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ARTICLE

Effects of big data capability on sustainable manufacturing and circular economy in Brazilian industries

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Abstract

Purpose – The objective is to analyze the relationship between big data analytics (BDA) capability and the development of sustainable manufacturing and circular economy (CE) in Brazilian industries.

Theoretical framework – The construction of BDA capability, according to the resource-based theory, is established through the implementation, integration and processing of big data resources. It is argued that BDA capability can contribute to the sustainable development of industries based on the collected data, as well as influencing the development of CE.

Design/methodology/approach – The research was descriptive and quantitative, and was conducted using a survey of employees in Brazilian industries that use big data. The hypotheses were tested using structural equation modeling.

Practical & social implications of research – BDA capability has a positive and significant relationship with sustainable manufacturing and CE. Sustainable manufacturing is a complementary mediator between BDA capability and CE.

Originality/value – The study provides knowledge on the interaction between BDA and the development of sustainable and circular practices in Brazilian industries, providing incentives for changes in manufacturing companies that can successfully reduce social pressures due to resource scarcity, sustainable production and supply chain uncertainty.

Keywords: Resource-based theory, big data capability, sustainable manufacturing, circular economy.

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1 Introduction

The technological advances unleashed by Industry 4.0 have an exponential impact on organizations, so in order to remain competitive in the market, they seek to implement strategies to adhere to technological innovations in order to achieve competitive and financial performance. The adoption of these technologies is related to the possibilities of generating value and seeking or maintaining competitive advantage through optimizing processes, improving customer relationships, and making accurate decisions (Ibarra et al., 2018; Bai et al., 2020; Kristoffersen et al., 2021).

In parallel, the adoption of these technologies for competitive advantage, growing socio-economic disparity, changing climatic conditions and depleting natural resources have forced organizations to rethink their operations management practices in order to address the pillars of sustainability (Kleindorfer et al., 2005; Tayal et al., 2020). In this sense, organizations have used technology to help achieve more sustainable production. However, it is necessary to develop the firm's capabilities, not just implement new technologies, which is achieved through the strategic combination of resources, according to the resource-based theory (RBT) (Barney, 1991; Grant, 1991; Yu et al., 2018; Mikalef et al., 2018).

Among Industry 4.0 technologies, big data stands out (Jabbour et al., 2019; Bai et al., 2020). Big data is understood as a technological disruption in business and academic ecosystems since the rise of the internet and the digital economy (Agarwal & Dhar, 2014), and is defined by the rapid processing of large volumes of data, structured or unstructured, of various types. It plays an important informational role in organizational decision making, so it is necessary to build the big data analytics (BDA) capabilities established by the implementation, integration, and processing of big data resources (Gupta & George, 2016).

Building BDA capability occurs through the skills applied to big data in conjunction with other resources that help visualize and analyze data (Gupta & George, 2016). When this capability is developed, it enables informed decision making, greater bargaining power in negotiations with suppliers and customers, improved supply chain, improved demand planning, better sales planning capacity, operations, and agility (Schoenherr & Speier-Pero, 2015; Zhang et al., 2017; Queiroz & Pereira, 2019; Cabrera-Sánchez & Villarejo-Ramos, 2019). As a result, big data technology is also attracting attention due to the possibilities related to safer processes, efficient resource consumption, and the development of more flexible and intelligent processes (Jabbour et al., 2018), i.e. with the potential for sustainable production in industries (Enyoghasi & Badurdeen, 2021).

In this way, the implementation of sustainable practices can be facilitated by BDA capability by providing information for more efficient use of energy and materials as well as better safety (Enyoghasi & Badurdeen, 2021), in addition to making processes more flexible and products of higher quality (Azeem et al., 2022). Therefore, it is argued that big data technology can contribute to the advancement of sustainability in industries based on the data collected. When big data is integrated with data visualization and analysis systems, BDA is implemented, which makes it possible to control and reduce energy consumption and improve service decisions, maintenance, quality, as well as product design and sustainable business models (Majeed et al., 2021; Enyoghasi & Badurdeen, 2021).

In addition to contributing to more sustainable manufacturing, BDA capability can have an impact on the development of circular economy (CE). According to MacArthur (2013), CE is an economic system that aims to introduce a circular pattern into the production chain, so that products can be reintroduced through remanufacturing, recycling and reuse. It is argued that CE is expanding with the help of Industry 4.0 technologies, which enable the creation of new business models that allow for less material consumption and the reuse of waste as a resource in other industrial processes (Majeed et al., 2021; Ang et al., 2021).

In addition, Okorie et al. (2018) point out that technological infrastructure such as sensors and RFIDs are increasingly being used in electronic equipment, allowing a product to be tracked for recycling and supporting remanufacturing and reuse of parts or components at the end of the product's useful life. This enables greater circularity (reducing waste in the production process and reusing waste as a material), among other sustainability benefits. Specifically, Kristoffersen et al. (2020) and Awan et al. (2021) point out that BDA is a facilitator of CE.

According to Gupta et al. (2019), big data functionalities can be used to generate insights for process integration and resource sharing. In the same vein, Awan et al. (2021) argue that BDA capabilities enable companies to successfully use their infrastructure and experience to develop processes and products that are compatible with the reuse of waste, as well as the possibility of recycling.

Given the observation that BDA capabilities influence sustainable manufacturing and CE, the research question guiding this study is: Is big data analytics capability related to the development of sustainable manufacturing and circular economy in Brazilian industries?

This question arises from the potential that Industry 4.0 technologies have given to manufacturing companies to face the challenges of limited natural resources and negative social and environmental impacts, which are challenges presented in the Sustainable Development Goals (SDGs) (United Nations, 2015; Awan et al., 2021; Enyoghasi & Badurdeen, 2021). Thus, considering that Brazil is one of the largest producers of greenhouse gas emissions and that environmental and socioeconomic issues are discussed globally, there is an urgent need to develop the CE paradigm (Nobre & Tavares, 2017).

This paradigm can be supported by BDA capability, which has shown its potential for sustainable practices (Nobre & Tavares, 2017; Raut et al., 2019; Kristoffersen et al., 2020; Awan et al., 2021). As technology and sustainability are increasingly being discussed in an integrated way, this integration is essential in organizations seeking to build capacities to overcome the challenges of the environment (Jabbour et al., 2019, 2020a; Raut et al., 2019). Furthermore, Raut et al. (2019) noted that BDA and sustainability practices can be different in developed and developing economies. Brazil, as an emerging economy, needs to develop, but it needs to be sustainable in light of the climate crisis. Therefore, this study makes it possible to map the relationship between BDA capability, sustainable manufacturing, and CE from the perspective of Brazilian industry.

2 Theoretical framework

2.1 Resource-based theory and big data analytics capability

Resource-based theory (RBT) states that organizations are made up of resources, routines, and capabilities for developing core competencies (Barney, 1991; Grant, 1991). These are derived from the combination of organizational resources integrated into complex patterns through routines (Barney, 1991; Grant, 1991, 1996).

Big data technology is a resource that has been adopted by industries to provide insights for decision making. Big data is known for its large volume of data, variety and speed of data production, and is considered to be a multidimensional structure (Tayal et al., 2020), which enables predictive analysis to be carried out, also known as big data analytics (BDA) (Ardolino et al., 2018). In order for this technology to be advantageous in an organization, it is necessary to build BDA capabilities (Gupta & George, 2016). Capabilities are understood as a set of routines consisting of a set of tangible and intangible resources (Peng et al., 2008).

Thus, the tangible resources of BDA are software, machine learning, data mining techniques, and computational statistics. The intangible resources are knowledge and wisdom. The first is experience, accumulated learning combined with information that results in valuable insights, enabling the application of artificial intelligence and algorithms to develop business intelligence and support decision making. The second is wisdom, which is established through ethical and social considerations and personal judgments applied to knowledge, supporting the appreciation and understanding of motive for decision making in terms of appropriate behavior (Ardolino et al., 2018).

Thus, when organizations include the set of BDA resources in their organizational routines, they constitute a BDA capability. Dubey et al. (2019b) believe that a company has BDA capability when it routinely: a) combines and integrates information from many data sources for use in decision making; b) uses advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making; c) uses data visualization techniques (e.g., dashboards) to help users or decision makers understand complex information; d) uses dashboards to break down information to aid in root cause analysis and continuous improvement.

BDA capability has a positive impact on organizational performance and favors more accurate decision making (Bag et al., 2021). In addition to enabling the sharing of data from various sources, linking cyber systems, the internet of things, and business management to provide insights and support organizational processes, it also enables the adoption of socio-environmental practices (Dubey et al., 2019a) and the management of sustainable operations in the supply chain (Tayal, Solanki & Singh, 2020).

2.2 BDA capability, sustainable manufacturing and circular economy

Sustainable manufacturing involves manufacturing companies integrating interdependent social, environmental and economic processes, products and practices into their systems (Enyoghasi & Badurdeen, 2021). Social and environmental practices can be facilitated by BDA capabilities (Dubey et al., 2019a), which enable the measurement and control of environmental indicators and the creation of new business models that promote sustainability (Gupta & George, 2016; Dubey et al., 2019b; Jabbour et al., 2019; Raut et al., 2019; Azeem et al., 2022).

According to the UN, technology can contribute to sustainable development by enabling production with less environmental impact. Among the technologies, big data stands out as an important tool for organizations to implement sustainable practices. For this to be possible, it is necessary to develop BDA capabilities to help manufacturing become more sustainable (Ren et al., 2019; Dubey et al., 2019a; Jabbour et al., 2019; Bai et al., 2020). According to Zeng et al. (2017), sustainable manufacturing is defined as manufacturing that adopts sustainable practices in its production chain, including environmental, social and economic aspects.

In Brazil, according to the National Confederation of Industry (CNI), industries have adopted practices aimed at avoiding water and energy wastage, developing reforestation activities, monitoring greenhouse gases and using renewable energy sources. These practices are possible thanks to the large volume of data available, which has the informational potential to generate knowledge, optimize performance indicators and provide decision support, feedback and forecasting (Nagorny et al., 2017).

In this way, BDA capabilities in environmental management can provide valuable information on resource use, energy efficiency, waste generation, and pollution levels, as well as alerting us to the need for corrections and opportunities in production. This can improve production capacity, reduce resource consumption, make manufacturing companies environmentally responsible, improve product quality and make processes more flexible (Carvalho et al., 2020; Azeem et al., 2022). In light of the above, the following research hypothesis is formulated:

> H1: BDA capability has a positive impact on the development of sustainable manufacturing.

The integration of big data technology with circular economy (CE) is advocated by Jabbour et al. (2019) due to the synergy between the two, providing a perspective of social and environmental sustainability. CE is a concept that aims to reintroduce waste into the production chain rather than discarding it into nature, and is a regenerative systems approach with a "cradle to cradle" perspective. It aims to eliminate waste, reduce energy consumption and improve sustainability performance through closer ties between organizations (MacArthur, 2013; Geissdoerfer et al., 2017; Navare et al., 2021).

The concept of CE has characteristics of closed-loop systems, adaptation of product design, creation of new business models, reversal of production cycles, and improvement of production technologies (Malek & Desai, 2019; Ellen MacArthur Foundation, 2022). In this sense, BDA capability can help plan strategies that make up the concept of CE, such as minimizing emissions, energy consumption, and tightening and closing energy and material loops through efficient and effective material flow management. This capability can also contribute to the development of products with intelligent design, which contributes to the implementation of circular businesses and benefits companies and society (Nobre & Tavares, 2017; Geissdoerfer et al., 2017; Jabbour et al., 2018, 2019; Desing et al., 2020).

BDA allows the creation of new business models that help develop the CE economic model, such as additive manufacturing, which uses 3D scanning, 3D printing and redistributed manufacturing to produce based on data, resulting in the optimization of products and the design of components (Moreno et al., 2017; Carvalho et al., 2020; Colorado et al., 2020; Majeed et al., 2021; Gupta et al., 2021). Another possible business model that has been implemented is servitization, which consists of offering services and business solutions that add value to consumers, rather than just products produced by industries. Although there are challenges to servitization, it has great potential to benefit sustainable practices and CE (Kamal et al., 2020).

In addition, BDA capability has led to information sharing and closer ties between organizations (Jabbour et al., 2020b), enabling the creation of tools to help select suppliers that support sustainable practices (Wang et al., 2021), and improving interactions between organizations, suppliers and customers, creating a sustainable supply chain network (Gupta & George, 2016; Zeng et al., 2017; Gupta et al., 2019; Awan et al., 2021). This makes it more feasible to share data through collaboration platforms (Tseng et al., 2018). Furthermore, globally, ISO/TC 323 on CE was established in 2008 to standardize the field of CE and develop support tools and guidelines for implementation (International Organization for Standardization, 2018).

In this way, BDA can provide benefits to CE. Therefore, the following research hypothesis is formulated:

> H2: BDA capability has a positive impact on the development of circular economy.

CE is considered to be holistic strategic perspective that includes green and sustainable business models (Reslan et al., 2022). Sustainable manufacturing involves the integration of the sustainable perspectives (social, economic and environmental) into products, processes and operating systems (Enyoghasi & Badurdeen, 2021). Industries that adopt this perspective contribute to the promotion of CE through recycling, reuse and remanufacturing (MacArthur, 2013). By focusing on companies and their products, the development of CE can maximize the lifespan of products (Alaerts et al., 2019), and waste can be reintroduced into the production chain as a resource. In addition, new business models such as additive manufacturing have shown great potential for environmentally clean production and reduced energy consumption, as well as lower costs, shorter production times and product customization (Majeed et al., 2021).

The concepts of sustainable manufacturing and CE are often used interchangeably in the literature, which can lead to confusion. While sustainable manufacturing focuses on integrating a sustainable perspective (social, economic and environmental) into manufacturing processes, products and operating systems, CE is an economic model that aims to promote sustainability in different sectors of the economy, including manufacturing, cities and regulations (Enyoghasi & Badurdeen, 2021).

For example, it can be seen that CE has been applied to networks of companies that adopt sustainable practices in their operations, with the aim of better managing the flow of products and controlling the waste generated. In this sense, collaboration between customers and suppliers in a closed-loop supply chain, through recycling, remanufacturing and reuse, has been widely explored as a way of promoting sustainability and reducing environmental impact (MacArthur, 2013; Desing et al., 2020; Navare et al., 2021; Acerbi et al., 2021). Therefore, the following research hypothesis is presented:

> H3: The development of sustainable manufacturing has a positive impact on CE development.

Some manufacturing companies that adopt BDA capabilities use their resources to observe products in real time, reduce processing costs and improve product lifecycles, contributing to the adoption of sustainable practices (Enyoghasi & Badurdeen, 2021). In addition, BDA capabilities can provide improvements in supply chain management and performance as well as in information monitoring (Nobre & Tavares, 2017; Bag et al., 2021; Jabbour et al., 2020a), reducing information asymmetry by enabling data sharing among supply chain partners (Nobre & Tavares, 2017; Dubey et al., 2019a).

The integration of BDA capability and CE has increased the quality of decision making in relation to CE development, adding informational and sustainable value. It has developed a fundamental role in society, changing perspectives on environmental conservation and human behavior, resulting in a paradigm shift (Nobre & Tavares, 2017; Desing et al., 2020; Awan et al., 2021). For example, governments have called for the creation of indicators suitable for effectively monitoring progress towards a CE (Alaerts et al., 2019). Therefore, the following research hypothesis is proposed:

> H4: BDA capability and CE development are mediated by sustainable manufacturing.

Based on the hypotheses presented, Figure 1 illustrates the theoretical model proposed in this research.

3 Research methods and procedures

The research is descriptive, quantitative and was conducted through a survey of employees in Brazilian industries that use big data technology. The population studied are Brazilian industries that use big data. The choice of this population is due to the fact that industries have been evolving rapidly due to technological advances,

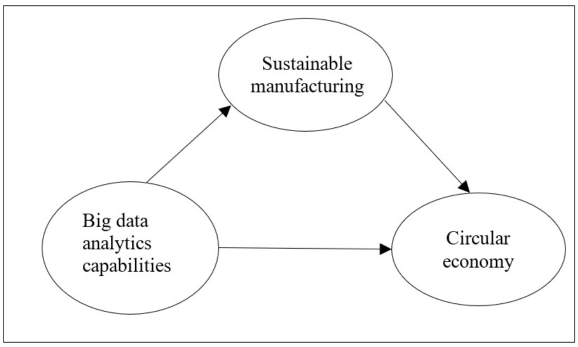

Figure 1. Theoretical research model
Source: Own elaboration

which has enabled the development of innovations for sustainable production, providing new business models that reduce environmental and social impacts (Elkington, 2019). Thus, a sustainable perspective has become urgent, resulting in innovations that bring together economic, social and environmental aspects (Malek & Desai, 2021; Ang et al., 2021). To access the target population and compose the sample, users of the LinkedIn platform were tracked using the terms "big data," "data analytics" and "data scientist," who are employees of Brazilian industries with functions related to the development of BDA capability. Thus, the sample is made up of respondents who hold positions such as: Data Scientist, Manufacturing Excellence, Infrastructure Analyst, Data Analyst, Manufacturing IT, Market Intelligence Analyst, Business Intelligence Analyst, Continuous Improvement Manager, Business Intelligence, Head of Manufacturing Excellence, and Quality Manager and Controller.

Next, 450 invitations to connect via LinkedIn were sent to employees of these companies who had roles related to management and BDA, of whom 204 accepted to join the network. Those who accepted the invitation were sent the link to the survey instrument via Google Forms. To increase adherence, the survey instrument was sent by e-mail if requested. This data collection period was from May 6 to June 1, 2021.

The minimum sample size was estimated using the G*Power3.1.9.4 software (Faul et al., 2009), using a test power of 0.80 and a median effect size (f2) of 0.15, according to the recommendations of Hair et al. (2021), which resulted in a minimum sample of 55 cases. There were a total of 154 responses, of which 41 were excluded, 18 because they did not use big data technology and 23 because they were not from the industrial sector. Therefore, the final sample consisted of 113 responses that were considered valid (Supplementary Data 1 – Database). This data collection period took place between April and July 2022.

The research instrument (Appendix A – Research Instrument) consists of three constructs: BDA capability, measured by four statements adapted from Dubey et al. (2019b); sustainable manufacturing, contained in five statements based on the studies of Zeng et al. (2017) and Bag et al. (2021); and CE, formed by five statements adapted from Zeng et al. (2017). As the statements used in the study came from foreign research instruments, the process of translation and back-translation was applied to avoid distorted measurements and to measure what was really intended. Subsequently, the research instrument was pre-tested with two professionals in the field and three PhD students to eliminate any possible ambiguity. The constructs were measured using 14 multiple items and the respondents' level of agreement was measured using a Likert scale ranging from (1) strongly disagree to (5) strongly agree. The description of the variables was organized into codes (Appendix A. Research Instrument). In addition to the statements, the survey instrument used a control question in order to select industries that use a large volume of structured and/or unstructured data.

The hypotheses were tested using structural equation modeling (SEM), using the RStudio program. The SEM was estimated using the partial least squares path modeling (PLS) method, due to the non-normality of the data distribution and the size of the sample. The SmartPLS software v.3.3.9 (Hair et al., 2021) was used to carry out the analysis.

To avoid common method bias, the study followed the recommendations of Podsakoff et al. (2003). First, the statements in the questionnaire were organized randomly to avoid any possible association between the constructs on the part of the respondents. The questionnaire was then sent directly to the participants. After collection, Harman's single factor test was carried out, where it was observed that one factor accounted for 24.24% of the variance, indicating that there was no evidence of common method bias.

4 Analysis and discussion of the results

4.1 Sample characteristics

Each response received represents one surveyed company. The characteristics of the companies whose employees took part in the survey are shown in Table 1.

When analyzing the characteristics of the industries, it was possible to see that companies with more than 99 employees accounted for 97.35% of the total responses, followed by companies with between 50 and 99 employees (2.65%). As for the industrial sectors, there was a rough segmentation between the activities according to the participants' comments. There were four groups with the highest percentages, with the food sector in first place with 32.74%, followed by agribusiness with 12.39%, the automotive group in third with 11.50%, and cosmetics in fourth with 11.50%.

Table 1
Company characteristics

Company Size	Frequency	%
From 50 to 99 employees	3	2.65
More than 99 employees	110	97.35
Sectors		
Food	37	32.74
Agribusiness	14	12.39
Automotive	13	11.50
Cosmetics	13	11.50
Mining and other commodities	7	6.19
Consumer goods	6	5.31
Pharmaceuticals and hospitals	6	5.31
Construction	5	4.42
Fuel	4	3.54
Apparel	3	2.65
Supplies	3	2.65
Appliances and Pulp and Paper	2	1.76

Source: Research data.

4.2 Evaluation of the measurement model

The evaluation of the measurement model (Supplementary Data 2 – PLS Algorithm) began with an assessment of the reliability of the indicator. The literature recommends that indicators have loadings above 0.708, but in social science studies, loadings below 0.708 can be considered in conjunction with a careful analysis of the effects on reliability and validity (Hair et al., 2021). Therefore, three indicators were excluded, two of which related to the sustainable manufacturing construct and one to CE (Table 2).

After the exclusion, indicator Q4 still had a lower loading than recommended (0.700), and it was decided to keep it because there was no significant change in composite validity (Hair et al., 2021). After adjusting the measurement model, it can be said that the items in the research instrument do not show redundancy or undesirable response patterns, and also that the constructs explain 64.6% (BDA Capability) or more of the variance of the indicators that make up the construct.

Next, the internal consistency of the measurement model was assessed using Cronbach's alpha and composite reliability. The Cronbach's alpha of the latent variables showed values above 0.70, which is considered satisfactory for the lower limit of acceptability according to Hair et al. (2021). With regard to composite reliability, values between 0.70 and 0.90 are presented for the latent variables, which is considered satisfactory to good, indicating that the indicators are valid and do not have redundancy problems. With regard to the average variance extracted (AVE) of the constructs, all the constructs have values considered acceptable, demonstrating the existence of convergent validity (Hair et al., 2021). Next, the discriminant validity of the constructs was estimated to measure the empirical distinction between the constructs. As shown in Table 3 (shaded), discriminant validity is present. As an additional discriminant analysis, the heterotrait-monotrait ratio (HTMT) was evaluated. Henseler et al. (2015) propose a threshold value of 0.85 for structural models with more conceptually distinct constructs, thus confirming the empirical distinctiveness of the constructs.

4.3 Structural model evaluation and hypothesis testing

The structural model was then evaluated (Supplementary Data 3 – PLS Bootstrapping), checking the model's collinearity (VIF), explanatory power (R2) and effect (Table 4). According to Hair et al. (2021), VIF values above 5 indicate the existence of probable collinearity problems between the latent predictor variables, but collinearity can also occur with values between 3 and 5. The values obtained in the internal VIF show that there is no collinearity between the latent predictor variables of BDA capability and sustainable manufacturing (Hair et al., 2021).

Next, the explanatory power of the model was assessed using the coefficient of determination (R2). R2 values range from 0 to 1. In the social sciences, R2 is considered weak, moderate and strong at 0.25, 0.50 and 0.75, respectively (Hair et al., 2021). In the case of sustainable manufacturing, the R2 value is 0.222, indicating that BDA capability explains 22.2% of the variation in sustainable manufacturing. With regard to the CE variable, there is moderate explanatory power, with a coefficient of determination value of 0.579, indicating that BDA capability and sustainable manufacturing explain 57.9% the CE variable.

Significance is assessed using the path coefficient t-values or confidence intervals calculated based on the bootstrapping sample (Hair et al., 2021). According to Hair et al. (2021), the bootstrapping samples estimate the PLS path model and determine the standard deviation and standard error of the estimated coefficients using the sampling distribution. Values greater than 1.96 were

Table 2
Model fit indices

	Indicator loadings	Composite Reliability	Cronbach's Alpha	Convergent Validity (AVE)
Big data analytics capability	Q1 – 0.846 Q2 – 0.858 Q3 – 0.801 Q4 – 0.700 Q5 – Excluded	0.879	0.823	0.646
Sustainable manufacturing	Q6 – 0.882 Q7 – 0.900 Q8 – 0.848 Q9 – Excluded	0.909	0.850	0.769
Circular economy	Q10 - 0.858 Q11 – 0.891 Q12 – 0.830 Q13 – Excluded Q14 – 0.714	0.895	0.842	0.682

Source: Research data.

Table 3
Discriminant Validity

	BDA Capability		Circular Economy		Sustainable Manufacturing
BDA Capability	0.803				
Circular Economy	0.537	0.610	0.826		
Sustainable Manufacturing	0.471	0.528	0.729	0.840	0.877

Source: Research data.

Table 4
Structural model fits

	R2	VIF		
		BDA Capability	Sustainable Manufacturing	Circular Economy
BDA Capability	-		1.000	1.285
Sustainable Manufacturing	0.222			1.285
Circular Economy	0.579			

Source: Research data.

Table 5
Significance and Relevance of the Structural Model

Relationship	Hipotheses	Total Effect	St. Dev.	T Statistic	p-values
Direct	H1 BDA Capability > Sustainable Manufacturing	0.471	0.086	5.506	0.000
Direct and Indirect	H2 and H4 BDA Capability > Circular Economy	0.536	0.059	9.032	0.000
Direct	H3 Sustainable Manufacturing > Circular Economy	0.612	0.074	8.322	0.000
Indirect	H4 BDA Capability > Circular Economy	0.288	0.064	4.522	0.000

Source: Research data.

considered for the t-values and p <0.05 for the structural path of the path diagram (Hair et al., 2021). The effect is verified by the path coefficient, which varies between -1 and +1, with values close to +1 indicating a strong positive relationship and vice versa, and the closer to zero, the smaller the relationship (Hair et al., 2021). Table 5 shows the significance and relevance of the theoretical model.

The results obtained indicate that each path in the structural model has a significant relationship, with p-values < 0.000 and t-values greater than 1.96 at a 5% significance level.

4.4 Discussion of the hypotheses

The first hypothesis (H1) seeks to analyze the relationship between BDA capability and the development of sustainable manufacturing. It indicates that the BDA capability construct is relevant in explaining the sustainable manufacturing construct, reflecting the development of sustainable practices in industries with the help of BDA (Raut et al., 2019; Zhang et al., 2022). This is because big data makes it possible to provide useful information that benefits decision making in the lifecycle and complex environments of businesses (Ren et al., 2019). It contributes to less resource-intensive manufacturing and more accurate environmental and social performance, through BDA capabilities that provide decision support, feedback and forecasting (Nagorny et al., 2017). BDA has transformed the manufacturing sector, making processes in manufacturing companies more flexible to new changes and enabling exploration for improvement (Azeem et al., 2022). It provides data-driven solutions and enables the analysis of product end-of-life and decision making in relation to production, energy consumption and pollutants (Cui et al., 2020).

The second hypothesis (H2) sought to verify the relationship between BDA capability and CE development, through the direct relationship between the constructs of BDA capability and CE. This relationship was significant, indicating that BDA capability can contribute to CE development, confirming the idea of Jabbour et al. (2019) about the integration of big data technology and CE, as BDA capability can help in the strategic planning of CE concepts, such as efficiency in material flow management, minimization of energy consumption and emissions of polluting gases, as well as in intelligent design projections that help in the implementation of circular businesses in society (Nobre & Tavares, 2017; Geissdoerfer et al., 2017; Jabbour et al., 2019; Desing et al., 2020).

According to Kristoffersen et al. (2020), BDA is considered a key enabler for CE, but there is little guidance on the potential of circular strategies. Despite this, data can provide patterns and help reduce uncertainty, operational complexity and resistance to adopting the CE paradigm (Gupta et al., 2019). In addition, Hapuwatte and Jawahir (2019) point out that predictive models, developed in conjunction with optimization processes that include sustainability data, can support product design and provide favorable and sustainable conditions for manufacturing. According to Cui et al. (2020), BDA can contribute to predicting the behavior of various production systems, allowing factories to implement preventative measures with precision.

The third hypothesis (H3) investigates the relationship between sustainable manufacturing and CE, which proves to be significant. It indicates the relevance in explaining CE, confirming the studies of Reslan et al. (2022), who point out that sustainable manufacturing is integrated in the holistic perspective of CE. Sustainable manufacturing contributes to CE through products with circular design, that is, products that are produced in a way that maximizes their useful life (Alaerts et al., 2019), or it provides processes related to projects for remanufacturing, disassembly and repairability (Jabbour et al., 2018).

It also enables better management of product flow between manufacturing companies through cooperation (Navare et al., 2021; Acerbi et al., 2021). In addition, smart devices such as RFIDs, readers, sensors and tags enable records that play a key role throughout the assembly process and subsequent lifecycle, improving records of energy consumption, fault history and material delivery, which can result in effective sustainable production (Ren et al., 2019).

The last hypothesis (H4) analyzes the relationship between BDA capability and CE development mediated by sustainable manufacturing. This analysis is based on the indirect relationship between BDA capacity and CE. It shows that sustainable manufacturing mediates the relationship between BDA capacity and CE, i.e. sustainable manufacturing contributes to CE. This mediation can be seen when managers in manufacturing industries use data to develop strategies that enable the transformation of linear production into a circular system, where BDA capability is fundamental for efficient decision making in the processes of material recovery and product reuse

(Awan et al., 2021). This is a useful finding because the emergence of new forms of digital business models and the digital economy has greatly increased the demand for data-driven decision making in strategic processes (Awan et al., 2021).

This is possible because BDA helps in collaboration and the sharing of information on pollution control, waste emissions and carbon footprints, enabling manufacturing firms to improve their sustainable business performance (Raut et al., 2019) and sustainability in supply chains (Dubey et al., 2019a). For this to happen, there needs to be a focus on developing capabilities that enhance integrated actions (Jabbour et al., 2018). This supports the study by Jabbour et al. (2020a), which shows that big data is useful in improving sustainable supply chains, and for the benefits of BDA to be applied to sustainable manufacturing, there needs to be science and guidance for sustainable management in supply chains. This will allow for better management of product flows between manufacturing companies through collaboration (Navare et al., 2021; Acerbi et al., 2021). In addition, smart devices such as RFIDs, readers, sensors and tags enable records that play a key role throughout the assembly process and subsequent lifecycle, improving records of energy consumption, fault histories and material delivery, which can lead to effective sustainable production (Ren et al., 2019).

5 Concluding remarks

Considering the economic, environmental and social issues being addressed globally, and the benefits that BDA provides in the sustainable development of manufacturing companies, this study aimed to identify the relationship between BDA capability and the development of sustainable manufacturing and CE in Brazilian industries. The results show that BDA capability is related to the development of sustainable manufacturing and CE.

It can be seen that BDA capability has benefited the development of CE, through the design of products for regeneration, i.e. waste can be used as a resource in new business models. Furthermore, in the interactions between organizations, improvements can be seen in the management and performance of supply chains, enabling sustainable practices between manufacturing companies and improving coordination between partners, leveraging the CE paradigm. Thus, in the manufacturing sector, BDA is a catalyst that allows the organization to grow and take care of the environment and resources, as well as gain competitive advantage.

The study draws on the literature to show that BDA capability is related to the development of sustainable manufacturing and CE. In the relationship between BDA capability and CE, the presence of the mediating variable sustainable manufacturing is noted, contributing to a better understanding of this effect in the relationship. The study focuses on Brazilian industries that use big data technology, providing better knowledge of the interaction between this technology and the development of sustainable and circular practices in industries, enabling incentives for changes in manufacturing companies that can succeed in reducing social pressures.

The proposed model uses a limited sample of different types of Brazilian industries, so a more comprehensive study is recommended, in addition to focusing on specific industries. In addition, a qualitative analysis is recommended to understand how operations management occurs in sustainable and circular practices through BDA capability. It is also suggested that the impact of BDA capability, sustainable manufacturing and CE on value creation and innovation generation in products, processes, management and marketing be analyzed.

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SUPPLEMENTARY MATERIAL

Supplementary Data 1 – Database
Supplementary Data 2 – PLS Algorithm
Supplementary Data 3 – PLS Bootstrapping
Supplementary material to this article can be found online at https://doi.org/10.7910/DVN/F659EN

APPENDIX A. RESEARCH INSTRUMENT

Big Data Capability (Dubey et al., 2019b)

Scale: (1) strongly disagree and (5) strongly agree

Q1. Our company easily combines and integrates information from many data sources for use in decision making.

Q2. Our company uses advanced analytical techniques (e.g. simulation, optimization, regression) to improve decision making.

Q3. Our company routinely uses data visualization techniques (e.g. dashboards) to help users or decision makers understand complex information.

Q4. Our dashboards give us the ability to drill down into information to support root cause analysis and continuous improvement.

Sustainable Manufacturing (Zeng et al., 2017; Bag et al., 2021)

Scale: (1) strongly disagree and (5) strongly agree

Q5. Our company uses clean energy (solar, wind, etc.) in the production process.

Q6. Our company is concerned about the logistics process to reduce environmental impacts.

Q7. Our company gives preference to partners who comply with environmental protection rules and regulations.

Q8. Our company works with product design and processes that strive to reduce waste.

Q9. Our company has a waste conversion or disposal program.

Circular Economy (Zeng et al., 2017)

Scale: (1) strongly disagree and (5) strongly agree

Q10. Our company is committed to processes that reduce the consumption of raw materials and energy.

Q11. Our company uses materials that can be reused.

Q12. Our company uses waste materials to manufacture other products.

Q13. The companies we work with participate in the management of manufacturing waste.

Q14. Our company is committed to lean manufacturing.

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