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Industry 4.0 technologies in the manufacturing sector: Are we sure they are all relevant for environmental performance?

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Abstract

This research contributes to the debate about the relevance of Industry 4.0 technologies in improving environmental performance in the manufacturing industry. We employed a qualitative–quantitative approach in which 19 Italian operations managers were interviewed and 260 managers responded to an online questionnaire. The effects of various technologies were ranked using ordinal regression. Comments and suggestions gave context to the quantitative results. Sensors, radio-frequency identification, artificial intelligence and analytics were found to be most relevant in improving environmental performance, whereas simulation software contributed moderately. Additive manufacturing, cobots, robots, automated mobile robots and automated guided vehicles had a negative effect, augmented reality had no effect and other technologies indirectly affected environmental performance. We also found a lack of knowledge and application as well as scepticism about technologies such as artificial intelligence and augmented reality. Finally, there was concern about the disposal of electrical and electronic waste produced by these technologies.

KEYWORDS

cybertechnology, environmental performance, Industry 4.0, smart technology

1 | INTRODUCTION

First introduced by the German government in 2011, the term Industry 4.0 (i4.0) is synonymous with the Fourth Industrial Revolution (Kagermann et al., 2011). i4.0 refers to cyberphysical systems (CPS) and smart technologies capable of integrating machines, shop floor and business processes, customers, end users and the supply chain as a whole. Smart technologies and CPS, assisted by artificial intelligence (AI) software, enable processes and machines to autonomously exchange information via the Internet of Things (IoT), activate actions, make decisions and control each other independently (Kagermann et al., 2013).

This digital industrial revolution represents the dawn of a new era for manufacturing companies worldwide, which may use i4.0 technologies in their strategic plans to improve performance related to costs, quality, productivity, scheduling and customisation of products and services (Chiarini et al., 2020). In a period in which environmental concerns are growing daily, the manufacturing industry is embracing i4.0 technologies. Consequently, i4.0 has been studied for its effects on environmental performance and its potential to create more environmentally friendly businesses (Bonilla et al., 2018; Oláh et al., 2020).

Nevertheless, it is well known that each industrial revolution has also endangered the environment. During the First Industrial Revolution, for instance, the United Kingdom suffered terrible air pollution from the burning of coal, whereas other industrial revolutions have led to severe environmental impacts such as resource consumption, waste and carbon emissions. We could think about the use of some plastics considered at the beginning as a revolution in terms of costs and quality characteristics but now a great concern for the environment (Biod et al., 1994; Bos-Brouwers, 2010; Pazienza & De

Lucia, 2020). Therefore, while we may be confident about the positive effects of i4.0 on cost reduction, quality and service, the jury is still out about the pros and cons of adopting i4.0 technologies for improving environmental performance, despite the positivity of a number of authors. i4.0 proposes and integrates a range of technologies, from additive manufacturing, smart sensors, autonomous mobile robots, augmented reality and artificial intelligence, to name but a few. Each of these technologies could affect environmental performance in some way, positively but also negatively. For instance, these technologies are ultimately based on electronic components, and it is well-known how discharged electronic equipment often contain chemicals that are harmful to people and the environment (Liao et al., 2013; Luan et al., 2013; Rodgers, 1995), not to mention the exploitation of workers and mines in certain areas of Africa (Amoah & Eweje, 2021; Idemudia et al., 2020; Kemp et al., 2021) due to rare raw materials. Therefore, we need to identify the potential i4.0 technologies affecting environmental performance and second rank the contribution of these technologies to the performance.

To the aim, we studied a sample of Italian manufacturing companies that had implemented i4.0 technologies in the previous 3 years and were committed to fostering a range of strategies to reduce their environmental impact. In terms of manufacturing, Italy is the second largest country in Europe and sixth in the world. At the end of 2016, the Italian Ministry of Economic Development launched the 'Industria 4.0 National Plan', a government-funded initiative to incentivise Italian companies to invest in new cybertechnologies. Given that the plan has been widely used by Italian manufacturing companies, we believe that our sample of Italian manufacturing companies possessed the relevant characteristics to answer the following research questions:

RQ1. What are the main relevant Industry 4.0 technologies used by manufacturing companies to improve their environmental performance?

RQ2. To what extent do these technologies contribute to the overall environmental performance of manufacturing companies?

To answer these questions, we employed a qualitative–quantitative inquiry, first interviewing a panel of 19 operations manager experts in both i4.0 and environmental management and then creating an online questionnaire based on a Likert scale, to which 260 managers responded. We developed an ordinal regression model to rank the different effects of these technologies on overall environmental performance. Qualitative notes from the interviewees and questionnaire respondents provided further context to the quantitative model. By such means, we analysed and discussed relevant suggestions made by experts and respondents, capturing other important issues for further research.

The remainder of this paper is structured as follows. The following section provides an overview of i4.0 technologies and a review of the literature. Then, the methodology and qualitative and quantitative results are presented. The results, along with comments and suggestions made by interviewees and respondents, are then discussed. The paper concludes with a recap of the findings and a comparison with those in the literature, highlighting novelties, limitations and avenues for further research.

2 | İ4.0 TECHNOLOGIES AND ENVIRONMENTAL SUSTAINABILITY

Ample literature has been dedicated to i4.0 applications and new technologies from both managerial and technological perspectives. These new technologies are often referred as 'cyber' or 'smart' technologies, whereas CPS refers to complex systems that integrate computation, communication and physical processes (Wang & Wang, 2016). At the heart of i4.0 is the so-called 'smart factory', which involves the integration of i4.0 technologies in manufacturing factory processes (Chen et al., 2017; Hozdić, 2015; Shi et al., 2020). i4.0 may be considered a business model based on the horizontal integration of CPS and smart technologies, vertical integration, in which big data collected from the shop floor and supply chain are managed through the different levels of the business, and end-to-end integration across the entire product life cycle (Chiarini et al., 2020).

i4.0 is based on various technologies; however, because these technologies have different names and often overlap, there is no unanimous consensus on how they should be classified. i4.0 technologies typically implemented in the manufacturing sector include the Industrial Internet of Things (IIoT), the cloud, automated mobile robots (AMR), autonomous guided vehicles (AGV), collaborative robots (cobots), analytics and AI, simulation, smart sensors and products, radio-frequency identification (RFID), additive manufacturing and augmented reality (Dalenogare et al., 2018; Hermann et al., 2016; Indri et al., 2019; Kostrzewski et al., 2020). Table 1 shows the key i4.0 technologies used in the manufacturing context along with their functions.

i4.0 technologies have the potential to address environmental issues such as environmental sustainability (Bag et al., 2018; Stock & Seliger, 2016), the circular economy (Massaro et al., 2020) and green processes (Vrchota et al., 2020). Some authors have begun exploring i4.0 technologies in terms of environmental management and sustainability. Stock and Seliger (2016) were among the first to study i4.0 technologies and environmental practices as a whole, claiming that i4.0 can improve the efficient allocation of resources such as water, energy and raw materials. Similarly, de Sousa Jabbour et al. (2018) concluded that i4.0 technologies have the potential to improve current manufacturing processes in terms of environmental management.

A first interesting line of inquiry is the ability of i4.0 technologies to reduce energy consumption. For example, Shrouf and Miragliotta (2015), Müller et al. (2018) and Said et al. (2020) confirmed the overall positive effect of i4.0 technologies interconnected through the IoT on energy use. Baccarelli et al. (2017) and Valerio et al. (2018) found that a particular type of software based on AI known as 'fog computing' is a possible solution for improving energy efficiency. Mohamed et al. (2019) conducted a more in-depth analysis

TABLE 1 Industry 4.0 key technologies

Industry 4.0 technology	Functions
Smart sensors and RFID	Electronic equipment used to identify resources and measure processes, which may be embedded or installed in machines, products, tools, assembling stations, logistics vehicles, etc. (Lasi et al., 2014). Has the possibility to measure process parameters or specific events and communicate with software systems (Petrov et al., 2019)
Industrial Internet of Things	Machines, electronic components, equipment and people are connected and synchronised with each other through software modules (e.g., enterprise resource planning modules and AI) and internet architecture (Gilchrist, 2016)
Cloud computing	On-demand availability of computer resources such as data storage, databases, software applications, etc. (Kumar et al., 2019)
AI and data analytics	AI is technology designed to emulate human brain analysis, learning and making assumptions. Divided into machine learning and deep learning. Data analytics are technologies used to analyse and identify data patterns and predict and make assumptions, often based on AI (Reavie, 2018)
Big data	A huge amount of data and information collected through the IoT by means of smart sensors, RFID, machines, computers, software, etc. Big data are usually stored in the cloud and managed through AI and analytics (Mikalef et al., 2019)
Collaborative robots (cobots)	Cobots enable closer work between people and robots and are intrinsically safe (Franklin et al., 2020)
AMRs and AGVs	Autonomous vehicles are used for production logistics activities. AMRs are typically used in assembly lines and AGVs for transportation and loading. AGVs need a precise path (Lee & Na, 2007)
Augmented reality	Technology that allows operators to view real processes (Esengün & İnce, 2018) overlaid by digital augmentation
Additive manufacturing	Also known as 3D printing, additive manufacturing enables the layer-upon-layer production of a three-dimensional object from a digital file (Kietzmann et al., 2015)
Simulation	Digital twin software that can obtain data from real processes by simulating the actions of these processes (Gunal, 2019)

Abbreviations: AGV: autonomous guided vehicle; AI: artificial intelligence; AMR: autonomous mobile robot; RFID: radio-frequency identification.

of the effect of i4.0 technologies on energy consumption, concluding that it depends on factors such as the type of process or technology and, above all, how the manufacturing factory collects and analyses data and acts on the processes.

da Silva et al. (2020) reviewed the literature on i4.0 and energy management, identifying a range of approaches to managing, monitoring and predicting energy consumption. Fifteen of the reviewed articles involved studies on sensors interconnected through the IoT, while others dealt with simulation tools, AI algorithms (Bag et al., 2021) and other approaches not classified as i4.0 technologies. Several authors (Baccarelli et al., 2017; Faheem & Gungor, 2018; Lin et al., 2016; Mohamed et al., 2019; Qin et al., 2017; Sherazi et al., 2018; Shrouf et al., 2014) used smart sensors connected through the IIoT to gather energy-related data. However, not all authors agree on i4.0 technologies as a vehicle for improving energy efficiency. Wang et al. (2015, 2016) and Waibel et al. (2017) argued that smart factories using massive electronic equipment will use more energy and resources compared with current factories, negatively affecting the environment.

Although it has been studied less from a managerial point of view, another interesting line of inquiry is the disposal of industrial waste. Qian et al. (2017) highlighted the need for studies on the generation and management of waste, including waste water, solid wastes and chemical and hazardous materials, and systems based on sensors, RFID and other technologies to identify, control and track down waste. Nascimento et al. (2019) recommended the use of a circular economy model for waste management, particularly the reuse of scrapped electronic devices. They found that i4.0 technologies, particularly the cloud and additive manufacturing, can improve business sustainability through the reuse of waste in the supply chain to manufacture products on demand. Some authors consider additive manufacturing a key technology in the conservation of resources such as raw materials (Achillas et al., 2015; Peng et al., 2018; Wang et al., 2016) and reduction of greenhouse gas emissions (Huang et al., 2016). Based on the results of a systematic literature review, Kamble et al. (2018) proposed an i4.0 technology framework in terms of improving sustainability. According to the authors, i4.0 technologies have been studied for their potential to reduce production waste and energy consumption. However, in line with other studies, Kamble et al. (2018) found that the extensive use of sensors and smart equipment could increase energy consumption. They also argue that there is a lack of inquiry regarding waste management and technologies for the identification and traceability of waste, but that additive manufacturing could conserve resources in terms of materials for making products.

This literature review shows that scholars and practitioners have started analysing relationships between i4.0 technologies and environmental management. In the manufacturing sector specifically, some companies are implementing solutions based on smart sensors and AI, especially for improving energy consumption, while others are focusing on additive manufacturing to conserve and reuse resources. Although some companies are implementing i4.0 technologies to address waste management, it is unclear what kind of i4.0 technologies may assist with this or with air and water pollution. On this uncertain ground, there are also authors who believe that i4.0 technologies may have a negative effect on environmental performance.

Notably, no author has attempted to determine the degree of importance of each technology in contributing to the overall environmental performance of manufacturing companies. Therefore, the aforementioned issues were translated into open questions asked during the semistructured interviews in the qualitative stage of study.

3 | METHODOLOGY

This research was based on a sequential mixed methods design combining qualitative and quantitative methods in triangulation (Raturi & Jack, 2006). During the first qualitative phase, semistructured interviews were conducted with a sample of 19 operations manager. The results of this phase were used to develop the quantitative phase, which involved a survey for quantitative data collection. In other words, we conducted an initial exploration of the research topic to generate variables for measurement. This approach is typically adopted when variables are unknown and there is no pre-existing theory or model to use as a guide. The main purpose was to evaluate the possibilities for generalising the qualitative findings to a larger sample.

3.1 | The qualitative phase

The initial qualitative phase involved conducting semistructured interviews with a sample of expert managers from Italian manufacturing companies. Given the lack of consensus on the appropriate sample size for qualitative inquiry, we followed the concept of data saturation (Guest et al., 2006), which refers to the point at which no new information or themes emerge from the data. We interviewed 19 operations managers from 19 manufacturing companies. To generate a sample of companies with similar environmental impacts and i4.0 technologies, companies were selected based on the following characteristics:

- located in the business-to-business manufacturing sector, which provides products to other companies rather than to individuals;
- potential for product customisation through both traditional and additive manufacturing;
- having a typical discrete manufacturing process, which implies the use of both assembly lines and machines;
- the absence of large capital-intensive machines typical of process manufacturing industries such as the chemical, pharmaceutical, refinery, iron and steel industries;
- implementation of i4.0 technologies in the previous 4 years;
- implementation of an International Organization for Standardization (ISO) 14,001 management system with third-party certification of compliance;
- highly committed to environmental management, with specific strategic plans dedicated to improving environmental performance; and
- more than 50 employees.

Table 2 shows the main characteristics of the 19 companies in terms of their products and dimensions.

The names of the 19 managers were derived from an Italian consultancy company specialising in operations management. All managers selected had strong expertise in both environmental management and i4.0 and had used an environmental management system for at least 5 years. All managers had participated as team members in i4.0 implementation projects and had attended several courses on the topic in recent years.

Operations managers were interviewed using a semistructured questionnaire with the following four open-ended questions based on the results of the literature review:

- What kinds of Industry 4.0 technologies are you using for improving energy consumption performance and with what results?
- What kinds of Industry 4.0 technologies are you using for improving the utilisation of resources (recycling, reusing, circular economy) and with what results?
- What kinds of Industry 4.0 technologies are you using for improving waste management, air and water pollution and with what results?
- Do you believe that there could be some drawbacks in terms of environmental impacts using these new Industry 4.0 technologies?

Each interview lasted 35–50 min and was digitally recorded. Thematic content analysis was used for analysis and coding, leading to the identification of a set of theoretical themes. All i4.0 technologies shown in Table 1 were examined and discussed with the managers during the interviews in terms of how they may help the company achieve its environmental goals. Table 3 shows each technology along with the coded theoretical themes that emerged from discussions with interviewees. It may be seen that not all technologies listed in Table 1 were considered relevant to improving company environmental performance.

The 19 operations managers unanimously agreed that smart sensors, AI and analytics were means of improving environmental performance; however, there was less consensus about the other technologies. Cobots, traditional robots, AGV and AMR were perceived to potentially worsen environmental performance in terms of electricity consumption. Additive manufacturing and simulation were believed to have moderate effects on environmental performance, while the effects of augmented reality were largely unknown. Some technologies were not considered direct means of improving environmental performance—for instance, the cloud, the IIoT and big data had to be combined with or support other technologies. During the transcription and analysis of interviews, several other interesting comments were found, which are discussed along with quantitative results and other notes in the discussion section.

3.2 | The quantitative phase

In the second, quantitative phase of the research, we attempted to test i4.0 technologies by transforming them into variables and consequently into hypotheses. Given that the 19 managers considered the

TABLE 2 Characteristics of companies involved in the first phase

Company	Product	Turnover	No. employees
1	Automotive interior components	€110 M	350
2	Bike components	€42 M	180
3	Drip irrigation components	€140 M	400
4	Gearboxes	€14 M	60
5	Heaters and boilers	€85 M	220
6	Hydraulic integrated circuits	€28 M	105
7	Hydraulic pumps	€260 M	800
8	Industrial vibrators	€38 M	150
9	Lift components	€102 M	300
10	Lightning products	€110 M	250
11	Mechanical rollers	€18 M	55
12	Medical devices	€32 M	100
13	Medical devices	€12 M	60
14	Motorcycle components	€70 M	210
15	Motorcycle components	€72 M	190
16	Oil and gas components	€20 M	80
17	Plastic valves	€25 M	90
18	Power transmissions	€55 M	200
19	Tractor components	€23 M	120

TABLE 3 Theoretical themes from the interviews

Industry 4.0 technology	Theoretical themes from the interviews
Smart sensors and RFID	Unanimous agreement (19/19) that this technology is relevant to collecting data and controlling and improving environmental performance in terms of energy, waste and air and water pollution. Few interviewees (3/19) believed that this technology could improve recycling and reuse of resources. Twelve interviewees were concerned about the future disposal of this type of electronic equipment
Industrial Internet of Things (IIoT)	Strong agreement (17/19) that the IIoT is not a direct means of addressing environmental issues but provides the infrastructure and backbone for i4.0 technologies
Cloud computing	Unanimous agreement (19/19) that cloud computing is simply a way to store big data collected from processes through the IoT. Fourteen interviewees believed that AI and analytics should be used to store and retrieve environmental data from the cloud
AI and data analytics	All interviewees (19/19) believed that AI and analytics were fundamental in the analysis and prediction of environmental impacts in general (e.g. waste, air, water, resources)
Big data	Strong agreement (16/19) that big data are not a direct means of addressing environmental issues but are the foundation for AI and analytics; environmental big data must be collected using smart sensors and CPS
Collaborative robots (cobots) and robots	The majority of interviewees (14/19) considered this technology to have little relevance in improving environmental management. Some (8/19) believed that it could increase electricity consumption
AMRs and AGVs	Some interviewees (6/19) believed that AMRs and AGVs could have a moderate effect on energy consumption if used to replace electric forklift vehicles. Others (9/19) believed they could increase electricity consumption and generate electronic waste
Augmented reality	Few respondents (3/19) believed that augmented reality would have a moderate effect on preventing environmental issues when used for equipment maintenance. Sixteen interviewees declared that they did not know the technology well
Additive manufacturing	Two of 19 interviewees believed that additive manufacturing could have a moderate effect on improving air pollution. Fifteen interviewees believed it could be similar to traditional manufacturing machines in terms of its environmental impacts
Simulation	Eleven of 19 interviewees believed that simulation could have a moderate effect on improving resource utilisation and predicting environmental incidents

Abbreviations: AGV: autonomous guided vehicle; AI: artificial intelligence; AMR: autonomous mobile robot; CPS: cyberphysical systems; RFID: radio-frequency identification.

cloud, the IIoT and big data to have only indirect effects on environmental performance, these were excluded from analysis. For each remaining i4.0 technology, we assessed the level of agreement in terms of its effect on environmental performance based on a 7-point Likert scale (7 = *entirely agree*; 6 = *mostly agree*; 5 = *somewhat agree*; 4 = *neither agree nor disagree*; 3 = *somewhat disagree*; 2 = *mostly disagree*; 1 = *entirely disagree*). For instance, the question for the first technology, smart sensors and RFID, was as follows:

Q1. Do you think that smart sensors and RFID are relevant in improving the overall environmental performance of your company?

The operationalised variable for this question was expressed as *SENSORS*. The other operationalised variables for the quantitative phase were expressed as *AI*, *COB/ROB*, *AMR/AGV*, *AUGMENT*, *ADDITIVE* and *SIMUL* for artificial intelligence, cobots/robots, AMR/AGV, augmented reality, additive manufacturing and simulation, respectively.

To avoid sampling bias, we began by identifying Italian manufacturing companies that had implemented i4.0 technologies along with their distribution. An Italian Ministry of Economic Development (MISE, 2018) survey of 23,000 Italian companies that had implemented i4.0 technologies showed that 47.1% of manufacturing companies were large companies with more than 250 employees, 35.5% had between 50 and 249 employees, and 17.4% of companies had fewer than 50 employees. The survey also found that small companies were less inclined to invest in i4.0. In light of these results and given that we did not include small companies in the first phase, we used stratified random sampling (Antonius, 2003) to create a sample comprising around 57% large companies and 43% medium-sized companies, with small companies excluded.

The we identified a sample of potential Italian manufacturing companies committed to environmental management. We selected 6000 of 25,000 companies from the Accredia (2020) database, which includes ISO 14001-certified Italian companies. These 6000 companies shared similar characteristics with the previous 19 companies; specifically, they were in the business-to-business manufacturing sector, used a typical discrete manufacturing process, were characterised by the absence of large capital-intensive machines and had more than 50 employees. Being ISO 14001 certified implied that they were required to establish environmental goals and attempt to improve their environmental performance (Arocena et al., 2020; Chiarini, 2019; Heras-Saizarbitoria et al., 2020).

We created an online questionnaire for the operations managers of these companies, explicitly stating on the first page that the questionnaire was intended for companies that had implemented i4.0 technologies in the previous 3 years. To this end, we asked operations managers to rank their level of i4.0 implementation on a 4-point scale (1 = *very poor*; 2 = *poor*; 3 = *fair*; 4 = *good*). Moreover, we asked them about the number of employees of the company and sector. Of the 492 completed questionnaires, 186 were excluded because the respondents declared that the level of i4.0 implementation had been either poor or very poor, leaving 306 completed questionnaires (194 from large companies and 112 from medium-sized companies). To retain the proportion of 57% large companies and 43% medium-sized companies, we randomly excluded 46 questionnaires from large companies. The final sample comprised 148 large companies (56.9%) and 112 medium-sized companies (43.1%) for a total of 260 manufacturing companies. Table 4 shows the distribution of the companies in the sample according to industry.

Given that our 7-point Likert scale was based on ordinal dependent variables and the key technologies were categorical independent variables, we employed ordinal regression. According to Rawat (2018), the ordinal regression model provides more reliable estimates when we analyse ordinal data. Amongst the cons of using this model, we should conduct the Brand Test to test that the relationship between each pair of outcomes is the same. In case of violation of this assumption, we need to change the ordinal regression model with different separate models. Thus, ordinal regression allowed us to investigate and predict the level of agreement (from 1 to 7) regarding the influence of i4.0 technologies on environmental performance and identify which of our independent variables (if any) had a statistically significant effect on our dependent variable (Agresti, 2002). SPSS was used to conduct ordinal regression. Table 5 shows the cross-tabulation results.

Table 5 shows that the variable *SENSORS* had the highest number of ratings for 6 (*mostly agree*) and 7 (*entirely agree*), whereas *AMR/AGV* had the highest number of ratings of 1 (*entirely disagree*) and 2 (*mostly disagree*). Moreover, there were no empty cells, increasing the goodness of fit (Agresti, 2002).

Table 6 shows the ordinal regression results. Using SPSS, we calculated the coefficients and their standard errors and conducted the Wald test to find their associated p values and 95% confidence interval of coefficients. Apart from *AUGMENT*, all variables were statistically significant ($p < .05$). According to the SPSS results, *SIMUL* was equal to 0 and thus was used as the reference variable. Given that the categorical independent variables *SENSORS* and *AI* were estimated

TABLE 4 Number and industry of companies in the sample

Industry	No.
Tools for wood machines	2
Industrial compressors	8
Dispensers	12
Components for agricultural machines	17
Medical disposables	18
Electrical and optical equipment	18
Equipment for mechanical machines	26
Pneumatic components	27
Electronic equipment	36
Basic metal and fabricated metal products	42
Automotive and motorcycle components	54
Total	260

TABLE 5 Variable–rating cross-tabulation

Variable	Rating 1	2	3	4	5	6	7	Total
ADDITIVE	16	4	24	130	62	18	6	260
AI	2	16	20	22	40	70	90	260
AMR/AGV	68	96	62	12	4	16	2	260
AUGMENT	16	14	24	66	80	38	22	260
COB/ROB	50	72	78	38	4	16	2	260
SENSORS	4	4	6	10	20	98	118	260
SIMUL	14	14	38	46	78	48	22	260
Total	170	220	252	324	288	304	262	1820

Note: *ADDITIVE* = additive manufacturing; *AI* = artificial intelligence; *AMR/AGV* = autonomous mobile robot/autonomous guided vehicle; *AUGMENT* = augmented reality; *COB/ROB* = cobots/robots; *SENSORS* = sensors and radio-frequency identification; *SIMUL* = simulation.

TABLE 6 Ordinal regressions, parameter estimates

		Estimate	*SE*	Wald	*df*	Sig.	95% CI Lower	95% CI Upper
Rating	1	−3.556	0.213	278.104	1	.000	−3.974	−3.138
	2	−2.327	0.187	155.414	1	.000	−2.692	−1.961
	3	−1.252	0.169	55.054	1	.000	−1.583	−0.922
	4	−0.087	0.160	0.294	1	.587	−0.400	0.226
	5	0.946	0.165	32.851	1	.000	0.622	1.269
	6	2.340	0.189	153.826	1	.000	1.971	2.710
Variable	*ADDITIVE*	−0.468	0.220	4.527	1	.033	−0.900	−0.037
	AI	1.442	0.227	40.259	1	.000	0.996	1.887
	AMR/AGV	−2.739	0.241	129.092	1	.000	−3.211	−2.266
	AUGMENT	−0.050	0.219	0.052	1	.820	−0.480	0.380
	COB/ROB	−2.255	0.234	92.635	1	.000	−2.714	−1.796
	SENSORS	2.241	0.239	88.147	1	.000	1.773	2.709
	SIMUL	0[a]	–	–	0	–	–	–

Note: *ADDITIVE* = additive manufacturing; *AI* = artificial intelligence; *AMR/AGV* = autonomous mobile robot/autonomous guided vehicle; *AUGMENT* = augmented reality; *COB/ROB* = cobots/robots; *SENSORS* = sensors and radio-frequency identification; *SIMUL* = simulation. Link function: logit.
[a]This parameter is set to zero because it is redundant.

as being greater than 0, it is likely that our respondents perceived that these variables would have a greater effect than *SIMUL* on environmental performance. In contrast, *ADDITIVE*, *AMR/AGV* and *COB/ROB* were negative, implying that they were perceived as having less influence compared with *SIMUL*.

For the logit link function, taking the exponential of the estimate will generate a cumulative odds ratio, providing a better interpretation of the magnitude of this comparison. Table 7 shows the exponential of each estimate apart from *AUGMENT*, which was not statistically significant, ordered from the highest to the lowest in comparison with the reference variable *SIMUL*.

We also conducted a test of parallel lines, also known as Brand Test, shown in Table 8. The assumption of this test is that the effects of any independent variable are consistent (proportional) across the seven different thresholds (Strand et al., 2011). In other words, the different technologies will have the same effect on the odds, regardless of their Likert values. Given that $p > .05$, we can accept the assumption of proportional odds.

Finally, we performed a test concerning the so-called common method bias. For this study, we were particularly interested in the potential source of common method bias which leads respondents to the propensity to maintain consistency in their responses to questions (Podsakoff et al., 2003, p. 882). The test has been performed by means of a factor analysis. Table 9 shows the results of this test.

The eigenvalue in the second total column is a measure of how much of the variance of the variables each of the seven technologies explains. The percentage of variance of the third column demonstrates that the first technology accounts for less than 50%. That means that common method bias does not affect the results.

TABLE 7 Cumulative odds ratio of the estimate values

Variable	Odd ratio
SENSORS	Exp (2.241) = 9.403
AI	Exp (1.442) = 4.229
SIMUL	Exp (0) = 1
ADDITIVE	Exp (−0.468) = 0.626
COB/ROB	Exp (−2.255) = 0.105
AMR/AGV	Exp (−2.739) = 0.065

Note: *SENSORS* = sensors and radio-frequency identification; *AI* = artificial intelligence; *SIMUL* = simulation; *ADDITIVE* = additive manufacturing; *COB/ROB* = cobots/robots; *AMR/AGV* = autonomous mobile robot/autonomous guided vehicle.

TABLE 8 Test of parallel lines

Model	−2 log likelihood	Chi-square	Sig.
Null hypothesis	290.466	–	–
General	254.186	36.280	.199

Each question in the online questionnaire had a space for comments and suggestions regarding the technology being addressed. Along with the data from the 19 semistructured interviews, this embedded qualitative component provided useful information for interpretation, giving more context to the quantitative results.

4 | ANALYSIS AND DISCUSSION

Hereafter, we refer to the 19 interviewed operations managers in the first phase as *interviewees* and the 260 operations managers who answered the online questionnaires in the second phase as *respondents*. Participants in both samples made interesting comments, which were analysed and interpreted along with the quantitative results.

4.1 | Smart sensors and RFID utilisation

From a statistical perspective, it appears that the use of smart sensors and RFID (*SENSORS*) may have a stronger influence on environmental performance compared with all other technologies (see Tables 6 and 7). To provide more context to this result, we analysed comments made by both interviewees and respondents. Respondents made no fewer than 48 comments, using similar words to highlight the potential of this technology in terms of environmental management. Moreover, as shown in Table 3, the 19 interviewees unanimously agreed with the relevance of this technology.

According to the results of the study of Qian et al. (2017), in 31 of the 48 comments from respondents and 16 from interviewees, participants stated that they have implemented or are going to implement RFID and smart sensor solutions for waste management. One respondent commented:

TABLE 9 Common method bias

Component	Initial eigenvalues		
	Total	% of variance	Cumulative %
1	3.478	49.686	49.686
2	1.287	18.386	68.071
3	1.173	16.757	84.829
4	0.640	9.143	93.971
5	0.265	3.786	97.757
6	0.144	2.057	99.814
7	0.013	0.186	100.000

> We identified all our waste bins by categories such as scrap metal, oil, chemicals, packaging materials, etc. by means of RFID tags. We are now able to identify each track waste bin and its content within the factory. The RFID tag is written with the right amount of weight every time the bin is filled. When the lorry empties the bin, the tag is read, and we know the exact amount inside. Moreover, we have reduced mistakes in terms of contamination with other kinds of waste and increased recycled quantities. One manager is in charge of controlling the amounts per week and per month trying to reduce this impact over time.

With respect to waste management, 17 respondents and 10 interviewees also believed that smart sensors and RFID could be useful in managing hazardous waste, consequently assisting in meeting health and safety management goals.

The use of smart sensors for energy management was the second most relevant application. As demonstrated in the literature (Baccarelli et al., 2017; da Silva et al., 2020; Faheem & Gungor, 2018; Lin et al., 2016; Mohamed et al., 2019; Qin et al., 2017; Sherazi et al., 2018; Shrouf et al., 2014), smart sensors are employed to monitor machinery energy use and reduce operating costs of the factory as a whole. We found 28 comments from respondents and 19 from interviewees describing how they had implemented smart solutions to monitor power usage, alarms in case of overconsumption and smart systems that moved energy consumption to low-demand periods. However, in disagreement with the literature, it is interesting to note that many respondents and interviewees considered smart sensors limited in their ability to reduce energy consumption. For instance, one interviewee stated:

> Smart sensors are intelligent meters that can collect many data from the shop floor and give us many signals regarding energy consumption. However, their ‘intelligence’ is limited. We are trying to develop machine learning and analytics software to figure out patterns within this huge amount of data and information.

Hence, the ideal solution may be the integration of smart sensors and AI software in a more efficient and evolved CPS.

Moreover, according to the comments of 10 respondents and 13 interviewees, smart sensors may assist in real-time pollution monitoring systems, with alarms signalling excessive pollution levels or leaking. There were no comments regarding the use of AI software to analyse and predict specific situations.

Finally, it is worth mentioning that seven respondents and 12 interviewees mentioned potential problems in terms of waste of electrical and electronic equipment (WEEE). Similarly, these managers declared that sensors, RFID, electric and electronic cables, computers and other equipment represented the most rapidly growing waste in their companies. This implies an increase in costs to comply with strict European Union directives such as WEEE and the Restriction of Hazardous Substances (RoHS) in electrical and electronic equipment.

4.2 | AI and analytics

The quantitative results show that AI was considered the second most effective technology to improve environmental performance. This finding was supported by respondent and interviewee comments. For instance, 41 comments indicated that AI is fundamental for analysing and finding patterns in data, predicting environmental impacts and reducing energy, and resource use, thus, is the quintessential software for environmental management. Bag et al. (2021) came to a similar conclusion. However, although this technology was considered highly relevant, we found some hindrances in its application. Fourteen respondents declared that it was difficult to find appropriate and personalised AI software aimed at environmental management. For instance, one respondent stated:

> I have read a lot and attended several courses about AI because I would like to find a supplier able to develop some analytics software for managing our environmental data. Unfortunately, I have only found off-the-shelf software, especially for energy management, but we need a complete customised solution.

Four other respondents stated that they had no idea how to implement AI software for managing environmental data, whereas 19 respondents were worried about how to introduce such a technology. Interestingly, one respondent wrote:

> When it comes to us[ing] an AI software for environmental data, it is a very complex and expensive business. First, you have to understand what kind of data and information you need, and we are talking about big data given the incredible number of sensors and other ways of collecting data over the IIoT. Secondly, you need to understand technologies behind AI, such as cloud, database and how to handle these big data. It could be machine learning or deep learning, and there are several different solutions. Finally, yet importantly, someone inside the company has to able to use the software and interpret the results. We are working in collaboration with a PhD student of the local university because we do not have any internal competency.

We also found some scepticism about the implementation of AI. Eight respondents, for instance, used similar words to explain that AI software may be useless for environmental management. They believed that in extreme conditions such as the emission of harmful gases, there was nothing better or faster than human problem solving. One respondent, for instance, highlighted that it was just a matter of having a prompt alarm, which did not necessitate the use of AI software.

4.3 | Simulation

Several interviewees and respondents considered that software used to simulate production processes may benefit company environmental performance in some way. Comments from 11 interviewees and 36 respondents highlighted that simulation could have a moderate effect in terms of reducing resource use and preventing potential environmental incidents. However, similar to the comments made about AI, we found a certain scepticism and uncertainty with respect to this particular technology. Although the majority of comments were positive with respect to the potential of production process simulation to save energy and resources in general, finding software to prevent potential environmental incidents appeared difficult. For instance, one interviewee stated:

> We bought an expensive digital twin software, which helps us in simulating cycle times, electricity equipment consumption along with raw material use. However, we are not able to simulate conditions which could lead to environmental impacts such as leaking, too much waste, explosions, etc. To do this we still rely on our manual risk analysis and alarms.

In relation to this, other respondents once more referred to the possibility of using AI software to analyse data and predict environmental events. However, according to the comments, there appears to be a lack of this kind of software and related knowledge.

4.4 | Additive manufacturing

Tables 6 and 7 show that additive manufacturing was considered to have a relatively low negative impact on environmental performance. The exponential value of .626 is low, and Table 4 shows that exactly half the respondents (130) answered this question with a 4 (*neither agree nor disagree*). Thus, it appears that respondents were uncertain about the use of 3D additive printing to improve environmental performance. Two interviewees and 14 respondents were positive about the use of this technology, claiming to have conserved not only time but also raw materials and electricity in the factory and probably across the supply chain. However, 15 interviewees and 23 respondents limited the environmental benefits to certain applications. In general, the comments showed that additive manufacturing was believed to have a moderate influence on environmental performance when prototyping complex products and producing small quantities and spare parts. Otherwise, participants did not consider it significant in improving environmental performance. One respondent stated:

> If you have to produce a 100-lot size of products, it does not make any sense to use a 3D printing, even for environmental reasons. You could end up with an increase in your electricity bill. In addition, when you print your prototypes, the achieved savings are very limited. We calculated an average 1% of electricity reduction and 4% of raw material saving. You have only advantage in terms of customisation of very few products.

Contrary to some literature findings (Achillas et al., 2015; Kamble et al., 2018; Peng et al., 2018; Wang et al., 2016), no interviewees or respondents highlighted the possibility of improving environmental performance in terms of recycling, reusing or the circular economy.

4.5 | Cobots and robots

Table 5 shows that the variable *COB/ROB* had a relatively high number of ratings of 1 (*entirely disagree*) and 2 (*mostly disagree*). Moreover, Tables 6 and 7 show that the interviewees believed cobots and robots had a negative effect on environmental performance compared with the other technologies. Eight interviewees and 18 respondents commented that this technology assisted greatly in reducing labour costs but not in improving environmental performance. For instance, one interviewee stated, 'we installed 15 new cobots and five traditional robots to reduce labour costs, increasing the safety and quality of many operations. However, we are having an increase by 5% of electricity consumption'. The issue of the use of more energy compared with current factories without i4.0 technologies was also highlighted by Wang et al. (2015, 2016) and Waibel et al. (2017).

4.6 | AMR and AGV

The quantitative results for the variable *AMR/AGV* were similar to those for *COB/ROB*. This variable had the highest number of ratings of 1 (*entirely disagree*) and 2 (*mostly disagree*) and the lowest negative result for the estimate in Table 6. The comments made were similar to those for cobots and robots. Indeed, 18 respondents and six interviewees considered that this technology may save electricity only when compared with large electric forklifts. The most interesting comment we found was:

> Over the years, we replaced all the big electric forklifts with lighter manual transpallet[s] for safety reasons. We have also gradually introduced first AGVs and now the new AMR. However, we have not saved consumption significantly; on the contrary, we have increased our environmental problems because we have now to cope with batteries and their end-of-life disposal.

Nine interviewees also directly reported a possible increase of electricity consumption.

4.7 | Augmented reality

Although the variable *AUGMENT* was not statistically significant and thus was not perceived to influence environmental performance, we examined the comments for clues in an attempt to provide some context to this quantitative result. First, only eight comments in total—five from respondents and three from interviewees—were made about this variable. This led to the second, more important, clue—that the managers were unlikely to have had a clear idea of how this technology could help them in improving environmental performance or even the potential of the technology. The latter was noted by no less than 16 of the 19 interviewees. One stated:

> I think that this sort of video game equipment, like the 3D glasses, could be good for the numerous, repetitive and identical activities performed in logistics and big dealers. I saw its employment in the plant of one of our big dealers. However, we do not need augmented reality in our manufacturing facility where we have to think about what we are doing every minute. I have neither anything in my mind regarding the possibility of using this technology to improve environmental performance and no software vendor[s] have contacted me proposing such an environmental application so far.

This comment, along with no results found in the literature review, also highlights the likely lack of technological proposals with respect to augmented reality and environmental issues.

5 | CONCLUSIONS

The literature review highlighted that the jury is still out and at times contradictory about the relationship between i4.0 technologies and environmental performance. Thus, we narrowed our research to the Italian manufacturing sector, using precise sample characteristics and performing a sequential mixed methods design combining qualitative and quantitative methods in triangulation. In the first (qualitative) phase, we interviewed 19 expert managers. In the second (quantitative) phase, we surveyed 260 managers and used ordinal regression to rank the i4.0 technologies according to their perceived effects on environmental performance. The quantitative results were enhanced by comments made by the 19 interviewees and 260 respondents. We believe that our final results will be of interest to academics and, even more so, practitioners.

With respect to the most-implemented i4.0 technologies listed in Table 1, we found that, in order of importance, smart sensors and RFID were highest in terms of their positive contribution to overall environmental performance, followed by AI and analytics. Simulation software made a moderate contribution, whereas additive manufacturing, cobots and traditional robots and AMR and AGV tended to have a negative effect on environmental performance. This represents the main novelty and contribution of this research, since no other studies have tried so far to rank the effect of i4.0 technologies on environmental performance. Further novelties show how augmented reality affected environmental performance neither positively nor negatively, being statistically insignificant. Its applications have not been studied and implemented yet from an environmental point of view. Moreover, technologies such as the IIoT, big data and the cloud were considered indirect means of affecting environmental performance, meaning that they had to be combined with or support other technologies.

Our findings confirm those of other authors who have found a positive effect of smart sensors and AI, especially in energy management. Besides, the managers highlighted other interesting applications, including in waste management and real-time pollution monitoring. AI and analytics were considered essential for analysing and finding patterns in data to predict a wide range of environmental impacts. Similarly, simulation software should be based on AI and focus on preventing environmental incidents.

In contrast to the literature review results, we found a certain indifference and even negativity towards additive manufacturing as a way of saving electricity and recycling and reusing resources. The managers also believed that cobots and robots could increase electricity consumption and that AGV and AMR would lead to a moderate saving of electricity only when compared with large electric forklifts.

With respect to other negative effects on environmental performance, managers were greatly concerned about the potential problems caused by the vast quantities of electrical and electronic components, including batteries, in the final stage of waste removal. One interviewee eloquently summarised this as follows:

> We replaced horses with cars hoping to save tons of natural waste, and we ended up with tons of CO_2. Now we are going to replace cars and industrial machines with new smart technologies; maybe we will end up with tons of new unimaginable kinds of waste.

Finally and interestingly, managers faced challenges when attempting to use AI, simulation software and other advanced technologies such as augmented reality and integrate them with environmental management. The managers commented on their lack of knowledge, poor current applications, scepticism and even suspicion towards the technologies.

6 | LIMITATIONS AND AGENDAS FOR FURTHER RESEARCH

The most important limitation of this research is that it was based on Italian manufacturing companies with specific characteristics such as being in the business-to-business sector, having more than 50 employees and not having big plants. Therefore, the findings should be validated in other geographic areas and compared with other industries. Different situations may be found in process manufacturing industries such as chemical, pharmaceutical, refineries and iron and steel industries. We also need more quantitative models to understand the real impacts on the environmental performance of each technology. Why from this sample of Italian manufacturing companies, results demonstrated a negative or neutral effect of technologies such as additive manufacturing, cobots, robots and AGV/AMR? There are some hidden factors that need to be analysed. Second, a more in-depth investigation of issues emerging from the qualitative comments made by the managers is needed. We would like to hear from other scholars about strategic issues such as how to develop better knowledge and applications about AI, analytics, simulation software, augmented reality and other unexplored smart technologies for environmental management. It is also important to conduct more in-depth investigations into the relationships between AI software and human problem-solving and decision-making processes with respect to environmental management, in particular the limitations and drawbacks of AI.

Finally, the topics of RoHS and WEEE associated with the disposal of i4.0 smart technologies deserve further investigation from different angles.

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REFERENCES

Accredia – The Italian Accreditation Body. (2020). Databanks – Certifications. https://www.accredia.it/en/databanks/certifications/, accessed 10 October 2020

Achillas, C., Aidonis, D., Iakovou, E., Thymianidis, M., & Tzetzis, D. (2015). A methodological framework for the inclusion of modern additive manufacturing into the production portfolio of a focused factory. *Journal of Manufacturing Systems*, *37*(1), 328–339. https://doi.org/10.1016/j.jmsy.2014.07.014

Agresti, A. (2002). *Categorical data analysis*. New York: John Wiley & Sons. Inc.. https://doi.org/10.1002/0471249688

Amoah, P., & Eweje, G. (2021). Impact mitigation or ecological restoration? Examining the environmental sustainability practices of multinational mining companies. *Business Strategy and the Environment*, *30*(1), 551–565. https://doi.org/10.1002/bse.2637

Antonius, R. (2003). *Interpreting quantitative data with SPSS*. London, UK: Sage. https://doi.org/10.4135/9781849209328

Arocena, P., Orcos, R., & Zouaghi, F. (2020). The impact of ISO 14001 on firm environmental and economic performance: The moderating role of size and environmental awareness. *Business Strategy and the Environment.*, *30*, 955–967. https://doi.org/10.1002/bse.2663

Baccarelli, E., Naranjo, P. G. V., Scarpiniti, M., Shojafar, M., & Abawajy, J. H. (2017). Fog of everything: Energy-efficient networked computing architectures research challenges, and a case study. *IEEE Access*, *5*, 9882–9910. https://doi.org/10.1109/ACCESS.2017.2702013

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*, 120420. https://doi.org/10.1016/j.techfore.2020.120420

Bag, S., Telukdarie, A., Pretorius, J. H. C., & Gupta, S. (2018). Industry 4.0 and supply chain sustainability: Framework and future research directions. *Benchmarking: An International Journal*. https://doi.org/10.1108/BIJ-03-2018-0056

Biod, A., Probert, J., & Jones, C. (1994). The packaging industry is not carried away by public opinion. *Business Strategy and the Environment*, *3*(1), 31–35. https://doi.org/10.1002/bse.3280030104

Bonilla, S. H., Silva, H. R., Terra da Silva, M., Franco Gonçalves, R., & Sacomano, J. B. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability*, *10*(10), 3740–3752. https://doi.org/10.3390/su10103740

Bos-Brouwers, H. E. J. (2010). Corporate sustainability and innovation in SMEs: Evidence of themes and activities in practice. *Business Strategy and the Environment*, *19*(7), 417–435.

Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M., & Yin, B. (2017). Smart factory of Industry 4.0: Key technologies, application case, and challenges. *IEEE Access*, *6*(3), 6505–6519.

Chiarini, A. (2019). Factors for succeeding in ISO 14001 implementation in Italian construction industry. *Business Strategy and the Environment*, *28*(5), 794–803. https://doi.org/10.1002/bse.2281

Chiarini, A., Belvedere, V., & Grando, A. (2020). Industry 4.0 strategies and technological developments. An exploratory research from Italian manufacturing companies. *Production Planning & Control*, *31*(16), 1385–1398. https://doi.org/10.1080/09537287.2019.1710304

da Silva, F. S. T., da Costa, C. A., Crovato, C. D. P., & da Rosa Righi, R. (2020). Looking at energy through the lens of Industry 4.0: A systematic literature review of concerns and challenges. *Computers & Industrial Engineering*, *143*(106426), 1–21.

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho Filho, M. (2018). When titans meet. Can Industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, *132*, 18–25. https://doi.org/10.1016/j.techfore.2018.01.017

Esengün, M., & İnce, G. (2018). The role of augmented reality in the age of Industry 4.0. In *Industry 4.0: Managing the digital transformation* (pp. 201–215). Cham, Germany: Springer. https://doi.org/10.1007/978-3-319-57870-5_12

Faheem, M., & Gungor, V. (2018). Energy efficient and QoS-aware routing protocol for wireless sensor network-based smart grid applications in the context of Industry 4.0. *Applied Soft Computing*, *68*(12), 910–922. https://doi.org/10.1016/j.asoc.2017.07.045

Franklin, C. S., Dominguez, E. G., Fryman, J. D., & Lewandowski, M. L. (2020). Collaborative robotics: New era of human-robot cooperation in the workplace. *Journal of Safety Research*, *74*, 153–160. https://doi.org/10.1016/j.jsr.2020.06.013

Gilchrist, A. (2016). *Industry 4.0: The industrial internet of things*. Berkeley, CA: Apress.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Gunal, M. M. (2019). *Simulation for Industry 4.0: Past, present, and future*. Springer. Switzerland: Cham. https://doi.org/10.1007/978-3-030-04137-3

Heras-Saizarbitoria, I., Boiral, O., & Díaz de Junguitu, A. (2020). Environmental management certification and environmental performance: Greening or greenwashing? *Business Strategy and the Environment*, *29*(6), 2829–2841. https://doi.org/10.1002/bse.2546

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industrie 4.0 scenarios. In *Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS), January 2016*. Koloa, HI: IEEE.

Hozdić, E. (2015). Smart factory for Industry 4.0: A review. *International Journal of Modern Manufacturing Technologies*, *7*(1), 28–35.

Huang, R., Riddle, M., Graziano, D., Warren, J., Das, S., Nimbalkar, S., Cresko, J., & Masanet, E. (2016). Energy and emissions saving potential of additive manufacturing: The case of lightweight aircraft components. *Journal of Cleaner Production*, *135*, 1559–1570. https://doi.org/10.1016/j.jclepro.2015.04.109

Idemudia, U., Kwakyewah, C., & Muthuri, J. (2020). Mining, the environment, and human rights in Ghana: An area of limited statehood perspective. *Business Strategy and the Environment*, *29*(7), 2919–2926. https://doi.org/10.1002/bse.2581

Indri, M., Lachello, L., Lazzero, I., Sibona, F., & Trapani, S. (2019). Smart sensors applications for a new paradigm of a production line. *Sensors*, *19*(3), 650–658. https://doi.org/10.3390/s19030650

Kagermann, H., Lukas, W.D., Wahlster, W. (2011). Industrie 4.0: Mit dem Internet der Dinge auf dem eg zur 4. industriellen Revolution. VDI Nachrichten, http://www.vdi-nachrichten.com/Technik-Gesellschaft/Industrie-40-Mit-Internet-Dinge-Weg-4-industriellen-Revolution, accessed 05 June 2020

Kagermann, H., Wolfgang, W., Helbi, J. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0, www.plattform-i40.de/finalreport2013, accessed 05 June 2020.

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*, 408–425. https://doi.org/10.1016/j.psep.2018.05.009

Kemp, D., Owen, J. R., & Lèbre, É. (2021). Tailings facility failures in the global mining industry: Will a 'transparency turn' drive change? *Business Strategy and the Environment*, *30*(1), 122–134. https://doi.org/10.1002/bse.2613

Kietzmann, J., Pitt, L., & Berthon, P. (2015). Disruptions, decisions, and destinations: Enter the age of 3-D printing and additive manufacturing. *Business Horizons*, *58*(2), 209–215. https://doi.org/10.1016/j.bushor.2014.11.005

Kostrzewski, M., Varjan, P., & Gnap, J. (2020). Solutions dedicated to internal logistics 4.0. In *Sustainable logistics and production in Industry 4.0* (pp. 243–262). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-33369-0_14

Kumar, V., Laghari, A. A., Karim, S., Shakir, M., & Brohi, A. A. (2019). Comparison of fog computing & cloud computing. *International Journal of Mathematical Sciences and Computing*, *5*(1), 31–41. https://doi.org/10.5815/ijmsc.2019.01.03

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *6*(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

Lee, Y. B., & Na, Y. N. (2007). Application of heuristic control technique to path planning of an autonomous guided vehicle. *International Journal of Computer Integrated Manufacturing*, *7*(2), 123–128.

Liao, C. S., Lou, K. R., & Gao, C. T. (2013). Sustainable development of electrical and electronic equipment: User-driven green design for cell phones. *Business Strategy and the Environment*, *22*(1), 36–48. https://doi.org/10.1002/bse.743

Lin, C. C., Deng, D. J., Chen, Z. Y., & Chen, K. C. (2016). Key design of driving Industry 4.0: Joint energy-efficient deployment and scheduling in group-based industrial wireless sensor networks. *IEEE Communications Magazine*, *54*(10), 46–52. https://doi.org/10.1109/MCOM.2016.7588228

Luan, C. J., Tien, C., & Wu, P. H. (2013). Strategizing environmental policy and compliance for firm economic sustainability: Evidence from Taiwanese electronics firms. *Business Strategy and the Environment*, *22*(8), 517–546. https://doi.org/10.1002/bse.1760

Massaro, M., Secinaro, S., Dal Mas, F., Brescia, V., & Calandra, D. (2020). Industry 4.0 and circular economy: An exploratory analysis of academic and practitioners' perspectives. *Business Strategy and the Environment*, *30*(2), 1213–1231. https://doi.org/10.1002/bse.2680

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

MISE – Ministero dello Sviluppo Economico. (2018). La diffusione delle imprese 4.0 e le politiche: evidenze 2017. https://www.sviluppoeconomico.gov.it/images/stories/documenti/Rapporto-MiSE-MetI40.pdf, accessed 14 October 2020.

Mohamed, N., Al-Jaroodi, J., & Lazarova-Molnar, S. (2019). Leveraging the capabilities of Industry 4.0 for improving energy efficiency in smart factories. *IEEE Access*, *7*(2), 18008–18020. https://doi.org/10.1109/ACCESS.2019.2897045

Müller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247–271. https://doi.org/10.3390/su10010247

Nascimento, D. L. M., Alencastro, V., Quelhas, O. L. G., Caiado, R. G. G., Garza-Reyes, J. A., Rocha-Lona, L., & Tortorella, G. (2019). Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal. *Journal of Manufacturing Technology Management*, *30*(3), 607–627. https://doi.org/10.1108/JMTM-03-2018-0071

Oláh, J., Aburumman, N., Popp, J., Khan, M. A., Haddad, H., & Kitukutha, N. (2020). Impact of Industry 4.0 on environmental sustainability. *Sustainability*, *12*(11), 4674. https://doi.org/10.3390/su12114674

Pazienza, P., & De Lucia, C. (2020). The EU policy for a plastic economy: Reflections on a sectoral implementation strategy. *Business Strategy and the Environment*, *29*(2), 779–788. https://doi.org/10.1002/bse.2445

Peng, T., Kellens, K., Tang, R., Chen, C., & Chen, G. (2018). Sustainability of additive manufacturing: An overview on its energy demand and environmental impact. *Additive Manufacturing*, *21*(2), 694–704. https://doi.org/10.1016/j.addma.2018.04.022

Petrov, D., Schmidt, M., Hilleringmann, U., Hedayat, C., & Otto, T. (2019). RFID based sensor platform for Industry 4.0 application. In *Smart systems integration; 13th International Conference and Exhibition on Integration Issues of Miniaturized Systems, April 2019*. Barcelona: VDE.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Qian, F., Zhong, W. M., & Du, W. L. (2017). Fundamental theories and key technologies for smart and optimal manufacturing in the process industry. *Engineering*, *3*(2), 154–160. https://doi.org/10.1016/J.ENG.2017.02.011

Qin, J., Liu, Y., & Grosvenor, R. (2017). A framework of energy consumption modelling for additive manufacturing using Internet of Things. *Procedia CIRP*, *63*, 307–312. https://doi.org/10.1016/j.procir.2017.02.036

Raturi, A., & Jack, E. (2006). Lessons learned from methodological triangulation in management research. *Management Research News*, *29*(6), 345–357.

Rawat, A. (2018). Ordinal Logistic Regression. *Towards Data Science*. https://towardsdatascience.com/implementing-and-interpreting-ordinal-logistic-regression-1ee699274cf5, accessed 12 March 2021.

Reavie, V. (2018). Do You Know The Difference Between Data Analytics And AI Machine Learning? *Forbes Agency Council Post*. https://www.forbes.com/sites/forbesagencycouncil/2018/08/01/do-you-know-the-difference-between-data-analytics-and-ai-machine-learning/?sh=1ad2125f5878, accessed 13 October 2020.

Rodgers, C. (1995). From 'start-up' to 're-boot': Product lifecycle strategies and competitive advantage in the computer industry. *Business Strategy and the Environment*, *4*(3), 128–134. https://doi.org/10.1002/bse.3280040304

Said, O., Al-Makhadmeh, Z., & Tolba, A. (2020). EMS: An energy management scheme for green IoT environments. *IEEE Access*, *8*, 44983–44998. https://doi.org/10.1109/ACCESS.2020.2976641

Sherazi, H. H. R., Imran, M. A., Boggia, G., & Grieco, L. A. (2018). Energy harvesting in LoRaWAN: A cost analysis for the Industry 4.0. *IEEE Communications Letters*, *22*(11), 2358–2361. https://doi.org/10.1109/LCOMM.2018.2869404

Shi, Z., Xie, Y., Xue, W., Chen, Y., Fu, L., & Xu, X. (2020). Smart factory in Industry 4.0. *Systems Research and Behavioral Science*, *37*(4), 607–617. https://doi.org/10.1002/sres.2704

Shrouf, F., & Miragliotta, G. (2015). Energy management based on internet of things: Practices and framework for adoption in production management. *Journal of Cleaner Production*, *100*(6), 235–246. https://doi.org/10.1016/j.jclepro.2015.03.055

Shrouf, F., Ordieres, J., & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. In *2014 IEEE international conference on industrial engineering and engineering management* (pp. 697–701). Bandar Sunway, Malaysia: IEEE.

Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. *Procedia CIRP*, *40*, 536–541. https://doi.org/10.1016/j.procir.2016.01.129

Strand, S., Cadwallader, S., Firth, D. (2011). Using statistical regression methods in education research. ReStore - National Centre for Research Methods. https://www.restore.ac.uk/srme/www/fac/soc/wie/research-new/srme/modules/mod5/3/index.html, accessed 02 June 2020.

Valerio, L., Conti, M., & Passarella, A. (2018). Energy efficient distributed analytics at the edge of the network for IoT environments. *Pervasive and Mobile Computing*, *51*, 27–42. https://doi.org/10.1016/j.pmcj.2018.09.004

Vrchota, J., Pech, M., Rolínek, L., & Bednář, J. (2020). Sustainability outcomes of green processes in relation to Industry 4.0 in manufacturing: Systematic review. *Sustainability*, *12*(15), 5968–5975. https://doi.org/10.3390/su12155968

Waibel, M. W., Steenkamp, M. W., Moloko, L. P., & Oosthuizen, G. A. (2017). Investigating the effects of smart production systems on sustainability elements. *Procedia Manufacturing*, *8*, 731–737. https://doi.org/10.1016/j.promfg.2017.02.094

Wang, L., Thorngren, M., & Onori, M. (2015). Current status and advancement of cyberphysical systems in manufacturing. *Journal of Manufacturing Systems*, *37*(2), 517–527. https://doi.org/10.1016/j.jmsy.2015.04.008

Wang, L., & Wang, G. (2016). Big data in cyber-physical systems, digital manufacturing and Industry 4.0. *International Journal of Engineering and Manufacturing*, *6*(4), 1–8.

Wang, S., Wan, J. D., & Zhang, C. (2016). Implementing smart factory of Industrie 4.0: An outlook. *International Journal of Distributed Sensor Networks*, *12*(1), 3159805. https://doi.org/10.1155/2016/3159805

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