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Industry 4.0 implementation: Environmental and social sustainability in manufacturing multinational enterprises

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ABSTRACT

By introducing digital technologies, Industry 4.0 may be transforming the traditional systems of the manufacturing industries, which are often blamed for high environmental degradation and social inequalities. Due to their power, size, and scope, manufacturing multinational enterprises (MNEs) are considered by other organizations as best practice references. If there is already evidence that digitalization favours environmental sustainability, social sustainability still needs to be explored. This study aims to analyze the contribution of the implementation of digital technologies in promoting environmental and social sustainability in European manufacturing MNEs using the Resource-Based View (RBV). A research model was formulated comprising five digital technologies (Artificial Intelligence, Cloud Computing, Robotics, Big Data Analytics, and Blockchain) and sustainable environmental and social practices. To test the model, the Partial Least Squares method was applied to a sample of 764 European manufacturing MNEs. The results show that European MNEs still have a low implementation of digital technologies in their business models. Digital technologies positively contribute to achieving these companies' environmental and social sustainability. However, the contributions of implementing each digital technology to environmental and social sustainability are not equal, allowing investment prioritization by manufacturing MNEs according to the strategically defined return. This study contributes to the evolution of RBV considering digital technology as a strategic resource. It focuses on assessing the contribution of five digital technologies to achieving environmental and social sustainability and demonstrates the importance of the digital transition towards greener manufacturing production in environmental and social terms. It also suggests practices managers and policymakers can implement to accelerate digitalization and achieve the United Nations Sustainable Development Goals.

1. Introduction

We live in a globalized world where multinational enterprises (MNEs) dominate business activities and are considered, by other organizations, as a reference for good practices and a model to replicate (López et al., 2019). In the European Union, 36% of manufacturing companies are multinationals (Eurostat, 2022). According to the EuroGroups Register (EGR), in 2020, there were 135,450 multinational enterprise groups represented by 468,000 companies and employed over 42 million people in European Union and European Free Trade Association (EFTA) countries. Moreover, 20 per cent of MNE groups are present in at least six countries (Eurostat, 2022).

The environmental and social impact of MNEs' activities worldwide has come under increased scrutiny. Between 2000 and 2020, carbon dioxide (CO_2) emissions from global combustion caused by industrial processes and fossil fuels rose by around 35% (34.07 billion tons) (Deloitte, 2021), resulting in increased resource consumption, pollution, and ecological degradation, and contributed to climate change (Tseng et al., 2018). Traditional manufacturing systems also cause social problems such as low income, poverty, wage disparity, lack of unity, and

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social disharmony (Mohamed, 2018). In this context, manufacturing companies have experienced challenges in meeting consumers' demands and growing preferences (Satyro et al., 2022), who have increasingly changed their buying habits toward more sustainable products (Esmaeilian et al., 2020). Manufacturing companies must preserve more natural resources that are essential for production (Satyro et al., 2022), and there is a belief that the development of technologies and their implementation will enable manufacturing companies to improve their performance (Amjad et al., 2021), and simultaneously achieve environmental, social, and economic sustainability to meet the UN 2030 Agenda for Sustainable Development.

According to Kagermann et al. (2013), technology is the main contribution to implementing Industry 4.0 in manufacturing companies. Industry 4.0 is also described as the fourth industrial revolution, and represents the current trend of automation technologies in the manufacturing industry and especially covers enabling technologies (e.g. Internet of Things (IoT), cyber-physical systems (CPS), cloud computing) (Kagermann et al., 2013; Xu et al., 2018). The First Industrial Revolution (Industry 1.0) introduced mechanical manufacturing systems using steam and water power. Mass production through electrical energy describes the Second Industrial Revolution (Industry 2.0). In the Third Industrial Revolution (Industry 3.0), the application of microelectronic technology and automation in manufacturing emerged. The implementation of Information and Communication Technologies (ICT) by manufacturing companies contributes a lot to this technological advance (e.g. made computer integrated manufacturing, computer-aided processing planning, computer-aided manufacturing, technologies for computer-aided design, industrial robots made flexible manufacturing systems, computer numerical control) (Feng et al., 2001). Although the Third Industrial Revolution focuses on the automation of machines and processes, Industry 4.0 focuses more on end-to-end digitization and the incorporation of digital industrial ecosystems, looking for fully integrated solutions (Tan et al., 2010; Xu et al., 2018). Industry 4.0 is based on nine technological pillars: Big Data, Cloud, Industrial Internet, Horizontal and Vertical Integration, Simulation, Augmented Reality, Additive Manufacturing, Cyber Security and Advanced Manufacturing. Therefore, Industry 4.0, by implementing continuous improvement methodologies and new advanced technologies, can provide an increasingly sustainable future (Jayashree et al., 2022).

In the pursuit of sustainability, and with the implementation of Industry 4.0, several benefits can be achieved, such as i) increasing the production of circular products (Yadav et al., 2020); ii) improving efficiency and quality, decreasing resource consumption, and increasing productivity (Asif, 2020; Satyro et al., 2022); and iii) produce particularized products with a shorter lead time (Asif, 2020; Satyro et al., 2022). However, there are difficulties in implementing Industry 4.0 resulting from: i) the difficulty in training and hiring human resources in digital technology (Birkel et al., 2019); ii) new management skills being required (Winter, 2020); and iii) the complexity of changing an organizational culture (Satyro et al., 2022).

Recent studies show that companies aiming to achieve environmental sustainability must implement Industry 4.0 technologies (Jayashree et al., 2022; Kamble et al., 2018; Müller et al., 2018). Jayashree et al. (2021) study the relationship between implementing Industry 4.0 technologies and the objectives for environmental sustainability. The authors conclude that the characteristics of technological innovation have a positive effect on the implementation of Industry 4.0 and on the objectives of environmental sustainability. Jayashree et al. (2022) analyze the dynamics in adopting Industry 4.0 to achieve environmental sustainability. The authors state that management leadership, external support, teamwork, and Information technology (IT) resources are relevant to implement Industry 4.0 and to achieve environmental sustainability. Satyro et al. (2022) identify the challenges and benefits of implementing Industry 4.0, analyzing potential social impacts. The authors conclude that Industry 4.0 has increased companies' competitiveness and improved production lines' quality. However, they identified difficulties in changing the organizational culture due to the difficulty in hiring/training human resources in digital technologies and the high investments that need to be made. The authors also state that environmental sustainability is considered secondary in formulating companies' strategies, and the social dimension is little considered. Grybauskas et al. (2022), through a systematic review of academic and gray literature, analyze the social implications of Industry 4.0. The authors conclude that the academic literature indicates that Industry 4.0 needs internal mechanisms to develop ways to achieve social sustainability. The authors also state that Industry 4.0 does not necessarily extend the corporation's social responsibility to the entire value chain. Furthermore, in the Industry 4.0 scenario, the delivery of social development values has never been among the main objectives of corporate governance (Grybauskas et al., 2022).

Despite this, only some authors agree that Industry 4.0 should have environmental and social sustainability as its primary goal (Ghobakhloo et al., 2021). However, policymakers have emphasized Industry 4.0 and its potential implications for sustainable development (Grybauskas et al., 2022). In this context, the scientific community has recently shown much interest in assessing the implications that Industry 4.0 has on environmental, social, and economic sustainability (Oztemel and Gursev, 2020). There is also a disconnect in the extant literature between sustainability and technologies in the context of manufacturing companies in Industry 4.0 (Nascimento et al., 2019). Hence, further studies are needed to analyze how different technologies can be applied to improve organizational social practices. Furthermore, there is a gap in the literature regarding how implementing Industry 4.0 technologies can lead to environmental sustainability (Ajwani-Ramchandani et al., 2021) and a deficit of research studying the impact of digitized industries on social and environmental sustainability (Chauhan et al., 2022). In this context, how can the role and effectiveness of each technology be evaluated in achieving social and environmental sustainability?

The present study aims to analyze the impact of digital technologies in promoting environmental and social sustainability in manufacturing MNEs, considering sustainability as a source of competitiveness in this type of business organization. This study is analyzed from the Resource-Based View (RBV) perspective considering digital technologies as resources and capabilities. The RBV has been used to explain how the use of digital technologies contributes to the superior performance of firms in specific markets (Huber et al., 2022). This study is expected to help manufacturing MNEs achieve environmental and social sustainability. To this end, through a quantitative methodology, five multiple linear regressions were estimated using the Partial Least Squares (PLS) method. This method is the most suitable for this study because it is based on variance, combining factor analysis with regression estimation. The data were collected from Gesis - Leibniz Institute for Social Sciences database in Flash Eurobarometer 486 published in 2020 (European Commission, 2020). The sample consists of 764 manufacturing MNEs. Five digital technologies were included in the study (Artificial Intelligence (AI), Cloud Computing, Robotics, Big Data Analytics (BDA), and Blockchain). The choice of digital technologies to be studied in this paper was due to the frequency with which they are implemented in the multinational manufacturing industries participating in the database sample.

This study makes three main contributions. First, this study contributes to recent work on implementing an Industry 4.0 strategy. Currently, there are no known studies that analyze simultaneously the contributions of five digital technologies to environmental and social sustainability. Previous studies have focused on presenting theoretical sustainable 4.0 business models (see, for example, Godina et al., 2020; Martin et al., 2021), while this study highlights that digital technologies AI, Cloud Computing, Robotic, BDA, and Blockchain) have positive impacts on the environmental and social sustainability of manufacturing MNEs, which in turn can be sources of competitiveness creation.

Second, in contrast to previous studies that did not include any theory as a perspective of analysis (García-Muiña et al., 2020), in this study, we examine the impact of digital technologies on promoting the environmental and social sustainability of manufacturing MNEs from the RBV perspective. With this approach, we expand the resources and capacities traditionally proposed in RBV, considering digital technologies as a specific capacity of companies based on Resources. Furthermore, we conclude that digital technologies are valuable for manufacturing MNEs to achieve strategic objectives and social and environmental sustainability. Finally, this study provides insights into how managers can accelerate environmental and social sustainability through digitalization. We also verified that there is an unequal contribution of different digital technologies to achieve the goals of social and environmental sustainability since we identified the probability that digital technology has greater value in the strategic context of manufacturing MNEs. To achieve environmental sustainability goals, manufacturing MNEs must invest in digital technologies that contribute more to the environmental practices already implemented in companies, prioritizing: (1) cloud computing, (2) blockchain, (3) robotic, (4) BDA and, (5) AI. With regard to social sustainability, manufacturing MNEs should prioritize: (1) cloud computing, (2) BDA, (3) robotic, (4) AI, and (5) blockchain.

2. Literature review

2.1. Resource-Based View theory

The Resource-Based View (RBV) has been used to explain a company's superior performance in markets, and the application and use of digital technologies can contribute to this (Huber et al., 2022). RBV is applied in strategic management studies to explain the relationships between companies' performance and their resources (Barney, 1991; Szalavetz, 2022). With the RBV, it is possible to relate companies' competitive advantages with the characteristics of the resources (valuable, rare, inimitable, and non-substitutable) that they possess or control (Barney, 1991; Lopes et al., 2021; Szalavetz, 2022).

For the present study, we consider digital technologies (Artificial Intelligent, Cloud Computing, Robotics, Big Data Analytics, and Blockchain) as resources and capabilities that a manufacturing MNE has to implement, integrate, assemble, and connect manufacturing processes. By enabling the application of an Industry 4.0 strategy (Huber et al., 2022), companies can also identify new business opportunities (Khin and Kee, 2022). Recent literature has studied the impact of digitization on firms. However, the literature focuses on identifying the resources and ways in which digitization (see, for example, Monostori et al., 2016), whereas, the present study takes a different approach as it uses RBV as a theoretical lens and analyzes the potential impacts of digital technology implementation on the environmental and social sustainability of manufacturing MNEs, considering sustainability as a source of future competitiveness.

2.2. Artificial intelligence

The concept of AI involves the application of computational skills to solve problems and achieve goals (Nishant et al., 2020). Studies on AI for sustainability have mainly focused on environmental sustainability, demonstrating the application of AI to improve biodiversity by assessing ecosystem systems (Nuortimo and Harkonen, 2018), conserving natural species and water resources (Russell and Norvig, 2016). Primarily, the focus has been on energy conservation and renewable energy, with more than 250 papers published between 2015 and 2019 on the latter issue (Nishant et al., 2020). At the Industry 4.0. level, AI has been used as a big data technology that collects, processes, and stores large amounts of data and is a source of industry competitiveness. One of the biggest challenges is how to endow the industry with sustainable production (Mathiyazhagan et al., 2019). In the case of manufacturing companies, manufacturing in a sustainable way has been circuitous since most of these companies find it difficult to safely manage the use of large quantities of highly environmentally hazardous chemicals due to environmental and safety impositions (Mao et al., 2019).

In addition, mass production, lack of early risk detection and safety-oriented decision-making systems in processes, the multiplicity of information and data, and classification of information in isolation were identified as the main problems preventing manufacturing industries from achieving a green manufacturing process (Mao et al., 2019). AI can help solve these problems and decision-making through error detection, the fusion of diverse data, and early detection of alert situations, enabling companies to achieve green manufacturing (Cioffi et al., 2020; Mao et al., 2019). It becomes clear that including tools, techniques and methods involving AI is an essential step for the exploration of companies' data and for the creation of applications that allow the efficient use of natural resources in productive and organizational systems (Onu and Mbohwa, 2021). Studies are still very scarce regarding the application of AI to achieve social sustainability (Lee, 2021), even though some authors consider it the most pertinent type of sustainability to achieve (Khakurel et al., 2018).

According to Joung et al. (2013), social well-being translated by health and safety practices and the promotion of human rights is social indicators that can be improved through AI in manufacturing companies' manufacturing processes, which can ensure that this type of industry's operations is socially sustainable. AI can promote social sustainability, namely when it increases work efficiency, reduces working hours, improves workers' physical and mental health, enables multi-tasking, automates routines, and promotes social and ethical actions (Khakurel et al., 2018). In this context, it is important to assess how manufacturing companies can benefit from sustainability indicators when implementing AI.

H1a. The application of AI in manufacturing industries positively influences the environmental sustainability indicators of these industries.

H1b. The application of AI in manufacturing industries positively influences the social sustainability indicators of these industries.

2.3. Cloud computing

Cloud computing involves a networked system that enables simple, easy, and comprehensive access to information and data, creating added value for organizations by reducing operational costs and physical and human resources and boosting business opportunities (Chang et al., 2010). According to Kusiak (2018), smart manufacturing industries are built on six pillars: technological manufacturing processes, materials, data, predictive-type engineering, sustainability, and networked resource sharing. The future trend is for cloud computing to be energy efficient, sustainable, and suited to the dictates of the manufacturing industry. To this end, Gill and Buyya (2019) presented a sustainable cloud computing model with applications and sustainability measures that enable energy management, virtualization, thermal recognition programs, renewable energy management, and the reuse of natural resources. Although the cloud computing solution has been used as a support for intelligent decisions in order to obtain more sustainable and efficient manufacturing, its application and objectives in manufacturing industries are still unclear (Fisher et al., 2018). In this way, it becomes important to evaluate the contribution of the application of cloud computing to environmental sustainability in manufacturing industries.

However, most studies on assessing the impact of cloud computing in Industry 4.0 do not yet consider the sustainability aspect to evaluate the performance of cloud computing, especially at the social level (Azadi et al., 2021). More recently, in the manufacturing industries, a new concept of "Social Manufacturing" has emerged, in which producers and individuals work in a collaborative way (Hamalainen and Karjalainen, 2017). Cloud computing complements this new concept by allowing and treating collective data and information and simulating more innovative projects (Ren et al., 2015), being indicated as a solution that can promote the sustainability of manufacturing companies (Bi and Wang, 2013). Furthermore, the introduction of cloud computing in industry 4.0 and other technologies is transforming the labor market since there are costs (economic, social and environmental) of migrating to the cloud, and the social aspect is receiving increasing attention (Mohammed et al., 2020). Cloud computing leads to many traditional professions tending to disappear, being replaced by smart technologies, but also causing new professionals with the skills to maneuver these new technologies to emerge (Bologa et al., 2017). These negative consequences of the implementation of cloud computing, especially in manufacturing companies with standardized and typified work functions, call into question its contribution to the social sustainability of this sector of activity.

H2a. Information migration to cloud computing in manufacturing industries positively influences the environmental sustainability indicators of these industries.

H2b. Information migration to cloud computing in manufacturing industries positively influences the social sustainability indicators of these industries.

2.4. Robotics

The application of robotics in the industry has allowed to decrease production costs, improve industrial performance, satisfy manufacturing quality requirements, customize the product, make production more flexible and apply sustainable practices (Gadaleta et al., 2019; Ogbemhe et al., 2017). In the case of manufacturing industries, robotics allows tasks to be performed faster, makes workers more skilled, saving time and money; reduces supervision time, increasing productivity; allows 24h production processes, reducing production costs and making the production system more sustainable; improves product quality (Enyoghasi and Badurdeen, 2021; Ogbemhe et al., 2017). Several studies have demonstrated the contribution of the application of robotics in manufacturing industries, despite the high investment involved in implementing this digital solution. As main contributions, these studies have highlighted the implementation of a more sustainable production process with reduced consumption of electricity, gas and water since operations are more efficient, there is a reduction in CO2 emissions and the use of raw materials, waste reduction and (Ajwani-Ramchandani et al., 2021; Yamamoto et al., 2020). In social terms, robotics in manufacturing industries can improve human working conditions by changing employment structures, decreasing routine and monotonous tasks, boosting workers' skills and qualifications through training to handle and deal with robotics applications, and boosting social sustainability practices (Radić et al., 2020). According to Gajšek et al. (2020), the addition of robotics in manufacturing industries can improve employees' physical and mental health, work productivity, and support better work decisions. Despite these benefits, the implementation of robotics applications often has economic sustainability objectives, neglecting environmental and social sustainability. Especially because robotics does not only have positive effects in social terms, depending on how it is implemented. Guenat et al. (2022) in their study concluded that the reinforcement of inequalities, the diversion of resources from already improved solutions, the reduction of freedom and privacy can be threats resulting from the implementation of robotics. Job loss and rising unemployment is another of the negative effects (Frey and Osborne, 2017; Lloyd and Payne, 2019). However, several studies have shown that the correct implementation of robotics solutions can contribute to the social and environmental sustainability of manufacturing companies, these companies can optimize and make their implementation more efficient.

H3a. The application of robotics in manufacturing industries positively influences the environmental sustainability indicators of these industries.

H3b. The application of robotics in manufacturing industries positively influences the social sustainability indicators of these industries.

2.5. Big data analytics (BDA)

BDA is the ability to rapidly generate and analyze a large volume of diverse data and is characterized by the five V's: variety, volume, velocity, value, and veracity (Duan and Xiong, 2015). BDA can be defined as a superior capability of organizations, based on the conditions of their operation, to realize a pooling of strategic resources (human and managerial and technical skills) that can improve their performance (Akter et al., 2016; Wamba et al., 2017). Exploiting this superior organizational capability can achieve a sustainable competitive advantage at the environmental and social levels (Dubey et al., 2019). In manufacturing industries, BDA can transform the practices of these companies by making them more environmentally sustainable. BDA has already been shown to positively impact operations at the green supply chain level (Doolun et al., 2018) and sustainable manufacturing level (Kaur and Singh, 2018). At the green supply chain level, BDA has allowed the creation of new tools to support decision-making, allowing to monitor of the supply chain in real-time and in an accurate way, managing risks and streamlining processes, allowing to achieve a competitive advantage at the sustainable level (Wamba et al., 2017). Sustainable manufacturing aims to optimize resource use, reduce waste, carbon, and toxic emissions, and save energy (Piyathanavong et al., 2019). In social terms, the BDA can manage and monitor labor issues such as the functions performed in the supply chain, the use of supplementary and continuous work, compensation and wage processing, safety standards, among others (Mageto, 2021). However, the contribution of BDA in terms of social sustainability is still little studied and the results of more exploratory studies have shown that the application of BDA can bring social uncertainty and as such, its application in promoting social sustainability is not a priority for companies (Gangwar et al., 2022). Despite the various benefits that manufacturing companies can obtain from the application of the BDA, there is still little evidence that demonstrates how the application of the BDA can contribute to the environmental and social sustainability of manufacturing companies, focusing essentially on economic benefits (Mageto, 2021).

H4a. The use of BDA in manufacturing industries positively influences the environmental indicators of these industries.

H4b. The use of BDA in manufacturing industries positively influences the sustainability indicators of these industries.

2.6. Blockchain

Blockchain technology is an innovation characterized by being disruptive and based on continuous advances in information computing that uses a central agent that coordinates data in a reliable, transparent, and shared way, being increasingly used in Industry 4.0. Recent studies on the link between blockchain technology and sustainability have focused primarily on supply chain management, technological infrastructure, energy, smart money, climate change, and technology integration (Parmentola et al., 2022). Blockchain technology can facilitate the sustainable production model, handle, monitor, and store data about the activities that enhance pollution and environmental devastation, and collect real-time data about green activities, helping in the management's decision-making (Parmentola et al., 2022). In addition, it can favor implementing a green supply chain (Mora et al., 2021).

We can conclude that these studies have evaluated the contribution of using blockchain in order to optimize production processes and supply chains for economic purposes, and it is unknown whether there are really environmental concerns in its implementation to ensure greater sustainability in this dimension. However, there are studies that have shown that the implementation of blockchain technology does not only have positive effects in environmental terms. Traditional blockchain systems require high energy costs, high CO2 emissions and to accommodate large servers, large installations are required, posing a threat in terms of forest devastation and the squandering of natural resources (Parmentola et al., 2022).

Also, blockchain technology has contributed to promoting social sustainability in manufacturing industries, with the main contributions being working conditions, human rights, societal engagement, customer issues, and business practices (Khanfar et al., 2021). At the level of working conditions, blockchain technology contributes to promoting the development of human capital in manufacturing industries, disseminating safety and health practices, reducing safety gaps, tracking and monitoring companies' health and safety certificates, improving working conditions, and tracking workers' work activity (working hours, salaries, benefits, overtime work among others) (Venkatesh et al., 2020). The defense and promotion of human rights can also be promoted by the use of blockchain technology through the tracking and monitoring of human rights, the prevention of social abuse and alarmism, the reduction and identification of situations of worker exploitation, forced labor, and child labor (Park and Li, 2021). Regarding societal engagement, blockchain technology can enable new business opportunities, make the business model more efficient, reduce costs and boost the social services (Schulz et al., 2020). Regarding customer issues, this technology can facilitate product customization, promote product innovation, optimize production and delivery processes and enable a direct relationship between stakeholders (Leng et al., 2020). Finally, blockchain can promote business practices by tracking and monitoring corruption situations and promoting a fair and balanced trade (Katsikouli et al., 2021). Thus, among the digital technologies evaluated in this study, blockchain seems to be the one that has contributed the most to social sustainability, and its role should be reinforced.

H5a. *The application of blockchain technology in manufacturing industries positively influences the environmental sustainability indicators of these industries.*

H5b. *The application of blockchain technology in manufacturing industries positively influences the social sustainability indicators of these industries.*

The research model for this study is presented in Fig. 1.

3. Methods

3.1. Sample and data

The objective of this study is to evaluate the contribution of five digital technologies (Artificial Intelligent, Cloud Computing, Robotics, Big Data Analytics, and Blockchain) (i) in environmental sustainability and (ii) in social sustainability. To this end, this study uses a sample of manufacturing MNEs selected from the Gesis - Leibniz Institute for Social Sciences database in Flash Eurobarometer 486 published in 2020 (European Commission, 2020). Data were collected by telephone and computer-assisted interviewing between February 19, 2020, and May 05, 2020. The geographical coverage of the companies interviewed covers all 27 member states of the EU and Bosnia and Herzegovina, Brazil, Canada, Iceland, Japan, North Macedonia, Norway, Serbia, Turkey, the UK, the USA, and Kosovo. The original database contains 16, 365 companies from various industries, and a filter was used to restrict the sample for this study to manufacturing MNEs, resulting in 764 companies. The criteria for determining the MNE belonging to the sample were: i) dimension measured by the number of employees (more than 250 employees) and ii) activity in more than one country.

The oldest company in the sample was registered in 1850, and the newest was in 2018. 78% of the companies had 250 employees or more in the last three years. In terms of turnover, in 2019, 66% of the companies' turnover of more than 50 million and 32% between 10 and 50 million euros. Since 2016, in terms of turnover, 82% of these companies grew by less than 30%, and in terms of the number of full-time employees, 74% of companies grew by more than 30%.

3.2. Variables

3.2.1. Independent variables and control variables

In the Flash Eurobarometer 486 survey, in question Q23, companies were asked (Appendix A): "Which digital technologies has your company adopted so far?". The following possible answers were presented (Table 1), and companies could choose more than one option. The answers are binary: 1 – yes, 0 – no.

Table 1
Options of digital technologies'

1 - Artificial intelligence, for example, machine learning or technologies for identifying objects or people, etc.
2 - Cloud computing, i.e. storage and processing of files or data on remote servers hosted on the Internet
3 - Robotics, i.e. robots used to automate processes, for example in construction or design, etc.
4 - Smart devices, e.g. smart sensors, smart thermostats, etc.
5 - Big data analytics, for example, data mining and predictive analytics
6 - High speed infrastructure
7 - Blockchain
8 - None of the above

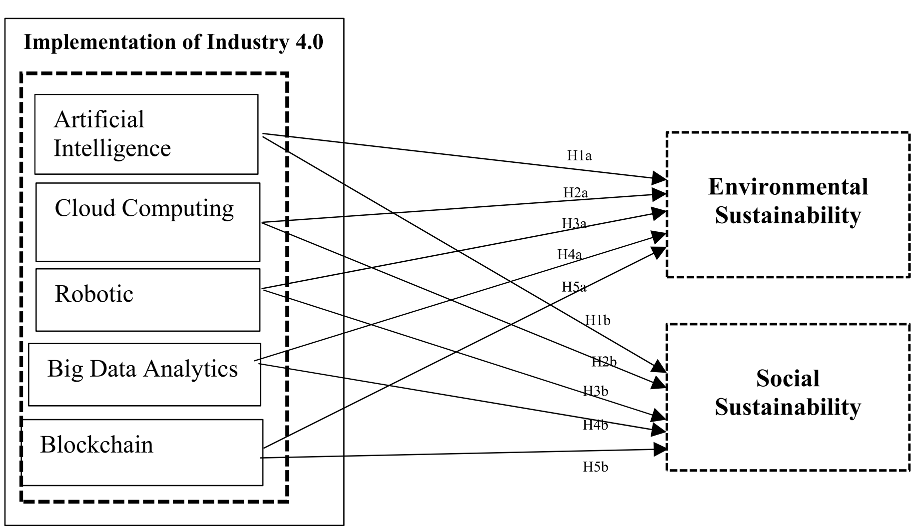

Fig. 1. Research model.

The choice of digital technologies to be studied in the present study resulted from the frequency with which they are implemented in the multinational manufacturing industries that participated in the database sample of the Flash Eurobarometer 486 questionnaire was greater than 10% (Table 2).

Firm age and size were used as control variables similar to other studies (e.g., Adomako et al. (2019). The firm age is measured by the age of the company (since initial registration) until 2019 and the firm size by the number of employees in the company three years ago.

3.2.2. Dependent variables

The indicators of the dependent variables, environmental and social sustainability, were measured by the answers of the surveyed companies to the following question (Appendix A): Which of the following sustainability measures is your company actively adopting? The answers are binary: 1 – yes, 0 – no. Response items are shown in Table 3.

3.2.3. Resume of variables and indicators

Table 4 shows the resume of items that measure the dependent, independent, and control variables.

3.3. Data analysis

First, a statistical analysis was performed on the variables and indicators that measure the variables contained in the research model using the SPSS (v.25) software. Afterwards, the Partial Least Squares (PLS) method in Smart PLS3.0., as Hair et al. (2017) suggested, was used to test the relationships established in the research model between the variables. The sample consists of indicators collected through a questionnaire and there is no normal distribution of data confirmed by kurtosis and skewness statistics. The PLS method has already been used in other studies to assess the relationship between digital technologies and sustainability such as Sun et al. (2022), Li et al. (2022) and Haseeb et al. (2019). The PLS method comprises two models: the outer model, a measurement model, and the inner model, a structure model. Since the PLS method is a variance-based method, it combines factor analysis with regression estimation, which is beneficial for the present study. Furthermore, PLS regression is computed separately for measurement and structural models.

Thus, the data from this study were analyzed in three steps.

i) Statistical analysis of variables and items that measure them;
ii) Analysis of the items that measure the constructs to ensure measurement validity and reliability;
iii) Testing the research model and hypotheses via bootstrapping.

Since in this study we have two dependent variables because we want to assess the individual contribution of each of the five digital technologies separately in environmental sustainability and social sustainability, we apply the PLS method to two models separately: i) model 1 whose dependent variable is environmental sustainability and which includes five regressions referring to a digital technology and ii) model 2 whose dependent variable is social sustainability and which also includes five regressions referring to a digital technology.

Table 2
Frequency of implementation of digital technologies in multinational manufacturing companies in the sample.

Digital Technologies'	Frequency (%)
1 - Artificial intelligence, for example, machine learning or technologies for identifying objects or people, etc.	12.2%
2 - Cloud computing, i.e. storage and processing of files or data on remote servers hosted on the Internet	45.3%
3 - Robotics, i.e. robots used to automate processes, for example in construction or design, etc.	19.3%
4 - Smart devices, e.g. smart sensors, smart thermostats, etc.	8.1%
5 - Big data analytics, for example, data mining and predictive analytics	13.8%
6 - High speed infrastructure	8.4%
7 - Blockchain	11.7%
8 - None of the previous	29.7%

Table 3
Indicators of environmental and social sustainable practices.

Environmental practices
Recycling or reuse of materials
Reducing consumption or impact on natural resources (e.g. saving water or switching to sustainable resources
Energy saving or switching to renewable energy sources
Sustainable product development
Social practices
Improvement of employees' working conditions
Promotion and improvement of diversity and equality in the workplace
Assessing your company's impact on society
Employee involvement in the management of the company
None of the previous

Table 4
Variables and indicators.

Variables	Items
Dependent	
Environmental Sustainability	ES1 - Recycling or reuse of materials
	ES2 - Reducing consumption or impact on natural resources (e.g. saving water or switching to sustainable resources
	ES3 - Energy saving or switching to renewable energy sources
	ES4 - Sustainable product development
Social Sustainability	SS1 - Improvement of employees' working conditions
	SS2 - Promotion and improvement of diversity and equality in the workplace
	SS3 - Assessing your company's impact on society
	SS4 - Employee involvement in the management of the company
Independent	
Artificial Intelligence	DT1 - Artificial Intelligence, e.g., machine learning or technologies for identifying objects or people, etc.
Cloud Computing	DT2 - Cloud computing, i.e., storing and processing files or data on remote servers hosted on the internet
Robotics	DT3 - Robotics, i.e., robots used to automate processes, e. g., construction or design, etc.
Big Data Analytics	DT4 - Big Data Analytics, e.g., data mining and predictive analytics
Blockchain	DT5 - Applying Blockchain Technology
Control Variables	
Firm Age	Length of time (in years) of the company from the initial registration of activity until 2019
Firm Size	Number of employees in the company three years ago

Note: ES – Environmental Sustainability; SS – Social Sustainability; DT – Digital Technology.

4. Results

4.1. Descriptive analysis

The sample of this study is composed of 764 manufacturing MNE. In terms of digital technologies, Table 5 shows the percentages of multinational manufacturing companies in the sample that use each of the digital technologies under study. Cloud computing is the most used digital technology (45.3%), followed by robotics (19.3%). 29.7% of companies have not implemented any of the digital technologies under analysis.

In terms of sustainability, the most of companies already implement environmentally sustainable practices (Table 6). Only 6% of companies do not have any environmental and social sustainability practices. Manufacturing companies use, and reuse materials is the most adopted

Table 5
Implementation of digital technologies in multinational manufacturing companies in the sample.

Digital Technologies'	Frequency (%)
1 - Artificial intelligence, for example, machine learning or technologies for identifying objects or people, etc.	12.2%
2 - Cloud computing, i.e. storage and processing of files or data on remote servers hosted on the Internet	45.3%
3 - Robotics, i.e. robots used to automate processes, for example in construction or design, etc.	19.3%
4 - Big data analytics, for example, data mining and predictive analytics	13.8%
5 - Blockchain	11.7%
6 - None of the previous	29.7%

Table 6
Practices of environmental and social sustainability in multinational manufacturing companies in the sample.

Environmental practices	Frequency (%)
Recycling or reuse of materials	64.6%
Reducing consumption or impact on natural resources (e.g. saving water or switching to sustainable resources	51.2%
Energy saving or switching to renewable energy sources	54.6%
Sustainable product development	36.7%
Social practices	
Improvement of employees' working conditions	70.7%
Promotion and improvement of diversity and equality in the workplace	53.5%
Assessing your company's impact on society	28.5%
Employee involvement in the management of the company	42.8%
None of the previous	6.0%

practice (64.6%), followed by energy saving (54.6%). In social terms, the results are no longer so uniform. Improving working conditions is the most implemented practice in manufacturing industries (70.7%), followed by promoting equal diversity in the workplace (52.5%). Only 28.5% of manufacturing companies evaluate their company's social impact on society.

4.2. Measures of reliability and validity

In order to assess the reflective nature of the research model, we first performed a confirmatory factorial (CFA). According to Hair et al. (2019), in reflective PLS models, the constructs are the common causes of the items or indicators that measure them and the observed constructs do not have causality effects on the corresponding constructs. All items that measure the variables have a high confirmatory factor loads (>0.70), as shown in Table 7. Goodness-of-fit (GoF) was also used to assess the goodness of fit of the model according to the formula by Tenenhaus et al. (2005). According to the criteria of Wetzels et al. (2009), if the GoF is between 0 and 1, the model fit is small, 0.25 is medium and 0.36 is large. As the GoF for model 1 is 0.361 and for model 2 it is 0.381, we can conclude that both models present an excellent fit. The Standardized Root Mean Square Residual (SRMR) is 0.058 for model 1 and 0.073 for model 2, below the reference value of 0.080 (Hair et al., 2017), proving the general adequacy of the research models. Additionally, the following model fit indices were calculated for models 1 and 2: i) the Goodness-of-Fit Index (GFI) (Model 1: 0.934 and Model 2: 0.965; reference value > 0.90); ii) Comparative Fit Index (CFI) (Model 1: 0.937 and Model 2: 0.945; reference value > 0.90); iii) Incremental Fit Index (IFI) (Model 1: 0.939; Model 2: 0.948; reference value > 0.90) and iv) Root Mean Square Approximation Error (RMSEA) (Model 1: 0.067; Model 2: 0.072; reference value < 0.08). The results of all these measurements are above the reference values, so we can conclude that models 1 and 2 have an excellent fit.

According to Hair et al. (2019), to assess the reliability and validity of the constructs, three measures should be used: Cronbach's Alpha (Cα > 0.70), Composite Reliability (CR > 0.70) and Average Variance Extracted (AVE >0.50). The Fornell-Larcker criterion should be used to assess the discriminant and R^2 validity of endogenous latent variables to assess their predictive prediction. The results of evaluation of reflective measurement model in terms of reliability, convergence and discriminant validity are shown in Table 7. The model presents reliability and convergence (Cα > 0.70, CR > 0.70 and AVE >0.50). Through the Fornell-Larcker criterion, we concluded that it also presents discriminant validity between the latent variables and the way they are measured.

Considering that the questions that gave rise to the indicators that

Table 7
Reliability, convergence and discriminant of constructs.

	Confirmatory Factor Loads	Cα	CR	AVE	ES	SS	IA	Rob	CC	BDA	Bchain	FA	FS
ES		0.772	0.803	0.508	**0.713**								
ES1	0.783												
ES2	0.810												
ES3	0.715												
ES4	0.723												
SS		0.762	0.797	0.597	0.540	**0.773**							
SS1	0.775												
SS2	0.784												
SS3	0.766												
SS4	0.787												
IA		1.000	1.000	1.000	0.173	0.049	**1.000**						
DT1	1.000												
Rob		1.000	1.000	1.000	0.197	0.142	0.213	**1.000**					
DT2	1.000												
CC		1.000	1.000	1.000	0.310	0.313	0.159	0.159	**1.000**				
DT3	1.000												
BDA		1.000	1.000	1.000	0.200	0.255	0.187	0.187	0.191	**1.000**			
DT4	1.000												
Bchain		1.000	1.000	1.000	0.144	0.104	0.075	0.075	0.190	0.180	**1.000**		
DT5	1.000												
FA		1.000	1.000	1.000	0.139	0.021	0.055	0.098	−0.004	0.015	−0.029	**1.000**	
FA	1.000												
FS		1.000	1.000	1.000	−0.003	−0.049	−0.064	−0.020	−0.051	−0.029	−0.073	0.011	**1.000**
FS	1.000												

Note: ES – Environmental Sustainability; SS – Social Sustainability; IA – Artificial Intelligenc; Rob – Robotic; CC – Cloud Computing; BDA – Big Data Analitic; Bchain – Blockchain; FA – Firm Age; FS – Firm Size.

measure the variables were collected through questionnaires, we carried out a common method bias (CMB) through the Harman one-factor test to assess whether there was any type of consistency in the responses or any bias. The research model contains six constructs with an accumulated variance of 60.8%. The largest factor explains only the 27.4% variance. Individually, no single factor explains a variance greater than 50%, so our data are unlikely to be affected by the CMB.

Finally, the R^2 of the dependent variables (environmental and social sustainability) and the Stone-Geisser (Q^2) were also evaluated to validate their predictive relevance based on the cross-redundancy approach. The results are shown in Table 8. The independent variables explain 25.7% of the dependent variable environmental sustainability (model 1) and 24.3% of the dependent variable social sustainability (model 2), thus having a "substantial effect" (Cohen, 1988). As Q^2 is greater than zero (ES – Q^2: 0.750 and SS – Q^2: 0.680), the models are relevant to predict the dependent variables.

4.3. Research model testing

Table 8 shows the estimation results of the two models (model 1 - environmental sustainability and model 2 - social sustainability) contemplating a total of five regressions for each model referring to digital technologies. The objective is to evaluate the contribution of each digital technology separately in social sustainability and environmental sustainability.

In environmental terms, the results reveal a positive and significant impact of digital technologies on the environmental sustainability of manufacturing companies, confirming hypotheses H1a, H2a, H3a, H4a, and H5a. However, the dimensions of this impact need to be balanced. Cloud computing is the digital technology that most positively influences the environmental sustainability indicators ($\beta = 0.277$), followed by blockchain ($\beta = 0.266$), robotics ($\beta = 0.210$), big data analytics ($\beta = 0.198$) and artificial intelligence ($\beta = 0.162$). The control variables also significantly influence manufacturing firms' adoption of environmentally sustainable practices.

In social terms, the adoption of digital technologies by manufacturing companies positively influences social sustainability indicators, confirming hypotheses H1b, H2b, H3b, H4b, and H5b. The use of cloud computing is the digital technology that has the most impact on the sustainable social practices adopted by manufacturing companies ($\beta = 0.314$), followed by big data analytics ($\beta = 0.217$), robotics ($\beta = 0.199$), artificial intelligence ($\beta = 0.159$) and blockchain ($\beta = 0.117$). Regarding control variables, firm age has a positive, albeit residual, impact on social sustainability indicators. However, firm size has a negative, albeit residual, impact on adopting sustainable social practices.

5. Discussion and theorical and practical implications

5.1. Discussion of results

This study considered AI, Cloud Computing, Robotics, BDA, and Blockchain digital technologies for Industry 4.0 implementation. In general, it was found that all these digital technologies positively impact the environmental and social sustainability of manufacturing MNEs and drive their competitiveness. These findings show that manufacturing MNEs have to increasingly consider environmental and social sustainability in their corporate strategy and objectives. Your decisions in these two areas will have an impact on the company's competitiveness. Our results are in line with that indicated by Müller et al. (2018), Kamble et al. (2018), Jayashree et al. (2022). The studies of these authors state that for companies to achieve environmental sustainability, and to be increasingly competitive, they have to implement Industry 4.0 technologies. Our results are complementary to those indicated by Huber et al. (2022). According to Huber et al. (2022). there is evidence that digital technologies in sectors such as healthcare, financial services,

Table 8
Output of multiple linear regressions.

		Regression 1			Regression 2			Regression 3			Regression 4			Regression 5		
Model 1 - Dependent Variable: Environmental Sustainability (Adj $R^2 = 0.257/Q^2 = 0.750$)		Coeff	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value
Independent Variables	Artificial Intelligence	0.162	9.708	0.000												
	Cloud Computing				0.277	16.143	0.000									
	Robotics							0.210	12.856	0.000						
	Big Data Analytics										0.198	12.430	0.000			
	Blockchain													0.266	17.201	0.000
Control Variables	Firm Age	0.063	3.651	0.000	0.065	3.871	0.000	0.061	3.349	0.001	0.064	3.754	0.000	0.070	3.994	0.000
	Firm Size	0.010	0.591	0.055	0.012	0.849	0.006	0.009	0.594	0.053	0.007	0.432	0.066	0.005	0.280	0.080
		Regression 1			**Regression 2**			**Regression 3**			**Regression 4**			**Regression 5**		
Model 2 - Dependent Variable: Social Sustainability (Adj $R^2 = 0.243/Q^2 = 0.680$)		Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value	Coeff.	T Statistic	P-Value
Independent Variables	Artificial Intelligence	0.159	9.109	0.000												
	Cloud Computing				0.314	19.381	0.000									
	Robotics							0.199	12.058	0.000						
	Big Data Analytics										0.217	13.486	0.000			
	Blockchain													0.117	6.549	0.000
Control Variables	Firm Age	0.002	0.981	0.002	0.003	0.020	0.084	0.003	0.169	0.866	0.001	0.017	0.087	0.008	0.424	0.072
	Firm Size	−0.001	0.501	0.001	0.003	0.191	0.049	−0.001	0.035	0.072	−0.003	0.178	0.059	−0.004	0.234	0.015

media, or telecommunications are a source of creating competitive advantage. However, only some technologies can equally contribute to environmental and social sustainability for manufacturing MNEs.

As far as AI is concerned, it is found to influence environmental and social sustainability indicators positively. This means that, with the implementation of AI, manufacturing MNEs can achieve their goals and simultaneously contribute to fulfilling the SDGs. Regarding environmental sustainability, our results are in line with that indicated by Onu and Mbohwa (2021). The authors state that the inclusion of tools, techniques and methods that involve AI are fundamental for the exploration of companies' data, as well as for the creation of applications that allow the efficient use of natural resources in the productive and organizational systems, thus making the company increasingly environmentally sustainable. This has recently been a significant challenge for manufacturing MNEs (Mathiyazhagan et al., 2019). In particular, since companies are currently facing an exponential increase in energy costs, the implementation of AI can help reduce the large number of resources (e.g., energy, water, chemicals) used in production while maintaining the number of products produced (Mao et al., 2019; Nishant et al., 2020). Regarding social sustainability, our results are in line with that indicated by Joung et al. (2013) and Khakurel et al. (2018). Social well-being, which can consist of health and safety practices, as well as the promotion of human rights, are social indicators that can be improved through the implementation of AI in companies (Joung et al., 2013). Furthermore, according to Khakurel et al. (2018) the implementation of AI can increase work efficiency, reduce working hours, improve the physical and mental health of workers, allow multitasking, automate routines and promote social and ethical actions. The results of this study concerning AI are still complementary to those indicated by Mao et al. (2019). One of the main problems identified in the literature is the lack of early risk detection and safety-oriented decision-making systems in processes, the diversity and abundance of available data information, and the related classification of information (Mao et al., 2019). The results of our study highlight that implementing AI can help manufacturing MNEs overcome such problems while achieving environmental and social sustainability. By optimizing all production processes with the help of AI, companies achieve efficiencies, can decrease employee work hours without the company losing competitiveness, improve working conditions resulting in increased employee satisfaction, and contribute to social sustainability (Joung et al., 2013; Khakurel et al., 2018).

The results also demonstrate that cloud computing positively influences environmental and social sustainability indicators. This means that the implementation of cloud computing will allow companies to increase their computing capacity and data storage, without the need for active and direct management by the company, which can improve their performance in terms of environmental and social sustainability. The implementation of cloud computing will allow companies to reduce operating costs, physical or material resources, and human resources, which is in line with what was indicated by Chang et al. (2010), Gill and Buyya (2019) and Bologa et al. (2017). According to Gill and Buyya (2019) a sustainable cloud computing model, with applications and sustainability measures, will enable more efficient energy management, virtualization, thermal recognition programs, renewable energy management, and even reuse of natural resources. Regarding social sustainability, increased information sharing through cloud computing can advance employee performance (Bologa et al., 2017), but may also result in some of the more traditional professions being replaced by smart technologies. Simultaneously, there is a need to develop and implement smarter technologies, and new professions will emerge from developing these new smart technologies (Bologa et al., 2017). However, Bologa et al. (2017) state that the implementation of cloud computing may not be consensual for society since it may increase unemployment for those who do not have skills directed toward new digital technologies.

Regarding Robotics, it is found to influence manufacturing MNEs' environmental and social sustainability indicators positively. Regarding environmental sustainability, this result means that through programmable robots it will be possible for the company to carry out tasks in a totally autonomous or semi-autonomous way. This will allow companies to reduce production costs, improve industrial performance, meet manufacturing quality requirements, customize the product, make production more flexible and apply sustainable practices. This result is in line with that indicated by Ogbemhe et al. (2017) and Gadaleta et al. (2019). Robotics is widely recognized for encouraging environmentally sustainable practices while optimizing the production of manufacturing companies (Gadaleta et al., 2019; Ogbemhe et al., 2017). Through robotics, it is possible to make production processes more efficient, decrease resource usage (e.g., electricity, gas, water), reduce CO_2 emissions without compromising the quality and quantity of goods produced, and decrease industrial waste and reusing waste in producing new circular products (Ajwani-Ramchandani et al., 2021; Yamamoto et al., 2020). Regarding social sustainability, our results mean that Robotics brings social benefits. This result is different from that indicated by Ogbemhe et al. (2017) and Enyoghasi and Badurdeen (2021), but is in line with what Radić et al. (2020). Ogbemhe et al. (2017) and Enyoghasi and Badurdeen (2021) afirmam que organizations and institutions need to ensure that they manage the negative aspects of increased robotics, including social problems, such as unemployment. However, according to Radić et al. (2020) the application of robotics in manufacturing industries can improve human working conditions, reducing monotonous and routine tasks, increasing the qualifications and skills of workers to be able to handle and deal with robotics applications, which will boost social sustainability practices.

It was found that BDA positively influences the environmental and social sustainability indicators of manufacturing MNEs. Este reultado significa que ao implementar a BDA as manufacturing MNEs ficam com uma capacidade maior de criar e analisar de uma forma mais rápida um maior volume de diversos dados. As manufacturing MNEs ficam também com uma capacidade superior de realizarem um agrupamento de recursos estratégicos (humanos e habilidades gerenciais e técnicas) que podem melhorar seu desempenho. Explorando essa capacidade organizacional superior, as manufacturing MNEs pode alcançar uma vantagem competitiva environmental and social sustainability. These findings are in line with that indicated by Akter et al. (2016), Wamba et al. (2017) and Dubey et al. (2019), but different from that indicated by Gangwar et al. (2022). An example of the good applicability of BDA, in terms of environmental sustainability, is its impact on the green supply chain (Doolun et al., 2018). By implementing BDA, manufacturing MNEs could develop new tools that accurately monitor the supply chain in real-time, decreasing risks and making processes more agile, allowing these companies to have an environmentally sustainable competitive advantage. Regarding social sustainability, Dubey et al. (2019) argue that with the implementation of BDA, manufacturing MNEs promote improved facilities, training for workers, gender equality, elimination of child labor, and greater social benefits, which is in line with the results of the present study. On the other hand, Gangwar et al. (2022) the application of the BDA can bring social insecurity. Therefore, its application in promoting social sustainability has been a priority for companies (Gangwar et al., 2022).

The present study it was found that the application of blockchain technology in manufacturing industries positively influences the environmental sustainability. This means that blockchain technology allows manufacturing MNEs to make continuous advances in the computation of information, using a central agent that coordinates data in a reliable, transparent and shared way, thus allowing to improve efficiency. Therefore, blockchain technology contributes to manufacturing MNEs being increasingly environmentally sustainable. Our results are in line with that indicated by Parmentola et al. (2022), Alles and Gray (2020), Saberi et al. (2019), Manupati et al. (2020) and Upadhyay et al. (2021). The implementation of blockchain technology allows, for example, to implement a sustainable production model, a green supply chain (Mora et al., 2021), monitor, manipulate and store data about activities that can increase pollution and environmental devastation, and also collect real-time data about green activities. It also helps managers in decision-making (Parmentola et al., 2022). Contrary to the results of the present study, Parmentola et al. (2022) states that traditional blockchain systems require high CO2 emissions and high energy costs. Furthermore, to store large servers, large facilities are needed, which poses a threat in terms of wasted natural resources and forest devastation (Parmentola et al., 2022). These results are not in line with those of the present study. The results of the present study reinforce the relevance of blockchain technology being implemented in manufacturing MNEs. Blockchain technology brings multiple advantages such as i) in reducing the hazardousness of outputs, inputs, and waste (e.g., monitoring and tracking of raw material used, products, and waste) (Alles and Gray, 2020); ii) in environmental management (e.g., certification and enforcement of environmental compliance, environmental budgeting, and employee implications) (Saberi et al., 2019); iii) natural environment (e.g., serves to support decisions regarding natural resource use, waste management, tracking the impact of manufacturers' activities on the ecosystem) (Manupati et al., 2020); iv) reducing land, air, and water pollution (e.g., facilitating the use of renewable energy; v) combating wasted inputs in production; saving resources; reducing the application of fossil fuels) (Saberi et al., 2019); vi) optimizing resource and energy use (e.g., promoting the use of renewable energy, motivating recycling) (Upadhyay et al., 2021).

Finally, this study confirms that the application of blockchain technology in manufacturing industries positively influences the social sustainability. This means that blockchain technology contributes to promoting social sustainability in manufacturing MNEs. Therefore, its implementation can, for example, improve working conditions, identify possible violations of human rights, and increase social engagement. Our results are in line with that indicated by Khanfar et al. (2021), Katsikouli et al. (2021), Venkatesh et al. (2020) and Park and Li (2021). According to Khanfar et al. (2021), blockchain technology can contribute to improving working conditions (e.g., disclosing safety and health practices); business practices (e.g., promoting fair and balanced trade; tracking and monitoring corruption situations) (Katsikouli et al., 2021)); reduce safety failures; promote product innovation) track and monitor companies' health and safety certificates; improve working conditions, and track workers' work activity) (Venkatesh et al., 2020); customer issues (e.g., optimizing production and delivery processes; enabling a direct relationship between stakeholders; facilitating product customization; societal engagement (e.g., making the business model more efficient; reducing costs; creating new business opportunities; boosting social services) (Schulz et al., 2020); and human rights (e.g., preventing social abuse and alarmism; reducing and identifying situations of worker exploitation) (Park and Li, 2021).

5.2. *Theoretical and practical implications*

In theoretical terms, the findings of this study are a good opportunity for the evolution of the RBV theory, since: (i) we expand the capabilities and resources traditionally considered in the RBV, by considering digital technologies as a specific capability of companies based on resources; (ii) we conclude that digital technologies are valuable to achieve strategic goals of companies in the field of environmental and social sustainability and (iii) we specify the unequal contribution of different digital technologies to achieve environmental and social sustainability goals, allowing us to determine the probability of a digital technology to have greater value in the strategic context of manufacturing MNEs. Furthermore, as far as we know, it is the first study to explore the individual contribution of five digital technologies to environmental and social sustainability at the same time, allowing to reach the interests of different stakeholders.

In practical terms, some implications can be inferred from the results of this study: (i) how it has been demonstrated that there is a positive contribution from the implementation of digital technologies to achieve the environmental and social sustainability of manufacturing MNEs and, as such, the resources digital technologies have to be a component of business strategies in order for companies to achieve sustainable development goals; (ii) the implementation of digital technologies in European manufacturing MNEs is still low and, consequently, private investment by companies must be channeled towards the digitization of manufacturing activities, with government officials playing an important role, namely in terms of granting subsidies for a faster digital transition and efficient design of tax benefits on expenses incurred in investing in these technologies; (iii) the different digital technologies contribute in an unequal way to achieving environmental and social sustainability objectives and as such, companies must prioritize their implementation strategies and invest in the training of workers in the technologies that contribute most to achieving the intended objectives; (iv) manufacturing MNEs should include environmental and social dimensions in their corporate strategy (Luthra et al., 2020) to promote their benefits to society (Ghobakhloo, 2020), and the implementation of digital technologies (Industry 4.0) should not be motivated only to increase productivity and performance and, consequently, competitiveness. Companies with high investments in Industry 4.0 cannot neglect or encourage the increase in unemployment, nor can they only be concerned with reducing waste and consumption of raw materials (Satyro et al., 2022). In addition, the effects of digital technology depend on how it is implemented and as such, companies must consider the direct and immediate consequences, but also the indirect consequences that may make the implementation of digital technologies unfeasible or amplify the positive effects (Lioukas et al., 2016). Thus, these results can contribute to the improvement of the implementation of digital technologies and to the search for continuous updating of the same, allowing the manufacturing industries to produce more environmentally friendly and socially sustainable, with the creation of value not only for this industry but for the stakeholders and society in general.

6. Conclusion

Manufacturing MNEs have been under increasing pressure to implement Industry 4.0. in their business models to accelerate environmental and social sustainability and simultaneously become more competitive. In this context, the present study aimed to analyze the contribution of digital technologies to promoting environmental and social sustainability in manufacturing MNEs. The literature review carried out demonstrates that the implementation of digital technologies in manufacturing MNEs has been carried out essentially to pursue economic objectives of better performance and value creation, and as such, economic sustainability. The contribution of digital technologies to achieving environmental and social sustainability goals has been neglected. However, in the present study we demonstrate that digital technologies (AI, Cloud Computing, Robotics, BDA, and Blockchain) positively impact manufacturing MNEs' environmental and social sustainability. Thus, digital technologies can be vital for manufacturing MNEs to be more competitive and simultaneously be environmentally and socially sustainable, thus contributing to sustainable development goals. In addition, this study demonstrates, through the diagnosis of 764 manufacturing MNEs in Europe, that the implementation of digital technologies is still low and that the contribution of the implementation of digital technologies is uneven, leading companies to prioritize investment in a certain technology (over another) to achieve environmental and social sustainability. This conclusion is possible because in a single study we were able to compare the contribution of five different digital technologies to economic and social sustainability. Thus, in order to achieve environmental sustainability goals, companies should invest in digital technologies that can contribute more to the environmental practices already implemented in companies, prioritizing cloud computing, then blockchain, robotic, BDA and, finally, the AI. In terms of social sustainability, the implementation of cloud computing is also the digital technology that contributes the most to social well-being, followed by BDA, robotics, AI and finally blockchain.

This study is not without limitations. As limitations of the study, we can point out the fact that we used only secondary data from a single database and as such, we are restricted to the sample of indicators collected by this database. Data goes back to 2020 and includes manufacturing companies from all 27 Member States. Therefore, more recent data can be included in future studies, the comparison of different sectors of activity, as well as the inclusion of other variables from other databases. Future studies can also consider other digital technologies such as smart devices, high-speed infrastructure, augmented reality, and IoT.

New studies can also be analyzed from the perspective of other theories, such as sustainability theory, stakeholder theory, and theory of everything. However, it was only possible to answer some questions, and the following should be considered for future studies: How quickly is the investment made in digital technologies recovered? When implementing digital technologies, what percentage of costs can be reduced? What are the first order and second order effects of the implementation of digital technologies in companies? What impacts does the deployment of digital technologies have on the brand of manufacturing MNEs? Do workers with robotics systems have better working conditions than traditional occupations? More study needs to be done on the social impacts that manufacturing MNEs have when migrating to cloud computing (Azadi et al., 2021; Mohammed et al., 2020). Additionally, we should replicate the questions from this study and broaden the range of digital technologies (e.g. include smart devices, high-speed infrastructure, augmented reality, and IoT) in MNCs from various countries to collect primary data and reinforce the results of this research.

CRediT authorship contribution statement

João J. Ferreira: Conceptualization, Methodology, Supervision. **João M. Lopes:** Data curation, Writing – original draft, preparation. **Sofia Gomes:** Visualization, Investigation, Software. **Husain G. Rammal:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136841.

References

Adomako, S., Amankwah-Amoah, J., Danso, A., Konadu, R., Owusu-Agyei, S., 2019. Environmental sustainability orientation and performance of family and nonfamily firms. Bus. Strat. Environ. 28, 1250–1259. https://doi.org/10.1002/bse.2314.

Ajwani-Ramchandani, R., Figueira, S., Torres de Oliveira, R., Jha, S., 2021a. Enhancing the circular and modified linear economy: the importance of blockchain for developing economies. Resour. Conserv. Recycl. 168, 105468 https://doi.org/10.1016/j.resconrec.2021.105468.

Ajwani-Ramchandani, R., Figueira, S., Torres de Oliveira, R., Jha, S., Ramchandani, A., Schuricht, L., 2021b. Towards a circular economy for packaging waste by using new technologies: the case of large multinationals in emerging economies. J. Clean. Prod. 281, 125139 https://doi.org/10.1016/j.jclepro.2020.125139.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018.

Alles, M., Gray, G.L., 2020. The first mile problem": deriving an endogenous demand for auditing in blockchain-based business processes. Int. J. Account. Inf. Syst. 38, 100465 https://doi.org/10.1016/j.accinf.2020.100465.

Amjad, M.S., Rafique, M.Z., Khan, M.A., 2021. Leveraging optimized and cleaner production through industry 4.0. Sustain. Prod. Consum. 26, 859–871. https://doi.org/10.1016/j.spc.2021.01.001.

Asif, M., 2020. Are QM models aligned with Industry 4.0? A perspective on current practices. J. Clean. Prod. 258, 120820 https://doi.org/10.1016/j.jclepro.2020.120820.

Azadi, M., Moghaddas, Z., Cheng, T.C.E., Farzipoor Saen, R., 2021. Assessing the sustainability of cloud computing service providers for Industry 4.0: a state-of-the-art analytical approach. Int. J. Prod. Res. 1–18. https://doi.org/10.1080/00207543.2021.1959666.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120. https://doi.org/10.1177/014920639101700108.

Bi, Z.M., Wang, L., 2013. Manufacturing paradigm shift towards better sustainability. In: Li, W., Mehnen, J. (Eds.), Cloud Manufacturing: Distributed Computing Technologies for Global and Sustainable Manufacturing. Springer London, London, pp. 99–119.

Birkel, H.S., Veile, J.W., Müller, J.M., Hartmann, E., Voigt, K.-I., 2019. Development of a risk framework for industry 4.0 in the context of sustainability for established manufacturers. Sustainability 11, 384. https://doi.org/10.3390/su11020384.

Bologa, R., Lupu, A.-R., Boja, C., Georgescu, T.M., 2017. Sustaining employability: a process for introducing cloud computing, big data, social networks, mobile programming and cybersecurity into academic curricula. Sustainability 9, 2235. https://doi.org/10.3390/su9122235.

Chang, V., Bacigalupo, D., Wills, G., Roure, D., 2010. A Categorisation of Cloud Computing Business Models. In: Paper Presented at the 2010 10th IEEE/ACM International Conference on Cluster. Cloud and Grid Computing, Melbourne, Australia, 17-20 May 2010.

Chauhan, C., Parida, V., Dhir, A., 2022. Linking circular economy and digitalisation technologies: a systematic literature review of past achievements and future promises. Technol. Forecast. Soc. Change 177, 121508. https://doi.org/10.1016/j.techfore.2022.121508.

Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., De Felice, F., 2020. Artificial intelligence and machine learning applications in smart production: progress, trends, and directions. Sustainability 12, 492. https://doi.org/10.3390/su12020492.

Cohen, J., 1988. Statistical Power Analysis for the Behavioral Sciences. Lwrence Earlbaum Associates, New York.

Deloitte, 2021. Sustainable Manufacturing: from Vision to Action. Retrieved from London, UK. https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Energy-and-Resources/gx-eri-sustainable-manufacturing-2021.pdf.

Doolun, I.S., Ponnambalam, S.G., Subramanian, N., Kanagaraj, G., 2018. Data driven hybrid evolutionary analytical approach for multi objective location allocation decisions: automotive green supply chain empirical evidence. Comput. Oper. Res. 98, 265–283. https://doi.org/10.1016/j.cor.2018.01.008.

Duan, L., Xiong, Y., 2015. Big data analytics and business analytics. J. Manag. Anal. 2, 1–21. https://doi.org/10.1080/23270012.2015.1020891.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F., Roubaud, D., 2019. Can big data and predictive analytics improve social and environmental sustainability? Technol. Forecast. Soc. Change 144, 534–545. https://doi.org/10.1016/j.techfore.2017.06.020.

Enyoghasi, C., Badurdeen, F., 2021. Industry 4.0 for sustainable manufacturing: opportunities at the product, process, and system levels. Resour. Conserv. Recycl. 166, 105362 https://doi.org/10.1016/j.resconrec.2020.105362.

Esmaeilian, B., Sarkis, J., Lewis, K., Behdad, S., 2020. Blockchain for the future of sustainable supply chain management in Industry 4.0. Resour. Conserv. Recycl. 163, 105064 https://doi.org/10.1016/j.resconrec.2020.105064.

European Commission, 2020. Flash Eurobarometer 486 (SMEs, Start-Ups, Scale-Ups and Entrepreneurship). https://doi.org/10.4232/1.13639. Retrieved from Brussels:

Eurostat, 2022. Structure of Multinational Enterprise Groups in the EU. Retrieved from. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Structure_of_multinational_enterprise_groups_in_the_EU#Multinational_enterprise_groups_in_the_EU_and_EFTA_are_mainly_active_in_the_manufacturing_sector.2C_and_employment_is_concentrated_in_a_small_number_of_sectors.

Feng, S., Li, L.X., Cen, L., 2001. An object-oriented intelligent design tool to aid the design of manufacturing systems. Knowl. Base Syst. 14, 225–232. https://doi.org/10.1016/S0950-7051(01)00100-9.

Fisher, O., Watson, N., Porcu, L., Bacon, D., Rigley, M., Gomes, R.L., 2018. Cloud manufacturing as a sustainable process manufacturing route. J. Manuf. Syst. 47, 53–68. https://doi.org/10.1016/j.jmsy.2018.03.005.

Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Change 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gadaleta, M., Pellicciari, M., Berselli, G., 2019. Optimization of the energy consumption of industrial robots for automatic code generation. Robot. Comput. Integrated Manuf. 57, 452–464. https://doi.org/10.1016/j.rcim.2018.12.020.

Gajšek, B., Stradovnik, S., Hace, A., 2020. Sustainable move towards flexible, robotic, human-involving workplace. Sustainability 12, 6590. https://doi.org/10.3390/su12166590.

Gangwar, H., Mishra, R., Kamble, S., 2022. Adoption of big data analytics practices for sustainability development in the e-commercesupply chain: a mixed-method study. Int. J. Qual. Reliab. Manag. 1–25. https://doi.org/10.1108/IJQRM-07-2021-0224 ahead-of-print.

García-Muiña, F.E., Medina-Salgado, M.S., Ferrari, A.M., Cucchi, M., 2020. Sustainability transition in industry 4.0 and smart manufacturing with the triple-layered business

model canvas. Sustainability 12, 2364. Retrieved from. https://www.mdpi.com/2071-1050/12/6/2364.
Ghobakhloo, M., 2020. Industry 4.0, digitization, and opportunities for sustainability. J. Clean. Prod. 252, 119869 https://doi.org/10.1016/j.jclepro.2019.119869.
Ghobakhloo, M., Fathi, M., Iranmanesh, M., Maroufkhani, P., Morales, M.E., 2021. Industry 4.0 ten years on: a bibliometric and systematic review of concepts, sustainability value drivers, and success determinants. J. Clean. Prod. 302, 127052 https://doi.org/10.1016/j.jclepro.2021.127052.
Gill, S.S., Buyya, R., 2019. A taxonomy and future directions for sustainable cloud computing: 360 degree view. ACM Comput. Surv. 51, 1–33. https://doi.org/10.1145/3241038.
Godina, R., Ribeiro, I., Matos, F., Ferreira, B.T., Carvalho, H., Pecas, P., 2020. Impact assessment of additive manufacturing on sustainable business models in industry 4.0 context. Sustainability 12, 7066. https://doi.org/10.3390/su12177066.
Grybauskas, A., Stefanini, A., Ghobakhloo, M., 2022. Social sustainability in the age of digitalization: a systematic literature Review on the social implications of industry 4.0. Technol. Soc. 70, 101997 https://doi.org/10.1016/j.techsoc.2022.101997.
Guenat, S., Purnell, P., Davies, Z.G., Nawrath, M., Stringer, L.C., Babu, G.R., Balasubramanian, M., Ballantyne, E.E.F., Bylappa, B.K., Chen, B., De Jager, P., Del Prete, A., Di Nuovo, A., Ehi-Eromosele, C.O., Eskandari Torbaghan, M., Evans, K.L., Fraundorfer, M., Haouas, W., Izunobi, J.U., Jauregui-Correa, J.C., Kaddouh, B.Y., Lewycka, S., MacIntosh, A.C., Mady, C., Maple, C., Mhiret, W.N., Mohammed-Amin, R.K., Olawole, O.C., Oluseyi, T., Orfila, C., Ossola, A., Pfeifer, M., Pridmore, T., Rijal, M.L., Rega-Brodsky, C.C., Robertson, I.D., Rogers, C.D.F., Rougé, C., Rumaney, M.B., Seeletso, M.K., Shaqura, M.Z., Suresh, L.M., Sweeting, M. N., Taylor Buck, N., Ukwuru, M.U., Verbeek, T., Voss, H., Wadud, Z., Wang, X., Winn, N., Dallimer, M., 2022. Meeting sustainable development goals via robotics and autonomous systems. Nat. Commun. 13, 3559. https://doi.org/10.1038/s41467-022-31150-5.
Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31, 2–24. https://doi.org/10.1108/EBR-11-2018-0203.
Hair Jr., J.F., Matthews, L.M., Matthews, R.L., Sarstedt, M., 2017. PLS-SEM or CB-SEM: updated guidelines on which method to use. Int. J. Multi. Data Anal. 1, 107–123. https://doi.org/10.1504/ijmda.2017.10008574.
Hamalainen, M., Karjalainen, J., 2017. Social manufacturing: when the maker movement meets interfirm production networks. Bus. Horiz. 60, 795–805. https://doi.org/10.1016/j.bushor.2017.07.007.
Haseeb, M., Hussain, H.I., Ślusarczyk, B., Jermsittiparsert, K., 2019. Industry 4.0: a solution towards technology challenges of sustainable business performance. Soc. Sci. 8, 154. https://doi.org/10.3390/socsci8050154.
Huber, R., Oberländer, A.M., Faisst, U., Röglinger, M., 2022. Disentangling capabilities for industry 4.0 - an information systems capability perspective. Inf. Syst. Front 1–29. https://doi.org/10.1007/s10796-022-10260-x.
Jayashree, S., Hassan Reza, M.N., Malarvizhi, C.A.N., Maheswari, H., Hosseini, Z., Kasim, A., 2021. The impact of technological innovation on industry 4.0 implementation and sustainability: an empirical study on Malaysian small and medium sized enterprises. Sustainability 13, 10115. https://doi.org/10.3390/su131810115.
Jayashree, S., Reza, M.N.H., Malarvizhi, C.A.N., Gunasekaran, A., Rauf, M.A., 2022. Testing an adoption model for Industry 4.0 and sustainability: a Malaysian scenario. Sustain. Prod. Consum. 31, 313–330. https://doi.org/10.1016/j.spc.2022.02.015.
Joung, C.B., Carrell, J., Sarkar, P., Feng, S.C., 2013. Categorization of indicators for sustainable manufacturing. Ecol. Indicat. 24, 148–157. https://doi.org/10.1016/j.ecolind.2012.05.030.
Kagermann, H., Wahlster, W., Helbig, J., 2013. Recommendations for Implementing the Strategic Initiative Industrie 4.0: Final Report of the Industrie 4.0 Working Group. Retrieved from Berlin, Germany. https://en.acatech.de/wp-content/uploads/sites/6/2018/03/Final_report__Industrie_4.0_accessible.pdf.
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 Saf. Environ. Protect. 117, 408–425. https://doi.org/10.1016/j.psep.2018.05.009.
Katsikouli, P., Wilde, A.S., Dragoni, N., Hogh-Jensen, H., 2021. On the benefits and challenges of blockchains for managing food supply chains. J. Sci. Food Agric. 101, 2175–2181. https://doi.org/10.1002/jsfa.10883.
Kaur, H., Singh, S.P., 2018. Heuristic modeling for sustainable procurement and logistics in a supply chain using big data. Comput. Oper. Res. 98, 301–321. https://doi.org/10.1016/j.cor.2017.05.008.
Khakurel, J., Melkas, H., Porras, J., 2018. Tapping into the wearable device revolution in the work environment: a systematic review. Inf. Technol. People 31, 791–818. https://doi.org/10.1108/ITP-03-2017-0076.
Khanfar, A.A.A., Iranmanesh, M., Ghobakhloo, M., Senali, M.G., Fathi, M., 2021. Applications of blockchain technology in sustainable manufacturing and supply chain management: a systematic review. Sustainability 13, 7870. https://doi.org/10.3390/su13147870.
Khin, S., Kee, D.M.H., 2022. Factors influencing Industry 4.0 adoption. J. Manuf. Technol. Manag. 33, 448–467. https://doi.org/10.1108/JMTM-03-2021-0111.
Kusiak, A., 2018. Smart manufacturing. Int. J. Prod. Res. 56, 508–517. https://doi.org/10.1080/00207543.2017.1351644.
Lee, K., 2021. A systematic review on social sustainability of artificial intelligence in product design. Sustainability 13, 2668. https://doi.org/10.3390/su13052668.
Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X., Liu, C., 2020. Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: a survey. Renew. Sustain. Energy Rev. 132, 110112 https://doi.org/10.1016/j.rser.2020.110112.
Li, Y., Sun, H., Li, D.K., Song, J., Ding, R.G., 2022. Effects of digital technology adoption on sustainability performance in construction projects: the mediating role of stakeholder collaboration. J. Manag. Eng. 38, 04022016. Artn 0402201610.1061/(Asce)Me.1943-5479.0001040.
Lioukas, C.S., Reuer, J.J., Zollo, M., 2016. Effects of information technology capabilities on strategic alliances: implications for the resource-based view. J. Manag. Stud. 53, 161–183. https://doi.org/10.1111/joms.12179.
Lloyd, C., Payne, J., 2019. Rethinking country effects: robotics, AI and work futures in Norway and the UK. New Technol. Work. Employ. 34, 208–225. https://doi.org/10.1111/ntwe.12149.
Lopes, J., Ferreira, J.J., Farinha, L., 2021. Entrepreneurship and the resource-based view: what is the linkage? A bibliometric approach. Int. J. Entrepreneurial Ventur. 13, 137–164. https://doi.org/10.1504/ijev.2021.114408.
López, L.-A., Cadarso, M.-Á., Zafrilla, J., Arce, G., 2019. The carbon footprint of the U.S. multinationals' foreign affiliates. Nat. Commun. 10, 1672. https://doi.org/10.1038/s41467-019-09473-7.
Luthra, S., Kumar, A., Zavadskas, E.K., Mangla, S.K., Garza-Reyes, J.A., 2020. Industry 4.0 as an enabler of sustainability diffusion in supply chain: an analysis of influential strength of drivers in an emerging economy. Int. J. Prod. Res. 58, 1505–1521. https://doi.org/10.1080/00207543.2019.1660828.
Mageto, J., 2021. Big data analytics in sustainable supply chain management: a focus on manufacturing supply chains. Sustainability 13, 7101. https://doi.org/10.3390/su13137101.
Manupati, V.K., Schoenherr, T., Ramkumar, M., Wagner, S.M., Pabba, S.K., Inder Raj Singh, R., 2020. A blockchain-based approach for a multi-echelon sustainable supply chain. Int. J. Prod. Res. 58, 2222–2241. https://doi.org/10.1080/00207543.2019.1683248.
Mao, S., Wang, B., Tang, Y., Qian, F., 2019. Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. Engineering 5, 995–1002. https://doi.org/10.1016/j.eng.2019.08.013.
Martin, M.G., Alvarez, A.P., Ordieres-Mere, J., Villalba-Diez, J., Morales-Alonso, G., 2021. New business models from prescriptive maintenance strategies aligned with sustainable development goals. Sustainability 13, 216. https://doi.org/10.3390/su13010216.
Mathiyazhagan, K., Sengupta, S., Mathivathanan, D., 2019. Challenges for implementing green concept in sustainable manufacturing: a systematic review. Opsearch 56, 32–72. https://doi.org/10.1007/s12597-019-00359-2.
Mohamed, M., 2018. Challenges and benefits of industry 4.0: an overview. Int. J. Supply Oper. Manag. 5, 256–265.
Mohammed, F., Olayah, F., Ali, A., Gazem, N.A., 2020. The effect of cloud computing adoption on the sustainability of e-government services: a review. Int. J. Adv. Sci. Technol. 29, 2636–2642.
Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., Ueda, K., 2016. Cyber-physical systems in manufacturing. CIRP Annals 65, 621–641. https://doi.org/10.1016/j.cirp.2016.06.005.
Mora, H., Mendoza-Tello, J.C., Varela-Guzmán, E.G., Szymanski, J., 2021. Blockchain technologies to address smart city and society challenges. Comput. Hum. Behav. 122, 106854 https://doi.org/10.1016/j.chb.2021.106854.
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, 247. 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. J. Manuf. Technol. Manag. 30, 607–627. https://doi.org/10.1108/JMTM-03-2018-0071.
Nishant, R., Kennedy, M., Corbett, J., 2020. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int. J. Inf. Manag. 53, 102104 https://doi.org/10.1016/j.ijinfomgt.2020.102104.
Nuortimo, K., Harkonen, J., 2018. Opinion mining approach to study media-image of energy production. Implications to public acceptance and market deployment. Renew. Sustain. Energy Rev. 96, 210–217. https://doi.org/10.1016/j.rser.2018.07.018.
Ogbemhe, J., Mpofu, K., Tlale, N.S., 2017. Achieving sustainability in manufacturing using robotic methodologies. Procedia Manuf. 8, 440–446. https://doi.org/10.1016/j.promfg.2017.02.056.
Onu, P., Mbohwa, C., 2021. Industry 4.0 opportunities in manufacturing SMEs: sustainability outlook. Mater. Today Proc. 44, 1925–1930. https://doi.org/10.1016/j.matpr.2020.12.095.
Oztemel, E., Gursev, S., 2020. Literature review of Industry 4.0 and related technologies. J. Intell. Manuf. 31, 127–182. https://doi.org/10.1007/s10845-018-1433-8.
Park, A., Li, H., 2021. The effect of blockchain technology on supply chain sustainability performances. Sustainability 13, 1726. https://doi.org/10.3390/su13041726.
Parmentola, A., Petrillo, A., Tutore, I., De Felice, F., 2022. Is blockchain able to enhance environmental sustainability? A systematic review and research agenda from the perspective of Sustainable Development Goals (SDGs). Bus. Strat. Environ. 31, 194–217. https://doi.org/10.1002/bse.2882.
Piyathanavong, V., Garza-Reyes, J.A., Kumar, V., Maldonado-Guzmán, G., Mangla, S.K., 2019. The adoption of operational environmental sustainability approaches in the Thai manufacturing sector. J. Clean. Prod. 220, 507–528. https://doi.org/10.1016/j.jclepro.2019.02.093.
Radić, I., Rupnik, B., Šinko, S., Kramberger, T., Gajšek, B., 2020. Redesign of the workplace for toolmakers towards industry 4.0. In: Karabegović, I., Kovačević, A., Banjanović-Mehmedović, L., Dašić, P. (Eds.), Handbook of Research on Integrating Industry 4.0 in Business and Manufacturing. IGI Global, Hershey, PA, USA, pp. 492–511.

Ren, L., Zhang, L., Tao, F., Zhao, C., Chai, X., Zhao, X., 2015. Cloud manufacturing: from concept to practice. Enterprise Inf. Syst. 9, 186–209. https://doi.org/10.1080/17517575.2013.839055.

Russell, S.J., Norvig, P., 2016. Artificial Intelligence: a Modern Approach, 3 ed. Pearson Education Limited, London, UK.

Saberi, S., Kouhizadeh, M., Sarkis, J., Shen, L.J., 2019. Blockchain technology and its relationships to sustainable supply chain management. Int. J. Prod. Res. 57, 2117–2135. https://doi.org/10.1080/00207543.2018.1533261.

Satyro, W.C., de Almeida, C.M.V.B., Pinto Jr., M.J.A., Contador, J.C., Giannetti, B.F., de Lima, A.F., Fragomeni, M.A., 2022. Industry 4.0 implementation: the relevance of sustainability and the potential social impact in a developing country. J. Clean. Prod. 337, 130456 https://doi.org/10.1016/j.jclepro.2022.130456.

Schulz, K.A., Gstrein, O.J., Zwitter, A.J., 2020. Exploring the governance and implementation of sustainable development initiatives through blockchain technology. Futures 122, 102611. https://doi.org/10.1016/j.futures.2020.102611.

Sun, Y., Shahzad, M., Razzaq, A., 2022. Sustainable organizational performance through blockchain technology adoption and knowledge management in China. J. Innov. Knowledge 7, 100247. https://doi.org/10.1016/j.jik.2022.100247.

Szalavetz, A., 2022. The digitalisation of manufacturing and blurring industry boundaries. CIRP J. Manufact. Sci. Technol. 37, 332–343. https://doi.org/10.1016/j.cirpj.2022.02.015.

Tan, W., Xu, Y., Xu, W., Xu, L., Zhao, X., Wang, L., Fu, L., 2010. A methodology toward manufacturing grid-based virtual enterprise operation platform. Enterprise Inf. Syst. 4, 283–309. https://doi.org/10.1080/17517575.2010.504888.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y.-M., Lauro, C., 2005. PLS path modeling. Comput. Stat. Data Anal. 48, 159–205. https://doi.org/10.1016/j.csda.2004.03.005.

Tseng, M.-L., Tan, R.R., Chiu, A.S.F., Chien, C.-F., Kuo, T.C., 2018. Circular economy meets industry 4.0: can big data drive industrial symbiosis? Resour. Conserv. Recycl. 131, 146–147. https://doi.org/10.1016/j.resconrec.2017.12.028.

Upadhyay, A., Mukhuty, S., Kumar, V., Kazancoglu, Y., 2021. Blockchain technology and the circular economy: implications for sustainability and social responsibility. J. Clean. Prod. 293, 126130 https://doi.org/10.1016/j.jclepro.2021.126130.

Venkatesh, V.G., Kang, K., Wang, B., Zhong, R.Y., Zhang, A., 2020. System architecture for blockchain based transparency of supply chain social sustainability. Robot. Comput. Integrated Manuf. 63, 101896 https://doi.org/10.1016/j.rcim.2019.101896.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.

Wetzels, M., Odekerken-Schröder, G., van Oppen, C., 2009. Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration. MIS Q. 33, 177–195. https://doi.org/10.2307/20650284.

Winter, J., 2020. The evolutionary and disruptive potential of Industrie 4.0. Hungarian Geographical Bulletin 69, 83–97. https://doi.org/10.15201/hungeobull.69.2.1.

Xu, L.D., Xu, E.L., Li, L., 2018. Industry 4.0: state of the art and future trends. Int. J. Prod. Res. 56, 2941–2962. https://doi.org/10.1080/00207543.2018.1444806.

Yadav, G., Luthra, S., Jakhar, S.K., Mangla, S.K., Rai, D.P., 2020. A framework to overcome sustainable supply chain challenges through solution measures of industry 4.0 and circular economy: an automotive case. J. Clean. Prod. 254, 120112 https://doi.org/10.1016/j.jclepro.2020.120112.

Yamamoto, T., Hayama, H., Hayashi, T., Mori, T., 2020. Automatic energy-saving operations system using robotic process automation. Energies 13, 2342. https://doi.org/10.3390/en13092342.