulted in dramatic and rather unanticipated environmental transformations, the sustainability consequences of Industry 4.0 need full academic consideration. The effects of Industry 4.0 and digital transformation on environmental sustainability are predicted to be significant (Kamble et al., 2018; Lopes de Sousa Jabbour et al., 2018). In the literature, we can find that the potential impact of industry 4.0 technologies on sustainability, supply chain management, and manufacturing sustainability is a well-discussed subject. However, on the other hand, few review papers have explored the use of industry 4.0 tools to achieve environmental sustainability. None of them studied the effect of each technology on the environment. (Jamwal et al., 2021) presented a review of Industry 4.0 technologies and the use of each one in a manufacturing sustainability context. The key findings are that additive manufacturing can contribute to economic and environmental sustainability. Big Data Analytics and

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Digital Twin can help to achieve high optimization, production management automation, production efficiency, and real-time monitoring. It can also contribute to recovering electronic and electrical equipment waste. Artificial Intelligence and Machine Learning can contribute to reducing manufacturing errors, reducing costs, and revenue growth in manufacturing industries. The Internet of Things, which is the main pillar of Industry 4.0, has an impact on the improvement of production process quality and reducing downtime through digitalization in manufacturing. In the same context, (Birkel & Müller, 2021) highlighted the potential outcomes of the combination of Industry 4.0, triple bottom line, and supply chain management. It is the first paper that combines all three concepts, as most research discusses only the combination of two of them. The study showed that for each supply chain aspect (plan and source, logistics, intralogistics, recycling logistics), Industry 4.0 could be used to achieve the three sustainability pillars. (Ahmad et al., 2021) examined how Cyber-Physical Systems can be implemented in each stage of the circular economy; the study highlighted that for the source stage, Cyber-Physical Systems can reduce the health risks associated with raw material extraction; for the design phase, it can contribute to the improvement of designs through feedback and data provided by the system in real-time; and, relying on technologies such as simulation and testing, it can contribute to the improvement of designs. The combination of manufacturing and CPS could solve many issues and prevent risks that are traditionally associated with manufacturing, such as machine condition monitoring, quality control, defect prediction, high energy consumption, and enabling smart factories. The study also highlighted the most important stage of CE, which is recycling, as the CPS and radio identification systems (RFID) can be used to collect and sort waste. Based on 73 articles and relying on Interpretive Structural Modelling (ISM), (Ghobakhloo, 2020) identified 16 Industry 4.0 functions for sustainability. Furthermore, it presented a contextual relationship among the identified sustainability functions.

The intersection of Industry 4.0 and sustainability aspects (economy, environment, and society) has been broadly studied in the literature (Beier et al., 2020; Rosa et al., 2020). However, this extant literature reviews studies Industry 4.0 as a single element and not a concept that gathers different technologies that have particular characteristics and are not necessarily combined. A similar gap was highlighted by (Birkel & Müller 2021). The authors pointed out the need for a study that defines Industry 4.0 technologies and highlights their contribution to the triple bottom line. In particular, the following paper fills the scientific gap of analyzing the combination of I4.0 technologies and environmental sustainability through a systematic literature review of six main technologies included in I4.0 and their potential benefits, as well as the challenges faced during their implementation for environmental sustainability purposes. The number of literature reported on various aspects of industry-4 technology is presented in Table 4.

**Table 1 Number of mentions of each I4.0 technology in the literature**

| Industry 4.0 technology | No. of reported literature |
|---|---|
| Internet of Things(IoT) | 252 |
| Cyber-Physical Systems (CPS) | 218 |
| AI/AM | 81 |
| Simulation | 38 |
| Blockchain | 30 |
| Augmented reality (AG) | 27 |
| Additive manufacturing | 23 |
| Digital twin | 20 |
| Virtual reality (VR) | 20 |
| cloud computing | 11 |
| Edge computing | 4 |
| Drones | 3 |
| Cobots | 1 |

Based on the 13 technologies included in Industry 4.0, the six most mentioned technologies were chosen to review their potential impact on different aspects of environmental sustainability. CPS has been mentioned in 218 articles, but it was not included in the research because even if CPS and IoT are not 100% similar, the difference between the two concepts is not made clear in most projects and academic research, and it is difficult to find a source that draws a clear-cut distinction between the two concepts. The majority of academics view the two definitions as distinct explanations of the same concept and use the terms interchangeably. The general trend appears to be that CPS is a U.S. term for IoT (Minerva et al., 2015).

## 2. Background and literature

### 2.1 Industry 4.0

The Fourth Industrial Revolution, often known as Industry 4.0, was first mentioned in 2011 at the Hanover Fair in Germany. It is characterized by the use of information and communication technology in business processes (Milošević et al., 2022). Its technical foundation is the Internet of Things, which enables communication, connections, and control among physical items, people, systems, and IT (Huber et al., 2022; Oberländer et al., 2018; L. D. Xu et al., 2018). In the context of Industry 4.0, IoT is frequently referred to as the "industrial internet", "The Internet of Things (IIoT)", or "cyber-physical systems (CPS)" (Duan & Da Xu, 2021). As IoT is the core of I4.0, there are numerous other technologies, such as blockchain, simulation, additive manufacturing, and artificial intelligence, that support various industries in enhancing performance and productivity (Turkyilmaz et al., 2021). In such a configuration, machines and equipment become linked to a single cloud and avoid centralized control systems. Furthermore, they have complete autonomy to make quick decisions when unexpected events occur (Alcácer & Cruz-Machado, 2019). All technologies may be used independently, but only their combination has the potential to revolutionize and improve traditional manufacturing methods (Issa et al., 2018).

Three prominent definitions of Industry 4.0 have been identified in the literature to date (Huber et al., 2022). (Cohen et al., 2019; Oesterreich & Teuteberg, 2016) defined I4.0 as the process of incorporating digital technology into the manufacturing industry. For (Kagermann, 2015; Vaidya et al., 2018), it is a new paradigm for industrial production with a focus on the process outcome, and the last one is a mixture of these two points of view (i.e. transformation process and its outcome), which makes I4.0 an umbrella term for innovative manufacturing technology and emerging concepts in manufacturing.

## 2.2 Environmental sustainability

Sustainability is defined as meeting the needs of the present generation without compromising future generations' ability to fulfil their own needs (Keeble, 1988). Regardless of whether one sees sustainability as a three-legged table consisting of the environment, the economy, and society, or as a dualistic relationship between human beings and the ecosystem they inhabit, there should at least be agreement that ensuring the provision of clean air, clean water, and clean and productive land is the foundation of a responsible socioeconomic system (Morelli, 2011). The environmental pillar focuses on ecosystems and their life-sustaining roles for humanity (Dong & Hauschild, 2017) . Environmental sustainability means ensuring that present and future generations have access to the resources and services they require without compromising the health of the ecosystems that deliver those resources and services (Morelli, 2011). Environmental sustainability encompasses a broad variety of challenges, ranging from local to global. Global challenges include GHG reduction, climate change, and renewable energy, whereas local ones include soil erosion, water management, soil quality, waste management, and air and water pollution (Ghosh et al., 2019). Environmental sustainability can be sorted into five main categories: 1-Societal Needs (e.g., examining the environmental characteristics of raw materials and making the environmental sustainability of the raw materials used in the production of new goods and services a primary consideration in the selection process). 2- Preservation of Biodiversity (e.g., utilizing sustainable and ecologically responsible energy sources and investing in energy efficiency improvement). 3- Regenerative Capacity (e.g., maintaining depletion rates of non-renewable resource inputs below the development rate of renewable alternatives). 4 -Reuse and Recycle (e.g., creation for reusability and recycling). 5- Constraints of Non-renewable Resources and Waste Generation (e.g., developing transportation parameters that emphasize low-impact types of transportation) (Goodland, 1995; Moffat & Newton, 2010; Morelli, 2011).

## 2.3 Industry 4.0 and environmental sustainability

It is challenging to formulate environmental policies because of the high level of stochastic uncertainty in the many components of the system, as well as the fact that many stakeholders have entirely opposing views. Market statistics and scientific research indicate that customers will act ecologically friendly only if pro-environmental purchases do not carry additional prices (Farjam et al., 2019; Gleim et al., 2013). The results of studies have shown that lack of knowledge is regarded as one of the most significant challenges to the adoption of environmentally friendly practices (O'Neill & Oppenheimer, 2002). In recent years, the combination of digital transformation and green practices has become apparent, at least on paper, in European policymaking. Political guidelines presented as part of Von Der Leyen's campaign included six "headline aspirations," two of which were "A European Green Deal" and "A Europe fit for the digital era" (Floridi, 2020). Since Von Der Leyen's nomination, Commission texts have begun to refer to the "twin transitions"—environmental and digital—that will determine Europe's medium- to long-term future. For ensuring a more sustainable future, the fourth industrial revolution has the potential to address many of the environmental limits of traditional industrial practices (Morrar & Arman, 2017). Industry 4.0 technologies can reduce the amount of energy and resources consumed by the detection and analysis of data across all stages of manufacturing and supply chain activities (Shrouf et al., 2014). Based on the availability of footprint data and traceable analysis, Industry 4.0 can decrease the environmental impact of a product, process, or service (Peukert et al., 2015).

The implementation of AI, robotics, and other advanced technologies across numerous economic sectors, such as the supply chain, distribution channels, and manufacturing, has a significant impact on the natural environment, resulting in a reduction in pollution, a decrease in greenhouse gas emissions, a decrease in energy consumption, and an increase in profits, simultaneously (Ejsmont et al., 2020)

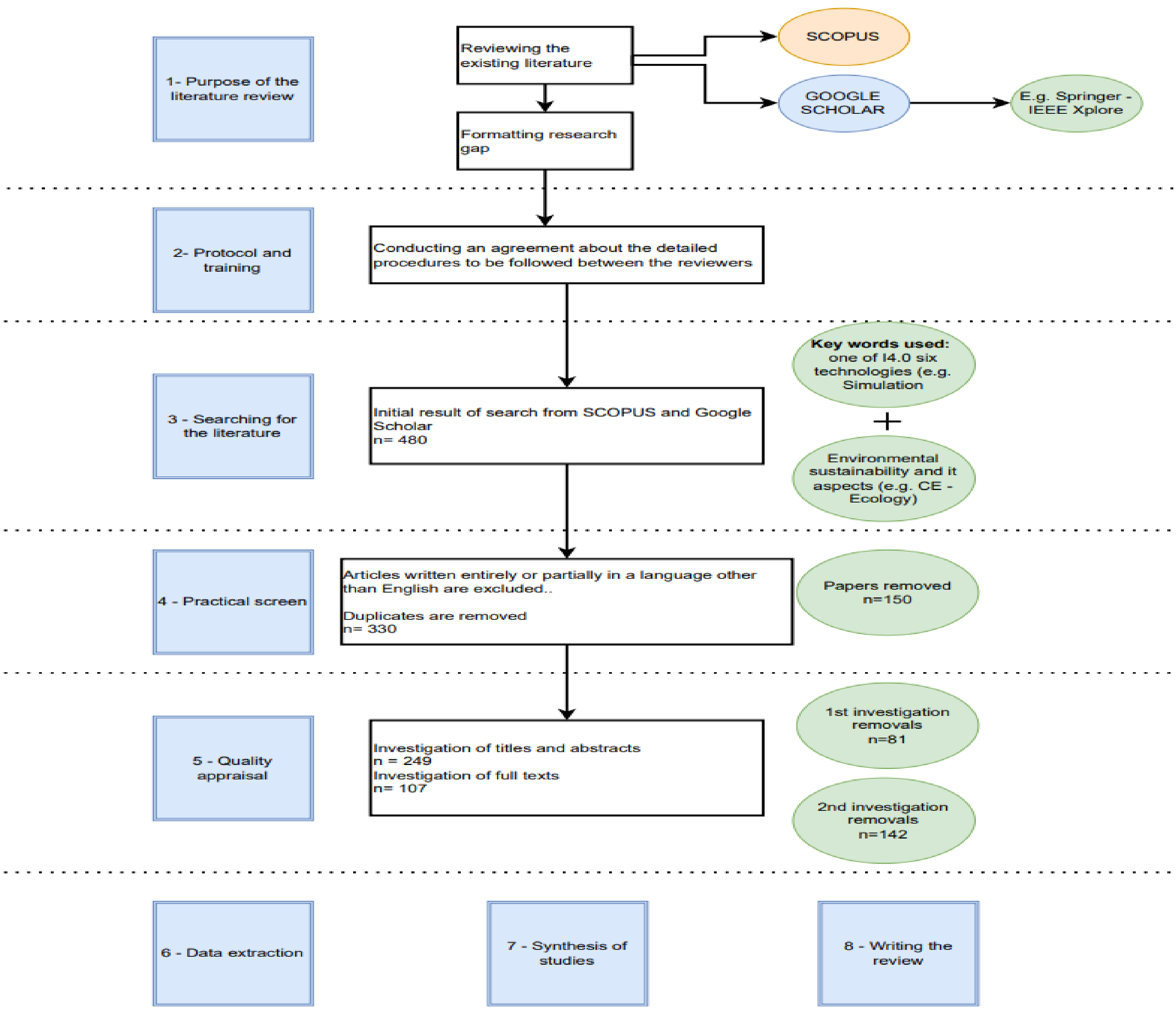


**Fig. 1 The systematic literature review guideline and selection process (proposed by (Okoli and Schabram, 2010))**

## 3. Methodology

The present paper synthesizes the available material on the combination of different technologies included in I4.0 and the environmental sustainability aspect. It also offers an academic critique of the theory through a systematic literature review (SLR). (Tranfield et al., 2003) defined SLR as a rigorous process that aims to minimize bias through exhaustive literature searches of published and unpublished research and an audit trail of the reviewers' decisions, methods, and findings.

The accessibility to literature that provides information about new technologies and research possibilities in industries is low. SLR can help to identify research trends and new potential in a specific research area (Antony et al., 2021). This article follows the 8-step guideline (Okoli & Schabram, 2010) as shown in Fig.1.

### 3.1Research gap and research questions

The study fills the gap of examining the potential effects of each Industry 4.0 technology on environmental sustainability. In order to address this gap, the following questions were formulated:

Q1: What are the benefits of the technological facilities included in I4.0 on environmental sustainability aspects?

Q2: What are the challenges and obstacles that need to be addressed in order to exploit the I4.0 technologies for environmental purposes?

Q3: What are the main research gaps that need to be addressed for a successful combination of Industry 4.0 technologies and environmental sustainability, and what research directions must be addressed in the future?

### 3.2 Search and selection process

The literature review search was conducted between January 2022 and April 2022. SCOPUS and Google Scholar were the main sources of data, taking into consideration that GS journals are indexed in a well-known database (e.g., IEEE Xplore, Web of Science, Springer). The new papers were prioritized, as most of the articles were published in the last four years, as shown in figure 2. The keywords used in the search process are

IoT or Internet of Things
AI/ML or Artificial intelligence or Machine learning or Deep learning
3D printers or 3D printing or Additive manufacturing or AM
Blockchain
Simulation
Augmented Reality or AR
**AND**
Environmental sustainability/protection/preservation/restoration
Circular economy
Ecology/Ecosystem
Waste management
Energy management/efficiency
Climate change
Natural resources management

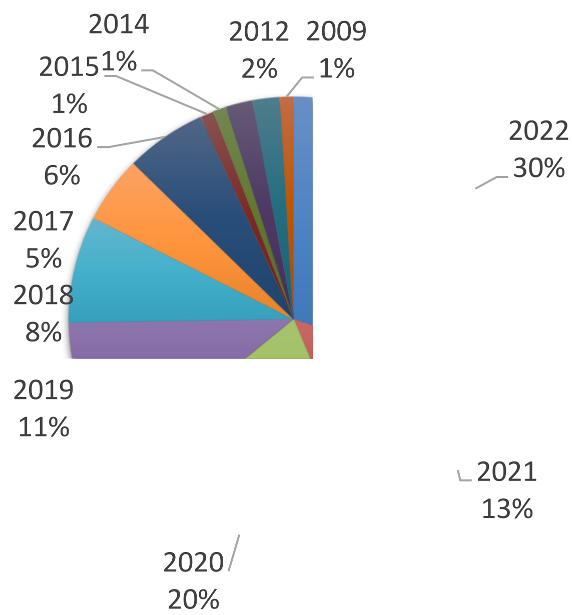


**Fig. 2 Year of the reviewed papers**

## 4 Discussion

### 4.1 The benefits of Industry 4.0 technologies on environmental sustainability

Industry 4.0 has great potential for environmental sustainability. This combination is expected to improve energy and material efficiency, while also increasing the adoption of renewable energy sources in industrial manufacturing (Ghobakhloo & Fathi, 2021), but it's becoming increasingly clear that sustainability advantages aren't a foregone conclusion, but rather must be deliberately integrated into the digitalization goals of each company (Renn et al., 2021). In this section, we will present how each technology included in Industry 4.0 can contribute to enhancing environmental sustainability and encouraging green practices.

### 4.1.1 IoT and environmental sustainability

The Internet of Things (IoT) is the fabric that facilitates the flow of data between people, things, and processes, resulting in a growing data sphere and complex traffic models based on a variety of data sources (Ibrahim et al., 2022). IoT enables citizens to get a variety of services and advantages in an automated way, including logistics product tracking, smart agriculture, smart intelligent transport systems (ITS), smart hospitals, smart grids, smart homes, and smart environments (Y. Li et al., 2017). It is not a surprise that attention has shifted toward the use of IoT to enhance environmental sustainability. As the IoT's main feature is tracking, and waste management has the largest share in the literature in this regard, the internet of things is the most practical way to enhance the effectiveness of municipal hazardous waste management with minimal waste and an efficiency of 95.09% (X. Xu & Yang, 2022). These values might seem exaggerated, but they are supported by several authors in the literature, such as (X. Chen, 2022), who suggested an algorithm based on the internet of things and machine learning for smart waste management. The IoT-powered devices can be put in waste containers, such as recycling bins, and it gives real-time information about how much garbage people produce. Image processing can be used to figure out how much garbage is at a disposal site. They give a clear picture of trash and recycling trends and give ideas for how to be more productive. The suggested approach led to an accuracy ratio of 96.1 percent, a cost-effectiveness ratio of 92.7 percent, a tracking rate of 89%, and an environmental production/recycle ratio of 91.9 percent, all achieved by the suggested approach in comparison to other ways, according to the trial data. In the same context, based on literature and expert consultation, (Turner et al., 2022) came up with a set of parameters to describe the produced asset to consider its circularity during its whole lifespan, with application to the automotive part relying on the internet of things. The model is in the form of a central component linked to the internet of things and sensors that operates as an automated maintenance process generator. This tool would recommend a dynamic method for the technician to follow based on sensor outputs, problem codes, and predictive models available for the vehicle. End users will be able to offer text replies and diagram comments about automobile repair operations, providing another data source for the auto-circular simulator.

The IoT benefits for the environment are not limited to waste management; (Parvathi Sangeetha et al., 2022) implemented a hybrid remote-controlled device based on the Internet of Things and Global Positioning System (GPS) with Radial Function Network (RFN), to manage the pump for storing and transporting groundwater to a farmer's field, as well as monitoring soil humidity, pressure, and temperature in a farm field. The IoT-based system met the goal of monitoring and regulating the agricultural irrigation system. Furthermore, the application provides a dashboard that allows the customer to monitor the irrigation system. In the case of an accident, the program monitors detector values and controls the water pump. Furthermore, a survey conducted by (Hu et al., 2022), based on 355 manufacturing employees in China to measure the impact of eco-sustainability motivational factors on organizations' adoption of the Green Industrial Internet of Things (GIIoT), a tool to achieve green innovation, Eco-sustainable motives have a substantial and beneficial influence on the adoption of GIIoT, according to the findings. Eco-efficiency, eco-effectiveness, eco responsiveness, and eco-legitimacy play major roles in increasing an organization's adoption of GIIoT. By integrating linked assets, real-time data processing, and monitoring, green industrial IoT solutions enable manufacturers to operate more efficiently while being flexible, informed, and in command. Integration of advanced manufacturing technologies with GIIoT can help manufacturers to achieve sustainable development goals while also improving their green innovation.

### 4.1.2 AI/ML and environmental sustainability

In most cases, artificial intelligence and machine learning go hand in hand. Until recently, artificial intelligence (AI) algorithms were mostly employed in the industry and enterprise sectors for low-level activities (Emmert-Streib et al., 2020). However, with machine learning, computers were able to evolve beyond simply executing what they were programmed to do (Galbusera et al., 2019). The three kinds of machine learning techniques are supervised, unsupervised, and reinforcement learning (RL). In supervised learning, a dataset of input and target values is used to train the artificial intelligence (AI) network to discover a mapping function to convert input data to output. Regression and classification are subcategories of supervised learning. Supervised learning includes linear regression, support vector machine, and random forest. Reinforcement learning employs algorithms from all branches in each situation (Ullah et al., 2020).While AI capabilities are broad, they may be classified into three categories: evaluation (e.g., receiving and recognizing information); inference (e.g., learning and processing from this information); and reaction (e.g., action and decision-making) (Rhodes, 2020).

Urbanization and civilization, as well as unsustainable practices and procedures, have led to the rise of artificial intelligence-based solutions that help with environmental sustainability (Saheb et al., 2022). Optimization of resource and energy management is one of the most acknowledged uses of AI (Zendehboudi et al., 2018). The ML now detects the features and produces accurate predictions without the need for human intervention. Increasing need for larger data sizes for various energy system applications, such as predicting photovoltaic (PV) generation (J. Wang et al., 2020), calculation of the battery's state of charge (Chemali et al., 2018), energy management of households (Coelho et al., 2017), the estimation of energy requirements for the distribution and individual appliances, as well as the planning and management of building energy consumption (Mocanu et al., 2016). By stacking multi-layer information processing modules, ML models are proven to have hierarchical underlying data prediction tendencies. The starring role of artificial intelligence in the energy sector includes data explosions, advances in deep learning and machine learning, smart robotics for infrastructure production and grid monitoring, improved integration of renewable energy, a significant increase in IoT in the energy industry, cyber attack prevention, and security privileges, and increased computational power, which solves a variety of problems in the energy industry (Yang et al., 2019). Energy efficiency can take different forms and be employed in different sectors. The energy industry's data may be generally classified into two categories: network system data; customer and supplier data; data on measurement/use, consumer data; and data on the customer's and supplier's real-time energy consumption. Power system operators and utilities should increasingly rely on artificial intelligence (AI) technology to improve human-to-asset/infrastructure interactions that support normal operations, asset management, and field service (Bose, 2017). By 2024, the global market for AI in energy management is expected to reach $12,200.9 million, up from $4,439.1 million in 2018 (Ahmad et al., 2021). (Batista et al., 2017) presented a module that demonstrates how AI technology combined with interconnected things and the smart grid can contribute to reducing energy consumption. Integrating and optimizing renewable energy sources with the power grid using AI technology can improve the power system's resilience, reliability, stability, efficiency, load planning, management, and so on (Ahmad et al., 2021). In spite of the energy required to train AI/ML models, many tasks that would normally require more time, space, human effort, and perhaps more power, can be made more efficient by using AI models (Narciso & Martins, 2020). Cloud computing practitioners are seeking new and inventive techniques to drastically lower the enormous energy expenses of data center operations and their impact on the environment (Avgerinou et al., 2017). Studies have shown that this sector alone consumes around 7% of worldwide power; by 2030, this percentage is projected to increase to 13% (Avgerinou et al., 2017). Since 2005, the quantity of data stored globally has quadrupled to 33 zettabytes in 2018 and is expected to reach 175 zettabytes by 2025 (Alex, 2018). In this regard, (Shaw et al., 2022) suggested an advanced reinforcement learning consolidation agent, ARLCA, an artificial intelligence method for optimizing virtual machine distribution across the data center. The study showed that implementing a Reinforcement Learning RL-driven virtual machine consolidation strategy, such as ARLCA, is less expensive than some of the other options presented in the literature. The suggested technique has broader ramifications since it has the potential to deliver a more sustainable green cloud infrastructure in support of global environmental sustainability.

Besides the energy sector, AI/ML has great potential in the waste management field. As organizations are pressured to produce recyclable goods, there are still many products that are recyclable by nature, but they are not treated and eventually become waste. At the top of the list, we can find textiles. In principle, 95 percent of waste textiles may be recycled, but in fact, recycling rates are quite low worldwide, with just 10–15 percent in China, 15.2 percent in the US, and 25 percent in the European Union (W. Li et al., 2021). According to (Du et al., 2022), textile waste may be identified and sorted with the use of artificial intelligence technologies. The authors presented an AI solution based on an online near-infrared (NIR) qualitative identification model based on NIRS technology for 13 different types of waste textiles. The experiment showed that the use of AI solutions is projected to tackle the bottleneck problem of difficult waste textile sorting and to provide an intelligent, efficient, and non-destructive sorting technology for waste textile categorization and high-value usage. The textile industry is not the only sector that suffers from a high amount of untreated waste. In fact, it is estimated that 1.3 billion tons (or more than $1 trillion in economic value) of produced food is wasted annually, of which 25% could feed the world's 795 million hungry people (Shahbazi & Byun, 2020). Meat is a perishable foodstuff that contributes 13% to food waste. Additionally, meat spoilage accounts for one-third of emissions (i.e., greenhouse gas emissions such as $CO_2$) and takes up 75% of the land space occupied by wasted food (Hülsen et al., 2022). To overcome this problem (Amin Amani & Sarkodie, 2022), suggested an intelligence strategy that is more efficient in minimizing human error and losses while simultaneously boosting the accuracy and availability in various sections of the meat supply chain than typical monitoring and control systems. Artificial intelligence (AI) technologies were used to train an image classifier system to identify wholesome foods from rotten ones, and this system was developed using a deep convolution neural network (DCNN) and a particle swarm optimization (PSO) algorithm. The suggested AI system demonstrated 100 percent accuracy in distinguishing fresh meat from rotten meat. By automating the separation process, the model is used at multiple stages of the meat supply chain, increasing productivity, lowering costs, and avoiding the microbial effects of rotting meat on healthy meat.

Third, fourth, and fifth on the list of the world's top 10 environmental risks based on effect are water shortages (Harper, 2020). To fulfil the increased need for clean drinking water, experts have resorted to renewable and ecologically acceptable sources of energy such as solar power (Pandey et al., 2021). Based on an artificial intelligence system, (Salem et al., 2022) demonstrated a deep learning model with an accuracy of 82.64 percent for inspecting the quality of cooling water in terms of the renewable water concept, as well as a local interpretable model-agnostic explanation (LIME) explainer capable of bridging trust between experts and non-experts in comparison to the proposed model to compare and improve the model that is untrustworthy through feature engineering.

#### 4.1.3 Additive manufacturing & environmental sustainability

Additive manufacturing (AM), also known as three-dimensional (3D) printing, is a revolutionary technology that produces complex-shaped, multi-material parts in a single process (Dvorak et al., 2018). Consequently, additive manufacturing has emerged as a direct digital production technique in the age of industry 4.0 (Bueno et al., 2020). Several studies have highlighted the potential sustainability benefits of additive manufacturing processes in different fields (Liu, Lu, et al., 2022), which is supported by the increasing number of studies analyzing the environmental effects of AM (Saade et al., 2020). Additive manufacturing has the potential to reduce energy consumption, and eliminate waste, including waste that affects the environment or threatens long-term sustainability (Ghobadian et al., 2020). When creating lightweight components, the product geometries may be improved, resulting in a reduction in the amount of material required during fabrication and the amount of energy utilized in operation. Due to the simple manufacturing of on-demand parts, transportation and inventory waste are reduced in the supply chain (Mani et al., 2014).

The construction sector has an important share of the literature regarding the impact of 3D printers on environmental sustainability (Khan et al., 2021; Lu et al., 2019). (Adaloudis & Bonnin Roca, 2021) applied grounded theory to analyze the potential effects of 3D printers within the construction business over the three elements of sustainability. Regarding the environmental aspect, the 3D printer can reduce waste and failures resulting from better quality control and reduce the environmental impact of concrete production and transportation. With a holistic design approach, it has the potential to improve energy efficiency and other performance parameters. (Weng et al., 2020) studied the economic cost, environmental effects, and productivity of a concrete bathroom unit. When compared to a precast counterpart, a 3D-printed bathroom unit may save 34.1 %, 85.9%, and 87.1 % on overall cost, CO2 emissions, and energy use, respectively.

The additive manufacturing process is constantly improving and can support plastics manufacturers in reducing their carbon footprint (Freitas et al., 2016). To reduce the amount of plastic used in a given product, topology optimization and generative design are used (Javaid et al., 2021). The 3D printer enables the printing of all plastics and eco-friendly materials. In contrast to other engineered materials, the material can be 3D printed and decomposed without the necessity for an industrial composting facility. Because of its lightweight and low cost, the material is suitable for additive manufacturing as a plastic substitute (Jiang & Fu, 2020). 3D printing not only minimizes waste but also enables the reuse of finished goods (Machado et al., 2019).

(Ford & Despeisse, 2016) considered how additive manufacturing (AM) can contribute to the development of more sustainable production and consumption systems. Furthermore, the environmental dimensions of sustainability have emerged as the most prominent in the research. Product and process redesign; material input processing; make-to-order component and product manufacturing; and closing the loop were highlighted as four primary categories in which AM is enabling sustainability. As a result, the benefits of AM for sustainability across the product and material life cycles have been identified, as well as the barriers that must be overcome. From a sustainability point of view, the main areas that AM can represent an advantage are material and energy reduction; minimizing waste;

increased durability for longer product life; increased fuel efficiency; reduction of the environmental impact of titanium powder production; and localized material recycling. (D. Chen et al., 2015) provided an overview of Direct Digital Manufacturing along with potential sustainability indicators and related sustainability research. According to this study, direct digital manufacturing has the potential to reduce waste by improving raw material utilization efficiency. Dematerialisation, as well as on-demand potential due to consumer proximity, results in less pollution and energy consumption. DDM reduces the need for inventory due to more decentralized value chains and better user orientation, resulting in energy and material savings for storage and a lower number of degraded products. DDM also requires fewer complex processing tools, which could result in energy and material savings. More concretely, (Mele & Campana, 2022) proposed a 3D liquid crystal display printer with an adaptive slicing strategy. The study aims to investigate the potential long-term benefits of this strategy over traditional slicing. The results show that it causes a significant reduction in environmental impacts, particularly in terms of human health and resource scarcity. In the cases of the dental model and the respirator adapter, this strategy allows for a reduction in total building time of up to 27.8% and 53.6%, respectively. Furthermore, according to the composition of ecosystem quality indices, the resin life cycle contributes between 59 and 86 percent of the total, and significant savings are also made in terms of energy consumption. Energy efficiency is widely discussed in the literature as one of the benefits of AM compared to traditional methodologies, (Wu et al., 2022) focus on a bottom-up approach to classify technical elements such as equipment, processes, and interfaces of materials recycling and manufacturing, followed by a benchmark between AM and conventional manufacturing (CM) processes, based on the collection-recycling-manufacturing model as the framework's core area, then it delves into sustainable manufacturing by combining recycling and additive manufacturing. The results show that AM can help to reduce transportation distance, $CO_2$ emissions, and energy consumption, as well as commit to cost savings and shorter lead times. Among all the key factors, design flexibility and localization can be tactical factors that enable AM to fully utilize the collection-recycling-manufacturing (CRM) model and augment AM's advantages.

#### 4.1.4 Blockchain and environmental sustainability

Blockchain technology was first introduced as a revolutionary tool that will make financial transactions without the involvement of a third party (e.g., Bank) possible by Satoshi Nakamoto, a pseudonymous developer. The currency used for these kinds of transactions is called Bitcoin, which is referred to as a cryptocurrency. By March 2022, more than 18.000 cryptocurrencies were on the market (HAYES, 2022). In 2013, a Russian developer named “Vitalik Buterin” published a white paper in which he said that Satoshi's blockchain was the first credible decentralized solution. And now, attention is rapidly starting to shift toward this second part of the blockchain, and how the technology concept can be used for more than just money (Buterin, 2014). Blockchain is characterized as a tamper-proof decentralized database system that provides consistent transactions across numerous users (Yetis et al., 2022). According to research, blockchain minimizes problems of distrust and suspicion by uniformly presenting confirmed transactions to all parties (Gorkhali et al., 2020). In addition, its scalability, traceability, and sustainability attract interest from several sectors. In contrast to classical systems, it is innovative as it also eliminates central authority (Leung, 2019).

Blockchain technology provides the ability for transparency that allows producers to share the production process step by step in a reliable way. Since green practices are not optional for corporations anymore, the tractability of processes has become more crucial than ever. Based on document analysis, field research, interviews, and focus groups, (Varavallo et al., 2022) designed, developed, and implemented a Blockchain-based traceability platform to ensure traceability in the agricultural and food industries with less environmental impact and lower costs for each transaction sent through the supply chain. The authors could create a Blockchain algorithm that allows the operators in the targeted company to keep a record of all transactions during the packaging stage with a low environmental footprint and overall cost savings. According to (Dey et al., 2022), food waste and loss account for nearly 6% of total greenhouse gas emissions worldwide. To overcome the food waste problem, the authors proposed a multi-layered Blockchain-based framework utilizing machine learning, cloud computing, and QR code in a decentralized Web 3.0 enabled smart city called SmartNoshWaste. The application focuses on the consumption of potatoes in the United Kingdom since it is one of the most common food items that is wasted. At each step of the supply chain, every stakeholder, including the consumer, has access to and can trace the food data. The app includes the ability to track the food items consumed or wasted during the week so that the user can make a more informed decision about what food to buy or not buy the next time they go grocery shopping. The data is processed and managed by a machine learning algorithm that shows that the Blockchain-based platform is capable of reducing food waste by 9.46 percent. (Erol et al., 2022) studied the potential of blockchain to mitigate the effects of barriers to successfully implementing a circular economy. The results showed that the most important functions of blockchain in overcoming CE adoption barriers are transparent supply chain traceability management, improved collaboration and coordination in supply chain ecosystems; superior trust in supply chain ecosystems; and enhanced business models through cooperation and prosumerism. (Kouhizadeh et al., 2019) studied the environmental and economic effects of the interaction between blockchain, circular economy, and product deletion. The study showed that multiple levels, including governments, communities, supply chains, companies, and people, are affected by the management and practical consequences of the relationships between the three concepts. The authors discussed how the blockchain can be used to help build the necessary CE infrastructure. If a product gets deleted, the difficulty arises from the inability to monitor the inventory of materials required for suitable development material flows and natural resource policies over a specified planning horizon. In this case, blockchain technology can contribute to identifying which items are accessible and which may be phased out, which might assist in ensuring that materials for certain sectors remain available. The research also discussed how blockchain could contribute to waste management if companies value and strategically exploit choices on product deletions, and then the inter-organizational system will be more proactive and transparent as a result of blockchain implementation. (Pizzi et al., 2022) investigated the potential effects of blockchain on sustainability reporting based on Banca Mediolanum, one of Italy's most important financial institutions. The company introduced a publicly available blockchain that contains the full report regarding sustainability practices; it has completed the modifiability credential of its sustainability report without relying on a third party that is traditionally responsible for the notarization of these kinds of reports. Due to the immutability feature of the blockchain, the company cannot change or amend its pledges after notarization because blocks have already validated the reliability of the hash. For that reason, the Italian corporation is considered the first mover that notarizes its sustainability statement on a public blockchain to address information gaps that harm stakeholder participation.

According to (Strepparava et al., 2022), the production of renewable energy is stochastic, it can only be done if the market is cleared in pseudo-real time, unlike the traditional energy, the use of cutting-edge information and communication technology is required for the application of renewable energy, blockchain, as a new ICT, opens up new possibilities for decentralized market architectures. For that reason, the authors proposed a market mechanism that is based on dynamic prices and is functionally dependent on the energy produced or consumed in real-time within the local grid. The method is based on a customized Blockchain solution that was developed using the Go programming language. 18 residential buildings in Southern Switzerland were used as part of a test pilot; the results showed the market was able to work without specific issues while avoiding the use of significant amounts of resources. However, the adoption of a blockchain solution is still hampered by the hardware limitations of smart meters.

#### 4.1.5 Simulation and environmental sustainability:

Process simulation is a software-based representation of physical, chemical, biological, and other unit operations (Pasha et al., 2021). Simulation models offer considerable potential for adjusting and predicting energy use, material consumption, and reducing rework to improve the performance of sustainable manufacturing (Turan et al., 2022).

Simulation has become an important tool in the construction business to create a more productive, safer, and higher-quality construction process with less negative environmental impact (Teng & Pan, 2019). According to global resource data, the construction industry consumes 32% of resources, generates 40% of greenhouse gas emissions, and creates 40% of construction waste (Han et al., 2020). The construction industry has increased massively and, simultaneously, prefabricated building destruction has also risen, resulting in massive carbon emissions (T. Luo et al., 2021). Building energy performance simulation software such as EnergyPlus, Ecotect, and eQuest is commonly used to simulate existing building energy performance and evaluate retrofit possibilities (Yudelson, 2010). (Liu, Li, et al., 2022) simulated different scenarios of the current situation of prefabricated building destruction. Energy consumption simulation for prefabricated building construction indicates that if prefabricated buildings are consistently marketed, the total carbon emissions would reach 32.87 billion tons by 2030. On the other hand, if the construction sector continues to adopt conventional methods, carbon emissions will reach 89.23 million tons. (Jia et al., 2017) carried out dynamic simulations and decision-making analyses to effectively manage construction and demolition waste. The simulation of the business showed that penalties could have a significant impact on the volume of waste that is illegally disposed of, and subsidies have the potential to increase the quantity of recycled and reused garbage significantly.

The construction business is not the only sector that can be environmentally friendly by relying on simulation; several other cases in different sectors are spotted in the literature. (Naseri-Rad et al., 2022) presented a sustainability assessment by simulating the clean-up of contaminated sites associated with health, environmental, economic, and social problems. The model enables site managers to understand the dynamics affecting the sustainability of each remediation scenario throughout the decontamination process's full life cycle. (Abadías Llamas et al., 2019) investigated the performance and environmental impact of the whole primary copper flowsheet by simulating the whole process of circular economy based on numerous metrics, including recovery rates, material and energy usage, and indicators from life cycle assessment (LCA). (Gbededo & Liyanage, 2020) analyzed the literature to determine the techniques, methods, and methodology used in sustainable manufacturing, which developed into a framework for conceptual modelling of integrated Simulation-based Sustainability Impact Analysis. (Burinskiene et al., 2018) simulated the warehouse's daily operations to make the flow as efficient as possible. The analysis demonstrates tremendous possibilities for reducing waste and achieving economy of distance. (Yeomans & Imanirad, 2012) used simulation-driven optimization (SDO) to produce diverse, maximally different, near-optimal policy solutions for waste treatment and disposal. (Ceschi et al., 2021) explored the impacts of societal norms on recycling behavior by simulating a Taiwanese district based on real data. Although societal norms are a powerful source for enhancing people's willingness to recycle, the findings also support the concept that the quantity of waste existing on the streets is a significant moderator variable that policymakers must consider. (Capellán-Pérez et al., 2019) used a simulation game “Global Sustainability Crossroads” whose primary goal is to increase individuals' understanding of the global sustainability quandary, emphasising climate change and the potential alternatives possible in the next decades to reverse present trends. (Ojstersek et al., 2020) assessed the impact of flexibility in manufacturing on sustainability and overcoming the challenges of high-mix, low-volume production by simulating the manufacturing schedule. The results showed that, on average, power usage is reduced by 10.6% when compared to other optimization techniques, and the scrap rate is reduced by 35% when compared to previous optimization methodologies. (M. Luo et al., 2022) navigated future uncertainties toward sustainability in China by using simulation tools according to 24 different scenarios spanning the years 2020–2100, each with 10 years. (Tinelli & Juran, 2019) used simulation models based on digital twin implementations to reduce water resource pollution through more precise and effective resource management.

#### 4.1.6 Augmented Reality and environmental sustainability

Augmented reality (AR) is a type of reality approximation in which physical items are connected to a virtual equivalent via contextual computer-generated information. AR has progressed from a science-fiction fantasy to a well-established scientific subject (Çakıroğlu et al., 2022). AR simultaneously stimulates several senses, including touch, hearing, and vision. This enables learners to overcome barriers, access various inaccessible locations, and actively participate in learning and teaching. It provides users with a sensation of presence and immediacy with the subject under investigation (Nincarean et al., 2013). Augmented reality is a technology that is becoming increasingly prevalent in a variety of aspects of our lives. From 2017 to 2019, 1119 articles were published in the SCOPUS database regarding augmented reality (Abad-Segura et al., 2020). The technology enables people to develop a more natural interface between humans and the physical environment, hence reducing the number of hardware devices we must carry (Fraga-Lamas et al., 2018).

As discussed In the simulation section, building energy performance simulation tools is the most widely used approach for modeling the energy performance of existing structures and evaluating various retrofit alternatives. Based on Energy Performance Augmented Reality (EPAR) modeling,(Ham & Golparvar-Fard, 2013) assessed and illustrated the differences between real and simulation results of the predicted energy performance of buildings. (Bekaroo et al., 2018) developed an Android augmented reality-based application named ARGY to help people better understand the energy use of electronic devices at home and in the workplace. Additionally, the program enables end-users to monitor the amount of energy spent by various devices, measure their energy efficiency, and get relevant suggestions and best practices to educate them about green practices. (Alonso-Rosa et al., 2020) developed an IoT energy device using augmented reality to easily visualize household appliance power quality

(PQ) parameters and energy usage in real time. Users simply need to point their smartphones at the appliance they are interested in to learn about the device's overall energy usage. (Mylonas et al., 2019) introduced a prototype incorporating augmented reality into a classroom exercise to help students learn about energy conservation of school buildings.

As the communication of product sustainability to customers is important, this space is still limited. That results in a lack of transparency, which is a primary challenge to environmentally friendly consumption (Trienekens et al., 2012). Augmented reality (AR) technology helps to enhance the actual environment with digital data and supports the decision-making process at the point of sale, as it provides high transparency over products' characteristics, including sustainability aspects (Javornik, 2016). AR-RAs (augmented reality-based recommendation agents) can be effective tools for directing consumers toward more sustainable purchasing decisions in the digital world and real-world physical shops. Customers choose more environmentally friendly products when they use this technology because it gives them information about the product's sustainability in a simple and contactless way (Joerß et al., 2021).

(Vikiru et al., 2019) developed an application based on AG that allows users to scan the barcode of any kind of waste (e.g., bottles, cans, bags) and it will direct the user to a list of links in which they have several options on how to manage the waste safely. (Somayaji et al., 2020) introduced a drone-based on augmented reality technology to navigate in the E-waste yards and assess the environmental impact of the dump yards. The findings indicated that there are few safety safeguards for workers at e-waste dump yards. The paper proposes a technique for remotely monitoring effluent levels in an e-waste disposal yard, minimizing human intervention in determining hazard levels, and providing staff with the opportunity to take appropriate safeguards.

(Theodorou et al., n.d.) assessed the impact of augmented reality applications to raise awareness of climate change by conducting a survey on 97 tourists on an island in Greece. The results showed that augmented reality technology reinforces tourists' cognitive abilities. Tourists that interacted with the augmented reality technology were responsive and showed an increase in knowledge, attitude, and desire to improve their behavior toward climate change. (K. Wang et al., 2021) evaluated the impact of an augmented reality game, P.E.A.R, in raising players' awareness of sustainability and climate change. The game dramatically enhanced players' awareness of sustainability, climate-change-related concerns, and numerous associated attitudes. According to a sample of 228 university professors, the use of AR in higher education in Saudi Arabia has the potential to have a significant positive impact on the country's environmental sustainability (Alahmari et al., 2019).

## 5 Conclusion and future research

### 5.1 Conclusion

This paper contributes to the literature by discussing the most relevant papers on the integration of industry 4.0 and environmental sustainability; the potential benefits of this combination, as well as the challenges expected, are discussed. If there is one lesson that could be learned from any new technology that appears in the modern world, it is that as many benefits as it might provide, a set of challenges and diverse outcomes come along with it. At this point, Industry 4.0 is an inescapable reality. Even if some communities may still doubt the enormity and significance of it, market leaders have already invested enormously in it, and eventually, most organizations will either jump on it or be left behind. However, it is crucial for decision-makers to monitor the expected results of I4.0, as these technologies can easily lead to controversial outcomes, as can be seen clearly in the energy management aspect. (Ahmad et al., 2021) explained precisely how AI/ML can help to manage and regulate energy planning and forecast demand and supply, which eventually will enhance energy production efficiency through real-time asset adjustments. On the other hand, (Cowls et al., 2021) acknowledged the benefits of AI on different aspects of environmental sustainability, but they highlighted that the development process of AI itself requires a tremendous amount of energy. What can be concluded is that if the implementation of Industry 4.0 is conducted with a disregard for the environment, it will potentially harm it more than it will protect it. The strategy for the implementation of the technological facilities should include the environmental aspect as one of the main objectives. The present SLR findings can be summarized as follows:

All six I4.0 technologies have the potential to reduce environmental sustainability impacts. I4.0 implementation for environmental preservation faces challenges, such as complexity, excessive energy usage, and massive data processing. Industry 4.0 technologies for energy management is the most discussed topic in this context. Several papers explain how these technologies can contribute to the increased use of renewable energy and energy efficiency. On the other hand, they can also be a reason for excessive energy usage.

**Table 2 Summary of Literature Review**

| I 4.0 technologies / Environmental impact | Internet of things | Artificial intelligence/ Machine learning | Additive manufacturing | Blockchain | Simulation | Augmented Reality |
|---|---|---|---|---|---|---|
| Waste management | (X. Xu & Yang, 2022), (X. Chen, 2022) | (Du et al., 2022), (Amin Amani & Sarkodie, 2022) | (Adaloudis & Bonnin Roca, 2021), (Jiang & Fu, 2020), (Ford & Despeisse, 2016), (Chen et al., 2015) | (Dey et al., 2022), | (Jia et al., 2017), (Naseri-Rad et al., 2022), (Burinskiene et al., 2018), . (Yeomans & Imanirad, 2012), (Ceschi et al., 2021), (Ojstersek et al., 2020) | (Vikiru et al., 2019), (Somayaji et al., 2020), |
| Energy management | X | (Zendehboudi et al., 2018), (J. Wang et al., 2020), (Chemali et al., 2018), (Coelho et al., 2017), (Mocanu et al., 2016), (Yang et al., 2019), (Bose, 2017), (Batista et al., 2017), (Ahmad et al., 2021) | (Adaloudis & Bonnin Roca, 2021), . (Weng et al., 2020), (Ford & Despeisse, 2016), (Chen et al., 2015), (Mele & Campana, 2022), (Wu et al., 2022) | (Strepparava et al., 2022), | (Ojstersek et al., 2020) | (Ham and Golparvar-Fard, 2013), . (Bekaroo et al., 2018), (Alonso-Rosa et al., 2020), (Mylonas et al., 2019 |
| Resource efficiency | (Hu et al., 2022) | (Zendehboudi et al., 2018), (Narciso & Martins, 2020), (Shaw et al., 2022) | (Ford & Despeisse, 2016), (Mele & Campana, 2022) | X | X | X |
| Gas emission reduction | X | X | (Weng et al., 2020), (Freitas et al., 2016), (Ford & Despeisse, 2016), (Chen et al., 2015), (Wu et al., 2022) | X | (Sha Liu et al., 2022) | X |
| Spread of awareness on environmental sustainability | X | X | X | X | (Capellán-Pérez et al., 2019) | (Trienekens et al., 2012)(Joerß et al., 2021), (Theodorou et al., n.d.), (Wang et al., 2021), (Alahmari et al., 2019). |
| Natural resources pollution | X | (Salem et al., 2022) | X | X | (Tinelli & Juran, 2019) | X |
| Climate change | X | X | X | X | (Capellán-Pérez et al., 2019) | (Theodorou et al., n.d.) , (Wang et al., 2021) |
| Circular economy | (Turner et al., 2022) | X | (Machado et al., 2019 | (Erol et al., 2022), (Kouhizadeh et al., 2019) | (Abadías Llamas et al., 2019) | X |

One of the most well-known uses of AI/ML is the optimization of resources and energy management. The use of AG does not have a direct impact on environmental sustainability; it provides an opportunity for spreading awareness visually. Still, the role of AG is crucial, as was mentioned earlier; lack of knowledge is regarded to be one of the most significant challenges to the adoption of environmentally friendly practices (O'Neill and Oppenheimer, 2002). IoT provides critical features that can achieve effective waste management. The summary of the literature review is presented in Table 2.

### 5.2 Future research

Industry 4.0 is a fertile ground for research, and it provides several business opportunities. Despite the fact that the scientific world has demonstrated a high interest in all aspects of Industry 4.0 in the last five years, the use of technological facilities for environmental purposes still contains many gaps. Future research should focus on:

Reviewing one aspect of environmental sustainability with each I4.0 technology with a high emphasis on energy management because there are many contradictory findings. Furthermore, the research should review each sector separately as each market/case has its own set of challenges and impediments that cannot be generalized.

There is a lack of concrete study cases of organizations that implemented I4.0 for environmental purposes. A study that focuses on successful implementation in a specific industry and projects it on the different common challenges in that industry is needed.

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