Sustainability orientation, industrial big data and product innovation: evidence from the European manufacturing sector

Abstract

Sustainability is one of the greatest challenges for industry today. The purpose of this paper is to study the influence of sustainability orientation on product innovation in the European manufacturing sector, with a particular focus on the direct and mediating effect of industrial big data use, something that has been largely neglected so far. The data used for the purpose of the present study were collected from the European Manufacturing Survey (EMS) 2018 edition, consisting of 1,123 surveys administered in Austria, Spain, Croatia, Lithuania, Slovakia, Slovenia and Serbia. Binary logistic regressions and Hayes mediation models are used to test the hypotheses. Results suggest that sustainability orientation practices and industrial big data use positively influence product innovation, and that industrial big data use mediates the relation between sustainability orientation and product innovation. The findings have implications for both theory and practice.

Keywords: Sustainability orientation, sustainability practices, industrial big data, product innovation, European Manufacturing Survey.

Funding: Open Access funding provided thanks to the CRUE-CSIC agreement with Elsevier

Declarations of interest: none

1. Introduction

The declaration of the United Nations Sustainable Development Goals in September 2015 marked a pivotal moment in an era increasingly attuned to the imperatives surrounding sustainable development. These 17 goals, targeted for attainment by 2030, have gained attention and spurred concerted efforts across diverse sectors. Within the private sector, the sustainability focus resonates with the earlier concept of the 'triple bottom line', a holistic approach considering economic, social and environmental aspects (Elkington and Rowlands, 1999). However, despite the growing emphasis on sustainability in business strategies, its seamless integration, particularly in the context of product innovation, remains intricate and subject to debate.

In this regard, sustainability orientation (SO) in business, defined as the extent to which firms integrate sustainability principles into their culture and practices, has become increasingly relevant (Claudy et al., 2016; Khizar et al., 2021; Kuckertz & Wagner, 2010; Usman Khizar et al., 2022). However, the inherent tensions between the economic, social and environmental aims of sustainability often pose challenges, particularly when developing new products and services (Fisher et al., 2020). The academic discourse reflects this complexity, with studies exposing varying perspectives on the relationship ranging from a positive outlook, in the sense that sustainability enhances product and service innovation (Ahmadi-Gh & Bello-Pintado, 2021) , to negative (Sen & Bhattacharya, 2001) and ambiguous (Abdul-Rashid et al., 2017; Surroca et al., 2010) ones.

In the manufacturing industry, which represents an important part of the private sector, embracing sustainability can enhance product quality, resource efficiency and working conditions, while reducing costs and environmental impacts (Moldavska & Welo, 2017). Sustainability has particularly been seen as an important aspect in the development of product innovation (Keskin et al., 2020), technological innovation and eventually competitive advantage (Ahmadi-Gh & Bello-Pintado, 2021; Claudy et al., 2016). Indeed, sustainability and product innovation are at the heart of the success of today's manufacturing businesses, so learning more about how they connect is critical and largely underexplored (Ahmadi-Gh and Bello-Pintado 2021; Hallstedt, Thompson, and Lindahl 2013; Lintukangas, Kähkönen, and Hallikas 2019). Furthermore, given the intricate and multidimensional nature of integrating sustainability objectives into business processes, scholars are calling for the construction of models that consider missing data and for the investigation of mediating mechanism factors (Ahmadi-Gh & Bello-Pintado, 2021; Akomea et al., 2022; Claudy et al., 2016; Roxas et al., 2017).

Sustainable development is inextricably linked to technological advancement, which itself is increasingly related to the use of big data (Bashtannyk et al., 2020; Huber, 2004; Yudhistyra et al., 2020b). Data generated by different means such as machine sensors, RFID and the Internet of things, together with the decreasing cost of data gathering, processing and storage, are facilitating massive data generation known as big data (Chatterjee et al., 2022). The advent of big data has heralded a new era in the manufacturing sector, particularly in Europe, where the fusion of traditional manufacturing practices with digital technology is reshaping the industry landscape (Zhong et al., 2016). Big data, characterised by its volume, velocity, variety, veracity and value-adding role (Addo-Tenkorang & Helo, 2016; Zhong et al., 2016), has become a pivotal element in this transformation. Industrial big data is a subset of big data sourced from various elements such as devices, control units, robots and other equipment on the factory floor (Kirmse et al., 2019). This research is focused on industrial big data use, understood as the application of big data collected in manufacturing settings to improve decision making within industrial settings.

Data-driven innovation is a crucial growth pillar and source of competitive advantage (Chatterjee et al., 2022). Big data is helping companies with detecting new opportunities, and is seen as the next milestone for innovation, competition and productivity (Ciampi et al., 2021; Hämäläinen & Inkinen, 2019). However, the effect of SO and big data use on product innovation has so far been little explored. While previous research has looked at the effect of other digital technologies on product innovation and the relation between SO and product innovation, the specific role of big data remains largely uncharted (Zhao et al., 2021).

To address these calls, this paper aims to answer the following questions: Do sustainability orientation practices and industrial big data use positively influence product innovation? Is there a mediating effect of industrial big data use on the relationship between sustainability orientation and product innovation? To answer these questions, three hypotheses are tested using data from the European Manufacturing Survey (EMS) 2018 edition, consisting of 1,123 surveys of firms located in seven European countries.

This study makes several contributions to the literature. First, the study focuses on how internal sustainability practices influence product innovation, contributing to the research line on sustainability-driven product innovation (Ahmadi-Gh & Bello-Pintado, 2021; Claudy et al., 2016; Keskin et al., 2020; Obal et al., 2020; Zhao et al., 2021), with the originality of exploring the role of industrial big data use. This analysis is pivotal for advancing our understanding of how sustainability practices and industrial big data usage synergise, providing a novel insight into their complementary effects.

Second, unlike many qualitative studies in this area (Keskin, Wever, and Brezet 2020; Zhao et al. 2021; Hallstedt, Isaksson, and Öhrwall Rönnbäck 2020), the present research employs quantitative methods, drawing on a detailed questionaire and an international sample that integrates manufacturing firms from across different industries.

The research also ventures into uncharted territory by simultaneously examining the relationship between sustainability, technology and innovation, filling a relevant gap in the literature where the confluence of these factors has not been yet explored . This comprehensive approach uncovers the multifaceted role of industrial big data use, assessing not only whether it independently influences product innovation but also if it acts as a mediator, enhancing the effects of sustainability orientation on innovation outcomes. The findings shift the perspective of industrial big data from their being a mere operational tool to their being a strategic asset that has the power to amplify the sustainability efforts of an organisation to produce innovation. The findings have significant implications for both theory and practice, providing guidance for firms in leveraging industrial big data use to enhance their innovation strategies within a sustainability framework.

The paper is organised as follows. Section 2 reviews the relevant literature and argues the hypotheses posited. Section 3 explains the method used for testing the hypotheses, including data collection, measurement and analysis, and the results and findings are presented in Section 4. Section 5 discusses the results and section 6 concludes with a reflection on the implications of the findings, offering insights for both theory and practice in the field of sustainable manufacturing.

2. Theoretical background and hypotheses

This research is based on and aims to link two streams of literature. The first concerns the relationship between SO and product innovation, and the second relates to the relationship between big data use – or industrial big data, when available –and product innovation. Prior to linking them, the concept of SO is defined and discussed. Figure 1 at the end of the section depicts the conceptual model proposed.

2.1 The concept of sustainability orientation

Sustainability Orientation (SO), which is evolving as a paradigm in strategic management and entrepreneurship, has garnered increasing attention (Khizar et al. 2022). The concept is rooted in the integration of environmental and societal considerations into business operations (Kuckertz & Wagner, 2010). Definitions vary, but tend to share acknowledgment of the significance of environmental and social issues in managerial perceptions (Shou et al., 2019) and the readiness of organisations to implement sustainability initiatives (Tata & Prasad, 2015). Shepherd & Patzelt (2011) view SO as embracing objectives that preserve nature and support community life, aiming at both economic and non-economic gains. As Claudy et al. (2016) suggest, SO is part of a higher-order construct of strategic orientation, which also includes market, entrepreneurial and learning orientations.

Organisations typically adopt SO in response to stakeholder pressures, including demands from customers, employees and policymakers (Schaltegger et al., 2019; UN, 2015). Other drivers may be the pursuit of long-term benefits such as sustainable competitiveness and economic gains derived from integrating sustainability principles (Calabrese et al., 2019; Khizar et al., 2021). The implementation of SO is not just a reactive measure but a strategic choice that aligns with the organisation's long-term objectives (Marco-Lajara et al., 2023).

Two dimensions are often considered in SO, namely sustainability culture and sustainability practices (Claudy et al., 2016). Sustainability culture refers to the organisational conventions, values, philosophies and beliefs that prioritise sustainability as a strategic norm (Adams et al., 2016; Iivari & Iivari, 2010). Practices involve including social and environmental considerations in operating strategies and procedures, and are further classified into internal practices, which are related to a company’s daily operations, and external practices, pertaining to the broader supply chain (Ahmadi-Gh & Bello-Pintado, 2021; Laari et al., 2016; Wang & Dai, 2018). It could be argued that sustainability culture translates into sustainability practices. Internal practices, the focus of this study, relate to daily internal operations (Laari et al., 2016) and aim to lower ecological impacts through reduced pollution and resource use, and to address social concerns such as employee health, safety and their human rights (Dangelico & Pujari, 2010; Pujari, 2006).

2.2. The effect of sustainability orientation on product innovation

Product innovation, as defined by OECD & Eurostat (2018), involves new or significantly improved goods or services that diverge from previous offerings. Product innovations must significantly enhance one or more performance requirements or features, be it user utility, the addition of brand-new features or the enhancement of already existing ones. Quality, technical details, dependability, durability, economic effectiveness in usage, affordability, convenience, usability and user friendliness are all relevant functional attributes. Not all product improvements must enhance all performance requirements (OECD & Eurostat, 2018). Product innovation as a critical outcome of the new product development processes is essential for maintaining competitive advantage (Kleinschmidt et al., 2007; Marion & Fixson, 2021).

In the innovation literature, SO has often been related to new product development as a natural consequence of the argument that product innovation needs to contemplate sustainability at every stage, starting from the design phase. Some recent studies examine both the direct and the indirect connection between SO and product innovation from different perspectives (Ahmadi-Gh & Bello-Pintado, 2021; Cheng, 2020; Claudy et al., 2016; Du et al., 2016; Keskin et al., 2020; Obal et al., 2020; Zhao et al., 2021). However, this remains one of the least understood areas of sustainability management (Adams et al., 2016; Cheng, 2020; Claudy et al., 2016). Inconsistent empirical results in the literature are another indication of the need to explore the relationship between SO and product innovation. Some research has found positive impacts of SO on the success of new products and innovations (Du et al., 2016), while others have found detrimental effects (Sen & Bhattacharya, 2001). This section will argue the effect of SO on product innovation based on the natural resource-based view, as a development of the resource-based view.

According to the resource-based view, businesses with valuable, rare, inimitable and non-substitutable resources are viewed as having the capacity to generate a competitive advantage (Barney, 1991). As a progression from the resource-based view, the natural resource-based view (Hart, 1995) posits that companies can achieve a competitive advantage if they can overcome the obstacles related to the natural environment. These businesses can enhance their strategic skills to address environmental pollution, product stewardship and sustainable development issues, while simultaneously improving economic performance. This implies that they may gain a competitive advantage by implementing more environmentally friendly practices into their daily operations. As a result, SO implementation is argued to enable innovation managers to identify innovative solutions to ecological and social problems, resulting in operational efficiencies, higher quality products and greater value for customers (i.e., differentiation advantage), thereby increasing the likelihood of innovation success (Claudy et al., 2016; Porter, 2015). To some authors, a significant strategic instrument for enhancing a company's corporate reputation, achieving market differentiation and gaining first-mover advantages is the application of SO in the new product development process (Du et al., 2016; Zhao et al., 2021).

In the context of manufacturing, a firm's internal sustainability practices are considered important manufacturing practices to create value in multiple dimensions, such as improving product quality, resource efficiency, health, safety and other working conditions, and to lessen environmental burdens such as air and soil pollution, waste and resource consumption (Ahmadi-Gh & Bello-Pintado, 2021; Moldavska & Welo, 2017). In the same vein, using SO in the new product development process has been identified as a valuable strategic tool for enhancing a company's brand, achieving market differentiation and gaining first-mover advantages (Du et al., 2016). By applying SO practices, innovation teams may be able to eliminate inefficiencies in product disposal (e.g., harmful materials) and product use (e.g., longer useful product life), or in manufacturing processes (e.g., less process waste) (Fiksel, 2009). Eliminating such inefficiencies is expected to boost product innovation profit margins and return on innovation investments. Furthermore, increased sustainability can lead to higher quality (e.g., enhanced materials or safety) and/or reduced prices, improving customer value and driving new product sales (Claudy et al., 2016). Thus, we hypothesise the following:

H1: The implementation of SO *practices positively influences product innovation.*

2.3 The effect of industrial big data use on product innovation

Big data is a term describing the storage and analysis of large and/or complex datasets using a series of techniques, including but not limited to NoSQL, MapReduce and machine learning (Ward & Barker, 2013). Big data is often described as 3V: Volume of data, Velocity in its generation and Variety in its nature (Dubey et al., 2019; Kristoffersen et al., 2020; Zhou et al., 2014). Others describe it as 5V, adding Veracity and Value (Addo-Tenkorang & Helo, 2016; Zhong et al., 2016), or 6V, adding

Variability (Trabucchi & Buganza, 2019; Wamba et al., 2015; Yudhistyra et al., 2020a). In their review, De Mauro et al. (2015, page 9) assert that “big data represents the information assets characterised by such a high volume, velocity and variety so as to require specific technology and analytical methods for its transformation into value.”

Industrial big data, originating from diverse sources including devices, control units, robots and other equipment, is a subset of big data within industrial settings (Zhang et al., 2020) starting from the factory floor (Kirmse et al., 2019). This concept is derived from the broader term big data, which encompasses various data types and sources, including social media, environmental and consumer data (Kirmse et al., 2019). Industrial big data is a critical segment of the larger big data ecosystem, playing a vital role in enhancing industrial production scheduling, risk detection, condition monitoring, safety supervision and quality management, among other applications (Shaolin et al., 2021).

The effectiveness of big data is amplified by integrating the Internet of Things and Cloud technologies. This combination enables the interconnection of different equipment and systems, including production and customer management systems. Regular updates and analyses of data enhance decision-making processes, leading to improvements in manufacturing flexibility, product quality, energy efficiency and equipment maintenance (Rüßmann et al., 2015; Strange & Zucchella, 2017).

According to the resource-based view (Barney, 1991), a theoretical approach deemed suitable for examining big data and its impact on sustainability (Hazen et al., 2016) argues that while physical technology can be easily replicated, the strategic exploitation of technology using complex social resources can yield a competitive advantage (Barney, 1991). Nevertheless, the exploitation of technologies generally involves the use of socially complex resources to reach its potential, meaning that a firm can obtain a sustained competitive advantage if it can exploit the technology better than other firms.

Big data applications with high potential in manufacturing include design, planning, material distribution and tracking, manufacturing process monitoring, quality control and equipment maintenance (Tao et al., 2018). Product design is particularly closely related to product innovation. In the era of big data, product design is evolving towards a data-driven approach, benefiting from industrial big data analytics (Kusiak & Salustri, 2007; Li et al., 2022). Innovative product features can emerge from integrating diverse data sources and using data-mining algorithms to reveal previously unseen value (Kusiak, 2009). For instance, to increase the difficult-to-attain quality of ceramic materials, a producer may monitor and enhance the machinery's functionality and the design of the finished product (Kusiak, 2017). Similarly, sensor-gathered data can identify product defects, leading to improvements in existing products (Niebel et al., 2019).

Recent studies show that predictive big data analytics positively influences product and process innovation (Saleem et al., 2020). In turn, prescriptive analytics, which involves complex mathematical models for business decision-making, has been linked to operational innovation and improved business performance (Aydiner et al., 2019). Big data has been shown to impact on new product development through new revenue creation and expansion of existing product lines (Addo-Tenkorang & Helo, 2016), and to enhance collaborative innovation (Feng et al., 2024) and supply chain innovation (Jaouadi, 2022). In summary, the effect of big data on product innovation has already been argued and found to be positive.

However, the challenge in manufacturing is not just the volume of data but also its variety and complexity. Industrial big data serve as the raw material for the information value chain, and the quality of these data is crucial for all subsequent processes. The relationship between industrial big data use and product innovation has not yet been tested, but as a particular type of big data, the same effect is hypothesised:

H2: The use of industrial big data positively influences product innovation.

2.4. The interplay between sustainable orientation, industrial big data use and product innovation

Having argued separately the positive expected effect of sustainable orientation and big data use on product innovation, this section explores the interplay among the three factors. Overall, it is assumed that big data use, as a valuable capability enabled by technology, can have an enhancing effect of SO practices on product innovation. This is so because firms focused on integrating economic, social and environmental challenges into their strategies are expected to place greater emphasis on exploiting the diverse opportunities provided by big data in the field of sustainability.

Big data technologies offer several advantages for sustainability. For example, while big data is widely regarded as one of the simplest methods for digitising the circular economy (Nobre & Tavares, 2017), it can also assist in the evaluation of cost-cutting initiatives such as remanufacturing (Ge & Jackson, 2014). Moreover, big data has been linked to improvements in energy and water management, waste recovery and recycling, and emissions reduction (Laskurain-Iturbe et al., 2021). Song et al. (2017) presented a study involving various papers that demonstrate different approaches to how big data can improve natural resource management, allowing natural resource consumption, energy efficiency, environmental efficiency and protection to be improved. Further, a study based on the Indian manufacturing industry supports these findings, indicating that big data and predictive analytics significantly contribute to social and environmental performance (Dubey et al., 2019).

According to the natural resource-based view, it is asserted that innovation teams are more likely to come up with novel solutions to ecological and social issues in organisations with a sustainability orientation, giving them a competitive advantage (Hart, 1995). There are additional hurdles when companies include sustainability in their innovation strategy because a firm's product innovation practices may be influenced by other agendas and steered in conflicting ways (Zhao et al., 2021). Given the intricate and multidimensional nature of integrating sustainability objectives into processes like new product development, scholars have suggested that the win-win paradigm proposed by the natural resource-based view may be oversimplified, while emphasising the significance of creating models that account for missing data, examining mediating mechanisms and assessing contextual factors (Ahmadi-Gh & Bello-Pintado, 2021; Akomea et al., 2022; Claudy et al., 2016; Roxas et al., 2017). In this direction, Zhao *et al.*, 2021 investigate the mediating role of 3D printing technologies in the link between SO and new product development processes, finding a mediation effect of 3D printing on product innovation. This result suggests that other technologies may also reduce the incidence of discrepancies between sustainability initiatives and product innovation. We argue that industrial big data use could have the potential to adequately handle these tensions.

In this line, when considering the influence of industrial big data on product innovation and its role in operationalising SO, it is plausible to hypothesise that industrial big data could serve as a mediating factor in the sustainability-product innovation nexus. In other words, industrial big data may be the key mechanism through which SO impacts product innovation. Based on these insights, this paper proposes the following hypothesis:

H3: The use of industrial big data positively mediates the effects of SO practices on product innovation.

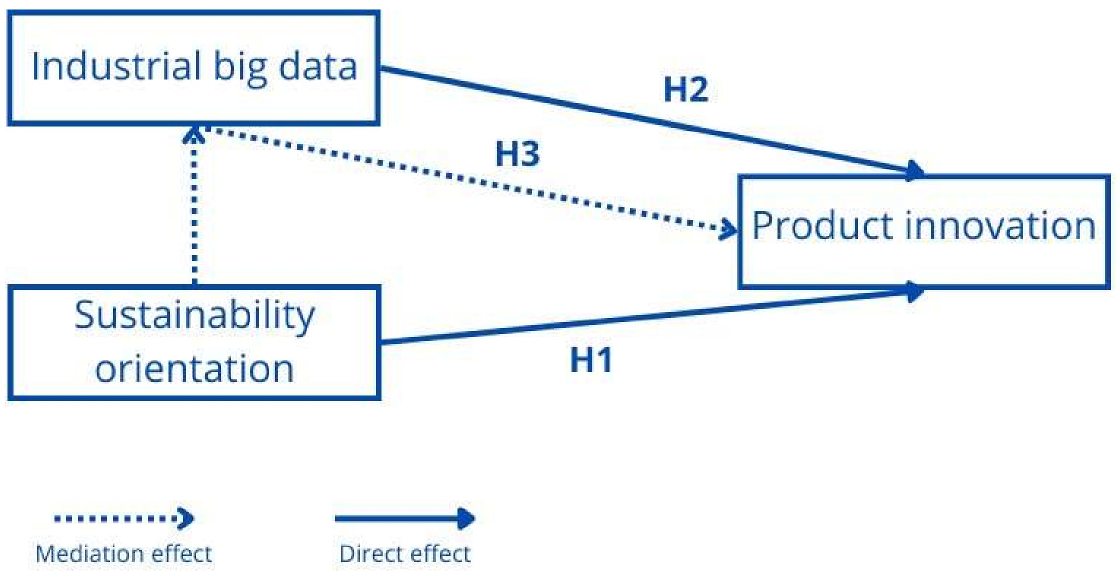

Figure 1. The framework of hypotheses

3 Method

3.1 Data collection

The data for this study come from the European Manufacturing Survey (EMS), directed by the Fraunhofer Institute for Systems and Innovation Research (ISI) (Fraunhofer ISI, 2023). The survey collects detailed information on innovations in manufacturing. The main goal of the EMS initative is to learn more about the utilisation of production and information technology, the manufacture of organisational approaches and the adoption of best management practices. Integrating the most recent developments among the topics of interest enhances already existing innovation surveys.

The EMS survey was co-designed and conducted by the authors of this study, who are part of the EMS consortium. The data provide a first-hand, direct account of the subject matter, keeping the information closely linked to the event being studied, so the data can be defined as primary data for this study (Cohen et al., 2007). Other editions of EMS data have been used in papers related to innovation (Armbruster et al., 2008; Llach et al., 2012a; Llach et al., 2012b; Manresa et al., 2019; Pons et al., 2018; Serrano-García et al., 2022), sustainability and green manufacturing (Palčič et al., 2013; Pons et al., 2013; Šebo et al., 2021), and digitalisation (Blichfeldt & Faullant, 2021; Dachs et al., 2019; Lerch et al., 2022; Manresa et al., 2021; Vilkas et al., 2022).

The eight-page long survey with 25 sections is conducted among manufacturing companies (NACE Revision 2 codes from 10 to 33) with at least 20 employees. The EMS consortium uses various techniques to collect reliable data that allow for international comparison and the aggregation of different countries' datasets, following the recommendations endorsed by Survey Research Center (2011) . These procedures are aimed at eliminating difficulties stemming from the use of multiple languages and national specialist terminology. To ensure uniformity, a basic questionnaire is first designed in English, translated into the national language and then subject to a reverse translation to check accuracy. This process involves translating the content intended for a specific language group back into the original source language. By comparing the original and re-translated versions in the source language, it becomes possible to identify and address any discrepancies or issues present in the translation for the target language audience. Pre-tests, which also help to detect possible translation mistakes, are undertaken in each participating country. Last, the same data harmonisation techniques are used (Bikfalvi et al., 2014).

The subsample of the EMS used in the present paper was collected in 2018. It consists of a total of 1,123 surveys, distributed as follows: Austria 253, Spain 85, Croatia 105, Lithuania 199, Slovakia 114, Slovenia 127 and Serbia 240. To meet the objectives of the present research in the innovation aspect, and given that the same questions and criteria for the sample selection were applied in each case, these countries' datasets were pooled, using as a criterion their ranking in the Global Innovation Index 2018. This index considers the most recent global innovation trends and ranks the innovation ecosystem performance of 132 economies, while highlighting innovation strengths and weaknesses and particular gaps in innovation metrics. The countries in the sub-sample selected for this study are in the second quartile in the ranking, indicating that they are among the most innovative and were chosen to facilitate a higher proportion of innovative firms in the database.

3.2 Measures

The study employs two primary constructs as independent variables: sustainability orientation (SO) and industrial big data (BD) use. The dependent variable is product innovation.

SO construct: the SO construct was calculated as the sum of different sustainability practices used in manufacturing firms, as listed in Table 1. Internal sustainability practices include a variety of environmental and socially responsible actions that a company adopts and puts into practice throughout its internal business operations. Environmental practices aim to reduce pollution and the use of both natural resources and conventional sources of energy, and include water efficiency management (Ahmadi-Gh & Bello-Pintado, 2021; Montabon et al., 2007), energy management (Montabon et al., 2007), environmental certification (Montabon et al., 2007; Wang & Dai, 2018) and re-use and recycling (Ahmadi-Gh & Bello-Pintado, 2021; Montabon et al., 2007; Wang & Dai, 2018). Internal practices include social, responsible management practices focused on emplyees' health, safety and human rights, including employment training and programmes to promote staff development and loyalty (Montabon et al., 2007; Wang & Dai, 2018). Since seven different practices were considered, the construct has values from 0 to 7, with each practice given a value of 1 when marked as used by respondent companies.

BD construct: the BD construct was composed of the different purposes for which companies employed collected data, to evaluate the intensity of their use. Since six different uses were evaluated, the construct had values from 0 to 6, with each use given a value of 1. The value of the construct was zero if data were not collected, or if collected data were not used at all. As for the different data uses, the respondents could choose from optimising production processes, planning maintenance and repairs, planning resource utilisation and application, preparing productivity or key performance indicators, risk analysis and other uses.

Dependent Variable: Product Innovation was obtained from the answer to the following survey question: '*Has your factory introduced products since 2015 that were new to your factory, or incorporated major technical improvements? (e.g., use of new materials, modifications of product function, changes in operating principles etc.)*'. Given that the possible answers were either yes or no, this is a dichotomic variable.

Descriptive statistics for the dependent and independent variables are detailed in Table 1, indicating that most of the firms in the sample had launched new products since 2015 (64%) and, with an average of 2.23 out of a maximum of seven, that the firms applied a relatively small number of SO practices. Furthermore, the number of different uses of industrial BD was rather low, at an average of 1.66 out of a maximum of six. Frequencies for the SO and BD constructs are shown in Figure 2.

Table 1. Descriptive statistics for the dependent and independent variables

		N	Min	Max	Mean	Std. Deviation
Dependent variable						
Product innovation		1,102	0	1	0.64	0.48
Independent variables						
SO construct		1,123	0	7	2.24	1.46
	Organisational concepts – certified energy management system	1,048	0	1	0.12	0.33
	Organisational concepts – certified environmental management system	633	0	1	0.41	0.49
	Human resources – instruments to promote staff loyalty	1,077	0	1	0.57	0.5
	Human resources – training on the job	1,074	0	1	0.71	0.45
	Energy efficiency technologies – water re-use and recycling	1,036	0	1	0.24	0.43
	Energy efficiency technologies – kinetic and process energy recuperation	1,044	0	1	0.25	0.43
	Product related services – take-back services (recycling, disposal, taking back)	1,055	0	1	0.22	0.41
BD construct		1,123	0	6	1.66	1.79
	Use of machines/systems that store operating data	1105	0	1	0.62	0.49
	Optimisation of production processes	685	0	1	0.62	0.49
	Planning maintenance and repairs	685	0	1	0.41	0.49
	Planning resource utilisation and application	685	0	1	0.41	0.49
	Preparing KPIs	685	0	1	0.55	0.5
	Risk analysis	685	0	1	0.58	0.49
	Other use	685	0	1	0.15	0.36
	No use of data	685	0	1	0.21	0.41

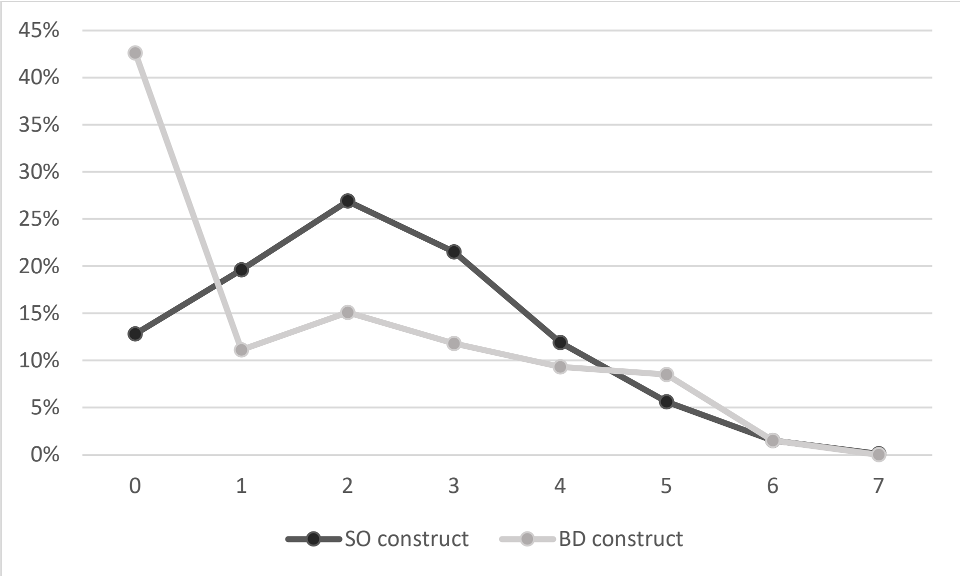

Figure 2 Frequencies of SO and BD constructs

Control Variables: In line with extant research, general resource availability, openness and sector innovation intensity were considered as control variables. The resources available to a company have a significant impact on its capacity to achieve its goals via various activities, including innovation-related ones. Resource availability will be considered in two dimensions, size and sector. The most common measure for resource availability is firm size, which is commonly considered a driver of innovation activities and an indication of a company's willingness to innovate (Cohen & Klepper, 1996). The most common measures of firm size include the number of people employed and the volume of turnover. The Oslo Manual 2018 suggests using both. Due to the fact that the number of employees does not follow a normal distribution, a transformation is required using parametric statistics (Tabachnick et al., 2007) and the natural logarithm of the original values, resulting in a normal distribution. Employees and turnover values are for 2018.

As regards openness, when businesses operate on a global scale, they develop in-depth knowledge of and acute responses to institutional settings, influencing new product performance (Zhao et al., 2021). This explains why export share and import share are included as control variables. In turn, innovation intensity is a control variable that classifies industries into five groups-low, medium-low, medium, medium-high and high innovative sectors, according to the Peneder taxonomy of innovative intensity (Peneder, 2010). Sector innovation intensity is used as a proxy for the differential innovativeness of different sectors, as is common in previous innovation research (Manresa et al., 2018; Marques et al., 2015). Descriptive statistics for the selected control variables are presented in Table 2.

Table 2. Sample distribution of companies by size, and sector innovation intensity

Size	Frequencies	%
less than 50	510	46%
between 51 and 249	447	40%
more than 250	150	14%
Country		
Austria	253	23%
Spain	85	8%
Croatia	105	9%
Lithuania	199	18%
Slovakia	112	10%
Slovenia	127	11%
Serbia	240	21%
Sector Innovation intensity		
Low	78	7%
Medium-low	170	15%
Medium	213	19%
Medium-high	249	23%
High	400	36%
Turnover millions EUR		
less than 2	245	25%
between 2 and 10	370	38%
between 1 and 50	255	26%
more than 50	117	11%

3.3 Data analysis

Because of the binomial nature of the dependent variable, a binomial logistic regression was used to test the hypotheses relating to the total effect of the independent variables on the dependent variable (H1 and H2). H3 was tested using the mediation model proposed by Hayes (2018). SPSS Version: 28.0.0.0 (190).

The control function approach is used to address endogeneity, with the residuals of the first-stage regression added as an additional regressor into the main regression (Ebbes et al., 2016; Petrin & Train, 2010). The idea is that the residuals capture the omitted variables that make independent variables endogenous. By including this term in the main regression, we control for endogeneity (Ebbes et al., 2016). For the first regression, market-related aspects were considered as the dependent variable, measured via the R+D market construct, composed of R+D shared with clients/suppliers and R+D shared with other companies. As the independent variable for the regression model, the construct SO was used for the first model and BD for the second model. The standardised residuals from this regression model were then used in the main logistic regression model.

Several procedural and statistical remedies were adopted to diminish common method bias (Podsakoff et al., 2003; Rodríguez-Ardura & Meseguer-Artola, 2020). First, the respondents were guaranteed that their answers were anonymous. Second, more than one single respondent was allowed to answer the survey, adding more information sources to gather data about constructs in the model. Third, Harman's single-factor test was performed, the result indicating that one factor explains only 17.03% of the variance, and that this factor did not capture most of the variance. These results therefore suggest that common method bias is not an issue in this study (Tehseen et al., 2017).

4 Results

4.1 Descriptive statistics

Figure 3 shows the adoption of sustainability orientation practices (SO practices) in European manufacturing firms. The predominant category of SO practices is the one related to human resources. Training on-job is clearly the most adopted sustainability practice, featuring in more than 70% of the companies, followed by instruments to promote staff loyalty. This could be due to the fact that the aforementioned practices were adopted earlier than the other analysed practices. Even though 25 % of the companies implemented technologies to recover energy, only 12% of them are certified for the energy management system. Environmental management certification is much more implemented, present in 41% of the companies. On analysing the median for the year when these systems were implemented, a clear advantage for the chronologically older available certifications can be seen: 2011 for the environmental system and 2014 for the energy system. Nevertheless, looking at their plans for implementation, 19% of the companies want to implement environmental systems and only 15% energy systems, suggesting that certified energy system levels will not reach environmental system levels in the coming years. Contrarily, the difference between their implementation will be increasingly pronounced.

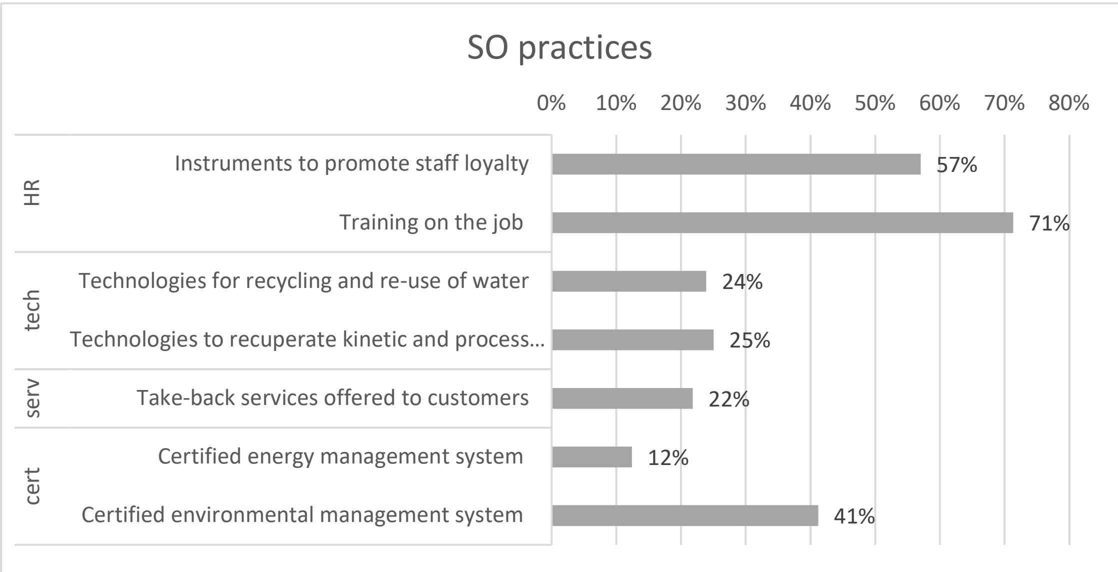

Figure 3. Implementation of SO *practices*

Technologies for recycling and water re-use, together with technologies to recover kinetic and process energy, have values of 24% and 25%, respectively, showing that they are not frequently employed in the companies. The forecast for the next three years shows that these proportions will not grow significantly: only 8% of the companies plan to adopt technologies for water treatment, and 11% for energy treatment. Both technologies have been updated in the adopting companies in the last three years by an average of 30%.

Figure 4 shows the extent to which the companies estimate the implementation of sustainability practices. The question in the survey asks respondents to evaluate the potential of use as low, medium or high on a scale of 1 (low potential) to 3 (high potential), meaning the extent to which the companies believe that sustainable practices are deployed inside the company. The data reveal that potential of use is highest in applying principles of environmental and energy certification. Contrarily, it appears that instruments to promote staff loyalty and technologies for energy recuperation could be better used.

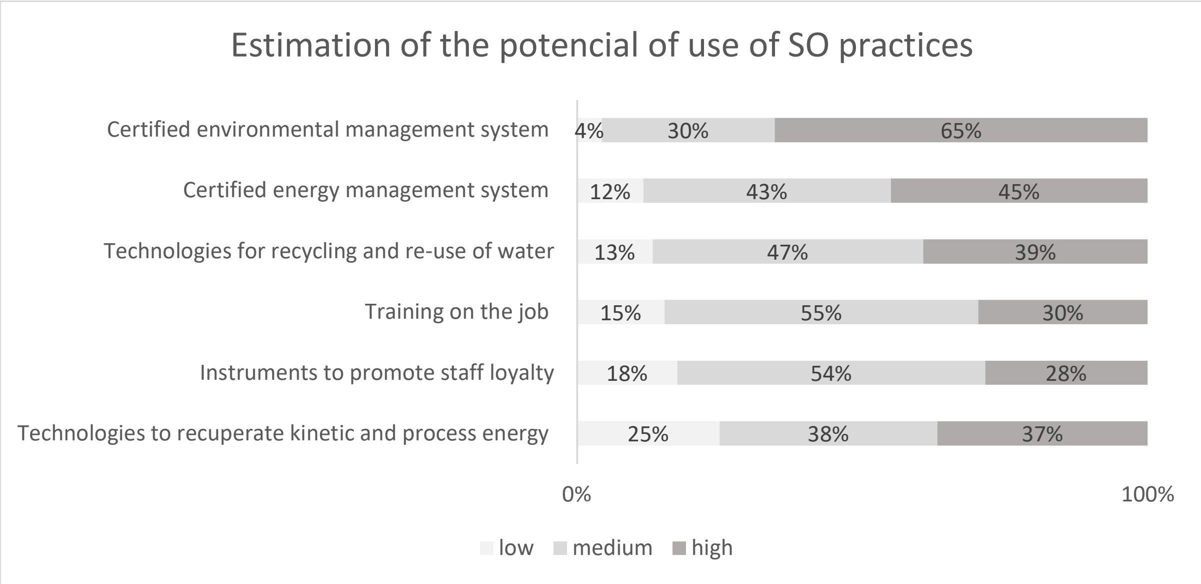

Figure 4. Potential of use of SO practices

The findings show that the rates of implementation of the studied internal environmental SO practices are relatively low in European manufacturing firms, ranging from 12% for certified energy management systems to 41% for certified environmental management systems. The level of social SO practices is higher, with percentages ranging from 57% to 71%. As for the intensity of use of the SO practices, companies state medium intensity use, with an average value of 2.26 on a scale of 1 to 3, clearly indicating that the practices are not being used to their full potential and there is room for growth. This untapped potential growth may be the sum of a number of factors, including the state of the economy, lack of expertise, managers believing that certain practices are unneeded given the modest size of the business, and so on.

Industrial big data use appears to be widely implemented among the companies (Figure 5): 62% use machines or systems that automatically store operating data. Companies use these data for different purposes, but mostly for optimising the production processes. However, 21% of the companies do not use the collected data at all, even though they are collecting them. There are different possible explanations for this, including insufficient technology and techniques to capture value from industrial big data, a lack of talent or incentives to make use of the data, or a lack of competitive intensity or present need to leverage the benefits of industrial big data.

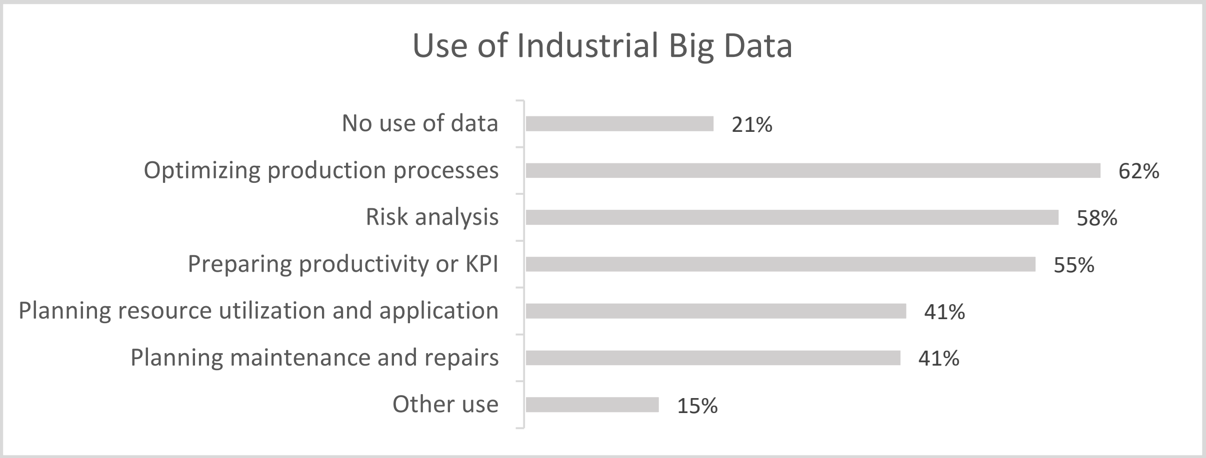

Figure 5. Use of industrial big data

When evaluating product innovation, new products were introduced in an average of 64% of the companies. Interestingly, product innovation is not growing in line with the level of sector innovation intensity. The group of companies where the proportion of new products is the highest coincides with the high innovation intensity sector, while the group of companies with less product innovators are categorised as medium intensity innovators as opposed to low intensity innovators, as seen in Figure 6.

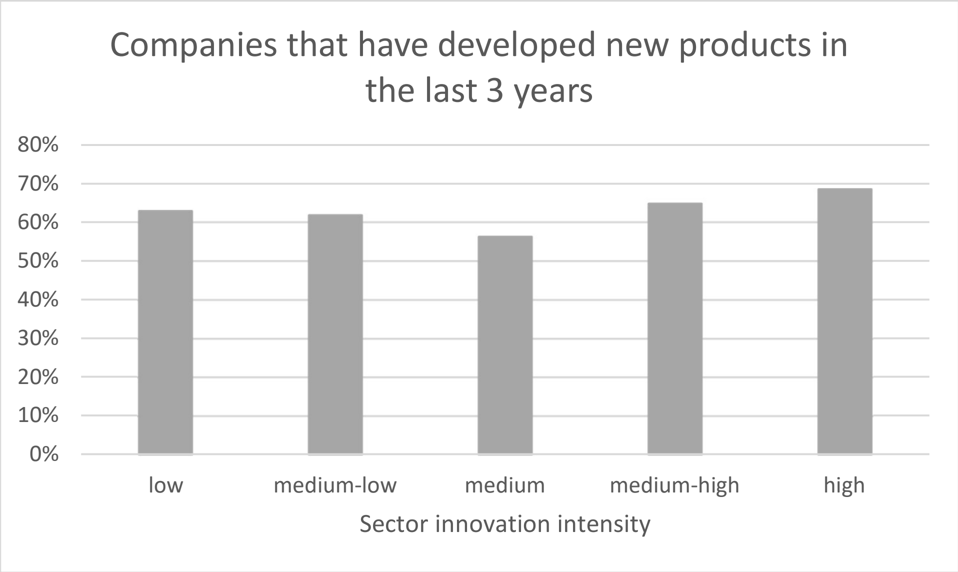

Figure 6. Product innovation by sector innovation intensity.

4.2 Hypotheses testing

To test the separate relationship between SO practices and industrial big data use in product innovation (H1 and H2, respectively), two sets of binary regression logistic models were performed. The results are given in Table 3.

The dependent variable in all cases was the product innovation measured as new-to-the-firm products (new products in the last three years), with values of 0 for no product innovation and 1 for new products for the company. First, a model with control variables was tested. The method used to obtain the control variables that are significant for the model was a binary logistic regression with backward Ward analysis. The variables entered initially were the number of employees, imports, exports, sector of innovation intensity and annual turnover. The backward Ward analysis was performed in four steps until the control variables with statistical significance for the model were determined. In the end, only the variables number of employees and imports proved to be relevant for the model. They were therefore the variables used for the following models to test the hypotheses.

The first model tested hypothesis H1. The construct of SO together with significant control variables were entered as independent variables. The model showed that the SO has significance in product innovation with a value $p<0.10$ (sig. 0.064) and a β of 0.094, providing support for the first hypothesis.

The second model tested hypothesis H2, using the industrial big data construct as the independent variable, together with the significant control variables. This model showed that the construct industrial big data has statistical significance with a value $p<0.050$ (sig. 0.015) and a β of 0.118, providing support for H2, that industrial big data positively influences product innovation.

Table 3. Regression models for total effect of SO and BD on product innovation

	Model I.		Model II.	
Dependent variable	Product innovation			
Independent variable	β	sig.	β	sig.
SO construct	0.094	0.064		
BD construct			0.118	0.015
Control variables				
Imports	0.005	0.01	0.005	0.014
Market Residuals	0.431	<0.001	0.425	<0.001
Number of employees	0.237	0.002	0.239	0.002
Number of analysed cases	913		913	
R^2 Cox & Snell	0.076		0.077	
R^2 Nagelkerke	0.103		0.105	

To test H3, the model used was the mediation model, which focuses on the estimation of the indirect effect of the SO construct on product innovation through an intermediary mediator variable, in this case the BD construct (Hayes, 2017).

The path of the direct effect from SO to BD (a) is positive and statistically significant ($\beta = 0.48$, $p < 0.001$). The path of the direct effect from BD to product innovation (b) is also positive and statistically significant ($\beta = 0.082$, $p < 0.05$). The path of the direct effect from SO to product innovation is positive, but insignificant ($\beta = 0.056$, $p > 0.05$). The indirect effect was tested using bootstrapping (5,000 re-samples in the model, 1-tailed significance), a nonparametric resampling procedure that does not impose the assumption of normality on the sampling distribution (Preacher & Hayes, 2008). If the zero falls outside the lower limit (LL) and the upper limit (UL) of the 95% confidence interval (CI), then the indirect effect is significant. Examining the indirect or mediating effect of BD on the relationship between SO and product innovation, calculated by *a*b*, the result is β = 0.0391, and this result is statistically significant at 95% CI = (Boot LLCI =0.001, Boot ULCI= 0.079). Therefore, the model suggests that BD has a positive mediating effect on the relationship between SO and product innovation.

The summary of the Hayes mediation model, calculated by PROCESS.SPS software for SPSS, is shown in table 4.

Table 4. Hayes PROCESS.SPS mediation model

Sample size: 1040

	Consequent: BD Model A: SO-> BD					Consequent: product innovation Model B: BD-> Innovation				
	R	R-sq				Cox & Snell	Nagelkerne			
	0.409	0.167				0.051	0.069			
Variables	β	SE	p	LLCI	ULCI	β	SE	p	LLCI	ULCI
SO	0.478	0.353	0.000	0.409	0.547	0.056	0.050	0.263	-0.042	0.154
BD						0.082	0.041	0.047	0.001	0.162
import	0.005	0.002	0.004	0.002	0.008	0.006	0.002	0.002	0.002	0.010
number of employees	0.099	0.508	0.052	-0.001	0.199	0.323	0.714	0.000	0.183	0.463

Direct and indirect effects					
Direct effect of SO on product innovation					
	effect	SE	p	LLCI	ULCI
	0.056	0.050	0.263	-0.042	0.154
Indirect effect of SO on product innovation through BD					
	effect	Boot SE	LLCI	ULCI	
BD	0.039	0.020	0.001	0.079	

The final research models with the above-described results of the analysis are presented in Figure 7.

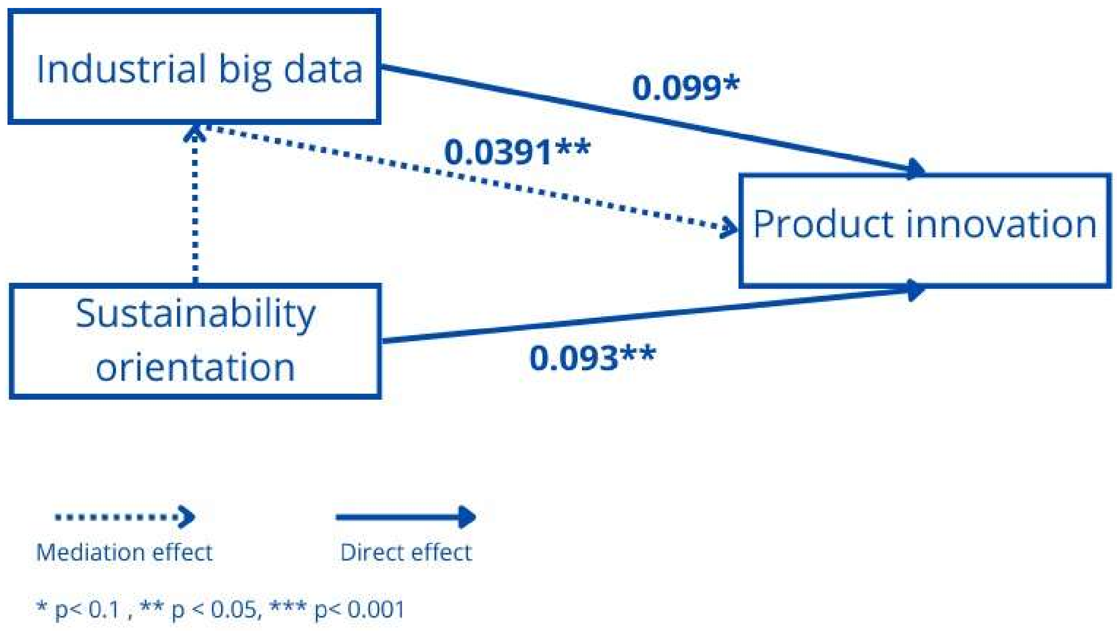

Figure 7. Research models with results

The results of the tested hypothesis can be found in Table 5.

Table 5. Summary of hypotheses testing

Hypothesis	Effect	Model	Result
H1	+	SO -> Product innovation	Supported
H2	+	BD -> Product innovation	Supported
H3	+	SO -> BD - > Product innovation	Supported

In summary, these results suggest that SO practices and industrial big data use positively influence product innovation. Industrial big data use positively mediates in the relationship between SO and product innovation, thereby helping to achieve a positive influence of SO on new products. The hypotheses are designed to capture the multifaceted influence of industrial big data within the context of SO and product innovation.

5. Discussion

5.1 Sustainability orientation direct impact on product innovation

The findings relating to Hypothesis 1 reveal a compelling narrative in favour of SO because of its positive influence on product innovation, adding further support to some existing findings (Claudy et al., 2016). The support for this hypothesis confirms that sustainability is not merely a compliance or ethical imperative but that it also serves as fertile ground for innovation.

Our findings particularly support that SO spurs innovation. The direct relationship between SO and product innovation can be explained by means of several mechanisms. First, an orientation towards sustainability often necessitates creative thinking and the reimagining of product life cycles, which inherently fosters innovation. Second, this orientation typically requires the adoption of new processes and technologies. Last, by adopting SO, firms can attract talent and collaborate with stakeholders who share similar values, thereby enhancing their innovative capacity.

5.2 The direct impact of industrial big data use on product innovation

While previous research has studied the positive effect of digital technologies on product innovation (Zhao et al., 2021), our findings enlarge this knowledge for the particular case of industrial big data. The substantiation of H2 provides evidence of the direct effect of industrial big data use, gathered from machines and systems in the production process, on product innovation within the manufacturing sector. This relationship is illustrative of the potential of the digital age to revolutionise traditional business models and processes. Firms that effectively utilise industrial big data are shown to be significantly more innovative, which suggests that the capacity to use and analyse large datasets is a critical driver of product development and competitive advantage.

The impact of industrial big data use on product innovation may manifest in several ways. It allows for the optimisation of the product development process by predicting potential failures and successes, thereby reducing costs and time-to-market. It also empowers companies to engage in predictive analytics, enabling them to foresee future trends and prepare innovative responses in advance.

This direct impact of industrial big data use on innovation also illustrates the shifting paradigms in product development. No longer is innovation confined to the R&D laboratories, but it is now increasingly taking place at the intersection of technology, data science and strategic business analysis. Firms that invest in industrial big data capabilities are positioned at the forefront of this shift, ready to capitalise on the opportunities presented by the data-driven economy. Our results are therefore consistent with Saleem et al. (2021), although we explore a further synergetic effect of industrial big data, as presented in the next section. Direct effects of the mediating variable on the dependent variable, and not only its mediating effects, have also been examined in previous studies related to sustainability and digitalisation (Črešnar et al., 2023; Rehman et al., 2022).

5.3 The mediating role of industrial big data use on product innovation

H3 delves into the intricacies of the mediating effect of industrial big data use on the relationship between SO and product innovation. This hypothesis is of particular interest as it reflects the transformative power of industrial big data in terms of actualising the principles of sustainability in a tangible and impactful way. The confirmation of this hypothesis underscores the pivotal role that industrial big data use plays in translating sustainability intentions into innovative outcomes.

The analysis supports the idea that industrial big data use acts as a critical intermediary that takes the intentions of SO and operationalises them into data-driven strategies for product innovation. While SO sets the strategic direction for innovation, industrial big data use provides the means to achieve it. The use of industrial big data enables firms to integrate sustainability into the product innovation process more effectively, connecting the gap between sustainability goals and marketable products. For instance, big data use can provide insights into sustainable materials and processes or help optimise supply chains for reduced environmental impact.

The mediating role of industrial big data also suggests that while SO can independently promote product innovation, the depth and breadth of this innovation are significantly enhanced when underpinned by data use. Firms can quantify and analyse their sustainability efforts, translate sustainability goals into specific innovation targets, and monitor the success of these initiatives through industrial big data use. Industrial big data thereby acts as the bridge that connects the conceptual (SO) with the practical (product innovation), enabling firms to implement their sustainability orientation in a concrete and measurable way. This mediation effect is particularly relevant in the context of the European manufacturing sector, where regulatory pressures and market dynamics demand both innovation and sustainability.

In essence, the validation of H3 enriches our understanding of the symbiotic relationship between sustainability orientation and industrial big data use to foster product innovation, which to the author's knowledge is new in the literature. It lays the groundwork for a more integrative approach to innovation strategy that leverages the power of industrial big data to fulfil the promise of sustainability in the competitive landscape of manufacturing.

6. Conclusion

This research explores the complex interplay between sustainability orientation (SO), industrial big data use and product innovation within the European manufacturing sector. We found robust support for all the proposed hypotheses, highlighting the dual role of industrial big data use as both an independent and a mediating variable. The simultaneous support for these hypotheses does not signify inconsistency but rather reinforces the complexity of the relationships at play. It highlights the comprehensive impact of big data on the innovation ecosystem, both as a standalone influence on product innovation and as an intermediary that enhances the effect of SO on innovation. This dual capacity of big data use aligns with the broader research objective of understanding its multifaceted role.

When considering the hypotheses in a joint context, it becomes clear that SO and industrial big data use are not mutually exclusive in their impact on product innovation. Instead, they operate in a synergistic manner. SO provides the vision and impetus for innovation, industrial big data use equips firms with the tools to realise this intention, and the innovation outcomes are the manifestations of this combined effect. Furthermore, industrial big data use does not merely support SO-driven innovation, but it also independently stimulates innovation by revealing new opportunities and offering the analytics capability to capitalise on them.

6.1 Theoretical contributions

First, this study adds knowledge to the ongoing debate about the relationship between SO and product innovation. Drawing on the natural resource-based perspective, a company's SO is a strategic orientation that is represented in its activities and culture (Hart, 1995). It was therefore postulated that implementing an SO at the organisational level would help new product development managers find creative solutions to ecological and social issues, which would lead to increased operational effectiveness, better product quality and greater customer value, ultimately increasing the likelihood of product innovation success (Porter & Claas van der Linde, 1995). Based on the results obtained, the models in this study indicate that the implementation of SO practices themselves presents a significant and positive relationship with product innovation. This contributes to the theoretical arguments that emphasise the positive effect of SO on product innovation, including the study by Claudy et al., (2016), which implies that implementing an SO has a beneficial impact on new product development performance. Moreover, our results suggest that the adoption of SO practices has a positive effect on product innovation regardless of innovation intensity sector, which has been scarcely considered in previous research.

Second, the study confirms the positive effect of industrial big data use on product innovation, which aligns with the resource-based view in that it identifies big data as a strategic resource that can directly fuel innovation. The capability to collect, analyse and interpret large volumes of data is a critical asset that enables firms to stay ahead in the innovation race. This capability is especially pertinent in today's data-intensive business environments where making informed, data-driven decisions is key to developing products that meet evolving market needs and staying ahead of competitors. This finding contributes to the literature on the role of digital technologies in product innovation, a relationship that has been relatively underexplored. The results of the study align with Saleem et al. (2021), who also observed a positive effect of big data from various sources on product innovation.

Third, an important contribution of this research is the identification of the route through which SO is related to product innovation. The results suggest that industrial big data use mediates in the innovation outcome of SO, extending the sustainability literature by uncovering a previously unrecognised relation of big data use and SO. This finding supports the logic that big data use has the potential to adequately handle tensions between the economic, social and environmental goals of sustainability—the well-known triple bottom line (Elkington & Rowlands, 1999), where firms may run into difficulties when implementing SO in the creation of new goods.

6.2 Practical contributions

In recent years, the focus on sustainability has become a significant concern for management boards, driven by societal and environmental demands. Many businesses are integrating sustainability into their models, viewing it as essential for maintaining or improving their reputation and brand value. This includes developing sustainability policies, managing carbon footprints and selecting suppliers with sustainability standards. However, there is still uncertainty among managers about the tangible benefits of these sustainable practices.

This study reveals that sustainability practices positively impact product innovation, although their implementation and potential exploitation remain limited in European manufacturing companies. Managers are encouraged to not only adopt these practices but also to intensify their application. Senior executives are advised to approach sustainability as a strategic priority, requiring advanced techniques, technologies and effective data utilisation to enhance product innovation.

The research indicates a stronger link between sustainability and product innovation when data are applied across various functions, such as performance indicators, production optimisation, risk analysis, resource planning and maintenance. The study highlights the importance of using big data in diverse applications, beyond just data collection and storage.

The results emphasise the need for a sustainability orientation that is actionable through industrial big data use. Policymakers should focus on promoting big data technology adoption as a driver of sustainable innovation. Investing in big data technologies, aligning the sustainability goals with IT strategies and cultivating data-analytic skills within the workforce are crucial for maintaining and enhancing innovation capacities. For theorists, these findings beckon a re-evaluation of innovation models to incorporate the role of data analytics as a fundamental component.

6.3 Limitations and future research

Using only manufacturing companies for the research is advantageous for acquiring a deeper knowledge about this particular sector. However, it is also a limitation, and scholars could examine other sectors to see if the relationships found are likewise valid.

The number of sustainability practices available for the study could be considered a limitation, so future analyses should include other SO practices to enrich the results. While the results uncovered the importance of internal sustainability practices, the research would be enriched by including external sustainability practices and sustainability culture, although it can be assumed that culture drives practices, as studied in this research. As regards the dependent variable, the authors were only able to assess new-to-firm product innovation, while ecological and social factors of innovated products were not considered (Fiksel, 2009). Future studies could evaluate how SO affects the social, environmental and economic facets of product innovation.

This study examines how industrial big data use mediates the relationship between SO and product innovation. In this regard, it may be advantageous to look at other important new technologies to resolve potential conflicts in sustainability programmes that support product development and innovation. It is conceivable that factors that were not considered in this study could influence both SO and product innovation, although these factors have not been consistently identified in the extant literature. The capacity to collect all potentially pertinent data was constrained by the data set used in this study, despite providing exclusive access to a wide range of data. Therefore, this study could be seen as a supplement to the body of literature, and as such future research could build on this basic foundation.

Our study revolves aroung the use of industrial big data, recognising that big data encompasses a broader concept. Future research could explore other types of big data to expand upon our findings, such as consumer and environmental data (Kirmse et al., 2019). Further, future studies are encouraged to delve into the specific uses of big data that catalyse innovation within different organisational contexts and sectors. This could encompass areas such as big data analytics in service innovation, the utilisation of big data in improving the innovation lifecycle, and the role of big data in fostering open innovation and collaborative ventures. Each application offers a unique perspective on how big data can be leveraged to stimulate innovation.

This article specifically focuses on product innovation within the context of sustainability orientation and its impact on the innovation process. However, it is important to acknowledge that innovation encompasses a broader spectrum than just product innovation. Other forms of innovation such as process, marketing and organisational innovations also play a crucial role in shaping businesses and industries. While our discussion is centered on product innovation, we recognise the importance of exploring how sustainability orientation influences the other types of innovation. This recognition not only broadens the scope of our inquiry but also encourages further exploration and studies in these areas, opening new avenues for future research, particularly within the framework of the natural resource-based view theory, thereby enriching our understanding of innovation in its various forms and its relationship with sustainability.

Despite the limitations, the results of the study enrich our understanding of the symbiotic relationship between sustainability orientation and industrial big data use to enhance product innovation, laying the groundwork for a more integrative approach to innovation strategy. This research opens avenues for further investigation into how different aspects of sustainability orientation (such as environmental management, social responsibility, etc.) specifically contribute to product innovation.

Data statement

Due to the sensitive nature of the questions asked in this study, survey respondents were assured that raw data would remain confidential and would not be shared.

Data not available / The data that has been used is confidential.

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