sustainability

MDPI

Article

The Synergy Between Industry 5.0 and Circular Economy for Sustainable Performance in the Chinese Manufacturing Industry

Muhammad Noman Shafique [1], Umar Adeel [2] and Ammar Rashid [3,*]

[1] CESAM—Centre for Environmental and Marine Studies, Department of Environment and Planning, University of Aveiro, 3810-193 Aveiro, Portugal; shafique@ua.pt
[2] Department of Computer Science and Engineering, American University of Ras al Khaimah, Ras al Khaimah 72603, United Arab Emirates; umar.adeel@aurak.ac.ae
[3] Department of IT, College of Engineering and IT, Ajman University, Ajman P.O. Box 346, United Arab Emirates
* Correspondence: a.rashid@ajman.ac.ae

Abstract: The industrial shift from Industry 4.0 to Industry 5.0 has transformed organizational thinking, moving the focus from purely technological implementation to a more human-centered approach. The current study has focused on the Industry 5.0 technological capabilities to bring into circular economy practices aligned with sustainable development goals, aiming to enhance sustainable performance. Moreover, the resource-based theory has grounded the development of the comprehensive framework on Industry 5.0 technological capabilities (artificial intelligence capabilities, big data analytical capabilities, Internet of Things capabilities, machine learning capabilities, and blockchain technology capabilities) and circular economy practices (eco-design, management system, and investment recovery) to achieve sustainable performance (environmental performance, social performance, and economic performance). Data have been collected from 179 respondents from the Chinese manufacturing industry. Additionally, data have been analyzed using the structural equation modeling technique. The results showed that Industry 5.0 technological capabilities directly affect sustainable performance. Moreover, circular economy practices played a dual, moderating, and mediating role between Industry 5.0 technological capabilities and sustainable performance. The current study has contributed to filling a gap in the literature on Industry 5.0 capabilities, especially in the circular economy and sustainable performance perspective. The practical contribution recommended is that if organizations focused on their Industry 5.0 technological capabilities, it would boost circular economy practices and sustainable performance to achieve sustainable development goals.

Keywords: Industry 5.0 capabilities; internet of things; artificial intelligence; big data; blockchain; machine learning; circular economy practices; sustainability; structural equation modelling

check for updates

Citation: Shafique, M.N.; Adeel, U.; Rashid, A. The Synergy Between Industry 5.0 and Circular Economy for Sustainable Performance in the Chinese Manufacturing Industry. *Sustainability* **2024**, *16*, 9952. https://doi.org/10.3390/su16229952

Academic Editor: Aurelija Burinskienė

Received: 11 October 2024
Revised: 4 November 2024
Accepted: 8 November 2024
Published: 14 November 2024

1. Introduction

The Industry 5.0 (I5.0) revolution has radically changed thinking styles, strategies, practices, and concepts from a technological perspective to a human-centric approach [1]. I5.0 has three main pillars: it is sustainable, resilient, and human-centric [2]. The human pillar has focused on empowerment, diversity, and talent. The resilient pillar has concentrated on agility and flexibility, using advanced information technologies, while the sustainability pillar has focused on environmental, economic, and social benefits [2].

I5.0 is an emerging concept introduced in the European Union workshops in 2020 [3]. In 2023, the market size of I5.0 was USD 52.2 billion, and it is expected to reach USD 255.7 billion in 2029. The compound annual growth rate of I5.0 is 31.2%, indicating rapid growth [4]. Additionally, I5.0 has increased society's well-being by empowering teams through training and developing evolving skills to gain a competitive advantage by reducing resource utilization and caring for the environment [2].

The impact of technological capabilities on economic growth was established in the early 1900s [5] because technological capabilities bring innovative performance [6]. The Brazilian economy grew 200% in the first decade of the twentieth century, even though, at that time, Brazil had low and medium-low technological industries [5,7]. In the contemporary era, Internet of Things capabilities (IoTCs) enhance the green supply chain performance [8]. The literature has focused on artificial intelligence—big data analytical capabilities (AI–BDACs) from the perspective of supply chain agility [9]. Additionally, big data analytics (BDA) has sharpened the supply chain performance and overall organizational performance [10,11].

RQ1: *How do technological capabilities contribute to enhancing sustainable performance?*

Circular economy (CE) has focused on environmental factors while aiming to gain economic, social, and environmental benefits. CE has focused on reducing raw material use, waste, and emissions through the reuse, repair, and recycling of products as much as possible [12,13]. Circular economy practices (CEPs) have a direct relationship with sustainable development goals (SDGs) to develop business models [14]. Additionally, a meta-analytic structural equation modeling study was conducted to find the CEP effect on the manufacturing firm's performance [15]. AI has played a vital role in this relationship [16].

I5.0 technological capabilities and CEPs play critical roles in achieving SDGs. Additionally, I5.0 technological capabilities and CEPs share the goal of protecting resources and the environment to boost sustainable performance (SusP), and both I5.0 and CE are crucial to achieving SDGs. Despite the importance of I5.0 technological capabilities and CEPs in achieving SusP, their study was missing in the literature and practice.

RQ2: *How do CEPs play a role in integrating I5.0 technological capabilities and SusP?*

This study has theoretically contributed to three perspectives. First, the current study has focused on I5.0 technological capabilities, while previous studies have either focused on Industry 4.0 or the implementation of advanced information technologies in organizations to enhance sustainable performance [17–19]. Second, the current study is grounded on the resource-based view (RBV) theory, while most studies have focused on the technological–organizational–environmental view (TOE) [17], the natural resource-based view (NRBV) [18], and the practice-based view (PRB) [19]. So, inconsistencies are found in the literature. Third, this study has developed and analyzed the comprehensive framework of the relationship between I5.0 technological capabilities, CEPs, and SusP, which was not found in the literature. So, this study has made a theoretical contribution to the literature [20].

In practice, the rapid boost of information technologies in the manufacturing industry is driving the industrial revolution from Industry 1.0 of mechanization to I5.0 of personalization. This evolution not only has fruitful results, but at the same time, it brings challenges for human beings. In I5.0, the biggest challenge is understanding the real capabilities of using advanced information technologies more efficiently in their operations for SusP. So, this study has contributed to filling a theoretical and practical gap. The current study has focused on technological-related I5.0 capabilities to perform CEPs and achieve SusP.

The current study follows the scientific method. The following section presents a literature review on I5.0 technological capabilities, CEPs, and SusP, which leads to integrating the resource-based theory to develop the theoretical foundation and hypotheses. After developing the hypotheses, the methodology section elaborates on the measurement and data collection methods. In the next section, results are interpreted using their threshold values. In the last section, conclusions are drawn, and limitations and recommendations are elaborated.

2. Literature Review

In this literature review section, the described literature on I5.0 technologies elaborates on the important technologies used in the fifth industrial revolution era, which needed to be focused on to develop the relevant skills and capabilities. CEPs have focused on the major practices employed by organizations in their operations to achieve SDGs. Ultimately, SusP has focused on the critical aspects of social, economic, and environmental advantages.

2.1. Resource Based View Theory

RBV theory has examined the antecedents for SusP as the deployment of organizational resources and capabilities to gain a competitive advantage by non-imitability, rarity, value, and non-substitutability [21,22]. RBV theory has further explored how organizational resources can be turned into capabilities to reduce costs and improve quality. Moreover, RBV has considered human, physical, and organizational capital as basic organizational resources [23]. Additionally, RBV has categorized resources into tangible, like IT infrastructure, and intangible, like knowledge and experience, which contribute to the non-imitability of production and logistics [24]. In contrast, capabilities are the ability to perform specific tasks, leading to core competencies. These have been utilized to make organizational processes and activities more efficient to gain long-term competitive advantage [25,26].

In this study, RBV theory establishes the conceptual framework of I5.0 technological capabilities and CEPs based on the core organizational capabilities to gain SusP. Moreover, I5.0 capabilities focus on technological abilities, and organizations must train employees to use these technologies. This creates an interaction between humans and technologies but has a more human-centric approach. These capabilities are challenging to replicate and establish a sustainable competitive advantage, which aligns this study's framework with RBV theory.

2.2. Industry 5.0 (I5.0) Technologies

In the I5.0 literature review, technologies were categorized into three distinct viewpoints; the first is the extension and continuation of existing technologies like industrial robots, blockchain (BC), IoT, cybersecurity and cryptography, big data, and enterprise systems. The second is related to revolutionary technologies like AI, humanoid robots, and the Internet of Medical Things. The third approach emphasizes adaptive (cognitive) robots, human recognition technologies, the Internet of Everything, and smart energy management systems [27]. Moreover, the major three I5.0 technologies are IoT, BDA, and BC [28]. Additionally, technologies have extended to IoT, AI, machine learning (ML), big data, BC, and cloud computing from the perspective of CE [29]. In the literature, the I5.0 technologies are cloud/IoT, Cobot, cyber–physical systems, digital twins, radio frequency identification, and edge computing [30].

The present study only concentrated on five prominent I5.0 technologies: AI, big data, IoT, ML, and BC. These were chosen because they align with the previous literature linking the relationship between selected technologies and CE. The literature established the relationship between AI capabilities and circular business models [31]. Additionally, generative AI had a positive and significant impact on CEPs and sustainable supply chain performance [32]. In the previous literature, the relationship between big data analytical capabilities and the CE performance of the Czech manufacturing industry was studied [33]. Moreover, big data analytical capabilities' positive impact on CEPs was found in the Indian [34] and Brazilian [35] manufacturing industries.

A bibliometric analysis established a relational framework between IoT and CE within the manufacturing sector [36]. Additionally, a systematic literature review supported the relationship between IoT and CE [37]. Moreover, the literature found a positive impact of Industrial IoT on CE in Jordan SMEs [38]. Following the same pattern, the relationship between ML and CE was developed in a bibliometric analysis and systematic literature review [39]. Furthermore, the ML approach was employed for CE initiatives in the plastic sector [40]. The fourth industrial revolution digital technologies affect CE, and it is aligned with SDGs [41]. Building on the previous logic, a systematic literature review was conducted on the relationship between blockchain and CE to bridge the gap in practice and research [42]. The multiple aspects of blockchain technology affect CE [43]. Additionally, blockchain affects CEPs [44].

2.3. Circular Economy Practices (CEPs)

CEP activities involve reusing, recycling, and repairing the products as long as possible. Additionally, CEPs have focused on reducing the utilization of resources and increasing the output, which was found in the supply chain literature [45]. Moreover, recycling and remanufacturing, circular design, and circular manufacturing constitute three principles of CEPs [26]. Furthermore, CEPs have governance initiatives, economic initiatives, cleaner production, product development, management support, and knowledge found in the recent literature [46]. Likewise, CEPs have eco-design (ED), management support (MS), and investment recovery (IR) [47,48]. Extensive research was performed to validate the relationships between CEPs and SusP found in the prior literature using meta-analysis [49]. Additionally, the positive effect of CEPs on SusP was found in the supply chain literature [50]. A literature review was performed to identify the CEPs (green manufacturing, investment recovery, eco-design, internet environment management) with sustainable performance from the viewpoints of SP, EP, and EVP [51].

2.4. Sustainable Performance (SusP)

SusP represents organizational performance that is interlinked with the environment. It comprises three pillars: environmental performance (EVP), social performance (SP), and economic performance (EP) [46–48]. Sustainable supply chain performance has been measured through EVP, EP, and SP [26]. The literature established a connection between CEPs and SusP in Vietnam SMEs [52]. Additionally, a meta-analysis was conducted to find the relationship between CEPs and SusP [49]. In the supply chain literature, CEPs had an impact on sustainable supply chain performance [53]. On the other hand, the relationship between CE and SusP was found within the Mexican manufacturing sector [54].

2.5. Research Gap

The comprehensive literature review on the relationship among I5.0, CEP, and SusP identified several research gaps. The key research gaps are listed below.

1. Studies have elaborated on adopting and implementing advanced technologies, but the literature is scant and has focused on technological capabilities. This study has focused on I5.0 technological capabilities.
2. The discrepancies were found in the theoretical perspective, especially the TOE, Natural Resource-Based View (NRBV), and Practice-Based View (PRB). So, the most appropriate theory is needed.
3. All the literature has focused on Industry 4.0, and no study has yet been published that has focused on I5.0. This study has established the relationship among I5.0 technological capabilities, CEPs, and SusP.

The literature summary in Table 1 elaborates on the research gaps as mentioned earlier.

Table 1. Literature summary.

Year	First Author	Theory	Method	Technology	Circular Economy	Sustainable Performance	Ref.
2024	Mohammad Nurul Hassan Reza	Technology–Organization–Environment (TOE)	Survey	Industry 4.0	-	Sustainable Performance	[17]
2024	Farrukh Shahzad, M.	Natural Resource-Based View (NRBV)	Survey	Industry 4.0	Circular Economy Practices	Sustainable Performance	[18]

Table 1. *Cont.*

Year	First Author	Theory	Method	Technology	Circular Economy	Sustainable Performance	Ref.
2024	Zhibin Tao	Practice-Based Theory, Information Processing Theory	Survey	Industry 4.0	Green Supply Chain Management Practices	Sustainable Performance	[19]
2023	Oguzhan Yavuz	Natural Resource-Based View (NRBV), and Technology–Organization–Environment (TOE)	Survey	Industry 4.0	Sustainable Operations Practices	Sustainable Performance	[55]
2023	Sachin S. Kamble	Organizational capability theory (OCT)	Survey	Industry 4.0	Circular Economy Practices	Sustainable Performance	[48]
2023	N. Harikannan	-	Survey	Industry 4.0	Sustainable Manufacturing Practices	Organizational Sustainable Performance	[56]
2023	Dounia Skalli	Practice-Based Theory (PBT)	Survey	Industry 4.0	Circular Economy	Sustainable Organizational Performance	[57]
2022	Priya Rani Bhagat	Natural Resource-Based View (NRBV)	Survey	Industry 4.0	Green Practices	Firm Performance	[58]
2021	Reza, Mohammad Nurul Hassan	Technology–Organization–Environment (TOE)	Survey	Industry 4.0	-	Sustainable Firm Performance	[59]
2020	Sachin Kamble	-	Survey	Industry 4.0	Lean Manufacturing Practices	Sustainable Organizational Performance	[60]

2.6. I5.0 and SusP

I5.0 has simultaneously influenced economic, social, and environmental contributions at both the micro- and macro-levels. From the economic standpoint, economic transparency, supply chain resilience, and supply chain adaptability represent the macro-level impacts, while resilient industrial operations, workforce productivity, resource efficiency, operational efficiency, material flow efficiency, and circular manufacturing constitute micro-level economic contributions [27].

Environmental macro-level contributions include waste and pollution reduction, supply chain productivity, preventing over-consumption, a circular supply chain, diminished post-consumer waste, and reduced rebound effects, while emission reduction, end-to-end environmental transparency, prolonged product life cycle, renewable resources, and waste reduction are the key environmental contributions at the micro-level [27].

From the social perspective, ethical value creation, higher product accessibility, employment growth, improved consumer experience, equal employment opportunity, and human-centric technology development are the macro-level impacts. At the same time, workplace dignity, enhanced working environment, customer satisfaction, workplace safety, sustainability talent management, and job satisfaction are micro-level social contributions and impacts [27].

The correlation between AI-BDACs and supply chain performance [61] and supply chain analytics and environmental performance [62] was found. Additionally, IoT capability had a direct effect on firm performance with the mediating effects of IoT-enabled supply chain integration and supply chain capability from the retail industry in the United Kingdom [63]. Moreover, the relationship between IoT capabilities and green supply chain performance was proved in a previous study [8]. Furthermore, the direct relationship between BDACs and sustainable supply chain performance was tested in the Indian manufacturing industry [47].

As mentioned, the literature has grounded the foundation for CEPs' role in technological capabilities and performance. Consequently, according to the same rationale and the scarcity of literature on I5.0 technological capabilities and SusP, the literature gap was confirmed during a literature search of the WoS and Scopus databases. Not a single paper has developed the relationship between I5.0 capabilities and SusP because the I5.0 concept was introduced in 2020 [3], as it is still an emerging concept. Hence, this has enabled the researcher to consider the logic mentioned above from the literature to establish the following hypothesis.

Hypothesis 1: *I5.0 technological capabilities enhance SusP.*

2.7. I5.0, CEPs, and SusP

CEPs have served a mediating role in business studies. In the previous literature, information system capabilities have a direct effect on business performance, and CEPs play the mediating role, while environmental uncertainty has a moderating effect between CEPs and business performance [64].

In the Industry 4.0 (I4.0) literature, CEPs were found to be a mediator between I4.0 and sustainable performance. Moreover, the implementation of I4.0 technologies directly impacts sustainable supply chain performance, and indirectly, I4.0 technologies' mediating effects through green supply chain management practices and CEPs were found in the garment sector in Bangladesh [26].

India's manufacturing industry has focused on the direct relationship between I4.0 and SusP, the mediating effect of CEPs between I4.0 and SusP, and the moderated effect of CEPs between I4.0 and SusP [48]. Additionally, BDACs have a direct effect on sustainable supply chain performance and mediating effect through CEPs [46,47], and sustainable supply chain flexibility was found in the manufacturing industry in India [47].

The I4.0 literature previously cited has established the basis for the role of CEPs between technological capabilities and performance. Therefore, the same arguments are used, considering the scarcity of research on I5.0 technology capabilities, CEPs, and SusP. A literature search using the WoS and Scopus databases validated the lack of research on the association between I5.0 capabilities, CEPs, and SusP. This is because I5.0 was proclaimed in 2020 [12]. The researcher has developed the following hypotheses by considering the logic from the I4.0 literature that was previously cited.

Hypothesis 2: *CEPs have a moderating role between I5.0 and SusP.*

Hypothesis 3: *CEPs have a mediating role between I5.0 and SusP.*

Based on the literature review and hypotheses, the conceptual framework is established and depicted in Figure 1.

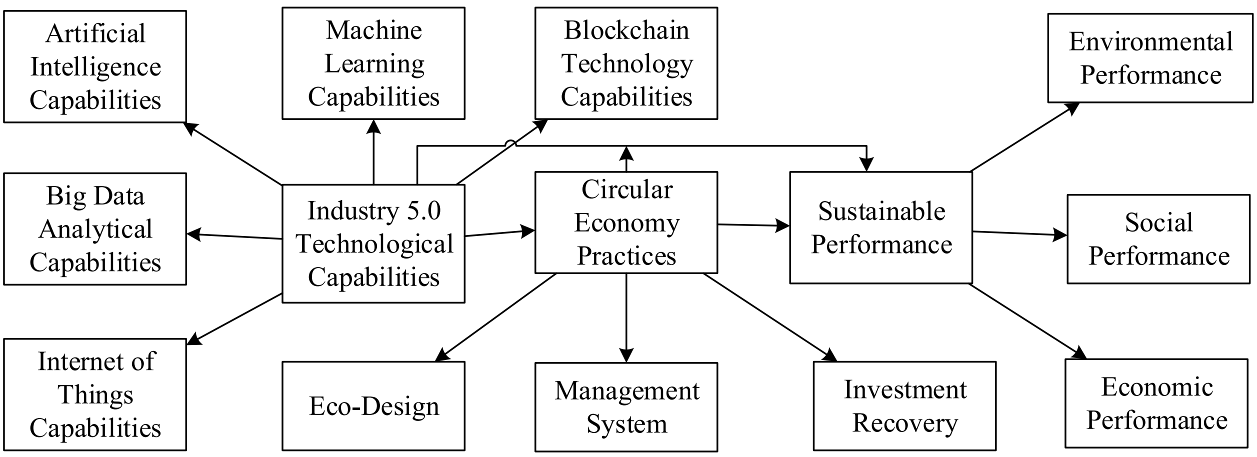

Figure 1. Conceptual framework driving Industry 5.0 to enhance circular economy practices.

3. Materials and Methods

This section elaborates on the measurement scale and explains how it was developed. It also explains the sample, sampling size, and population. Moreover, it elaborates on the data collection techniques.

3.1. Measurement Scale

The present study examined three primary constructs: I5.0 capabilities, CEPs, and SusP. Each construct is founded on subconstructs, measured through different measurement items. Every item was measured on a five-point Likert scale. The I5.0 capabilities were measured through AICs, BDACs, IoTCs, machine learning capabilities (MLCs), and Blockchain technological capabilities (BCTCs). AICs, BDACs, and IoTCs have four, and MLCs and BCTCs have five items of each sub-construct developed using ChatGpt. CEPs have three subconstructs: MS, ED, and IR. MS was measured using six, and ED and IR were measured using five items for each subconstruct, adapting from the prior literature [47,65–67]. SusP comprises three subconstructs, EP, EVP, and SP, with each subconstruct measured using five items adapted from the previous literature [47,60,68,69]. Instruments were adapted from the previous literature because these instruments have already measured the same constructs and subconstructs in similar aspects. Additionally, the reliability and validity of the instruments have been established, and the instruments measure the core concepts that are the focus of this study. If the items had a factor loading less than 0.70, they were deleted [70]. The measurement items are attached in Appendix A.

3.2. Population and Sample

The Chinese manufacturing industry has been at the top for the last 14 years. In 2023, the manufacturing industry reached USD 5.57 trillion, which indicates the importance of the manufacturing sector [71]. Additionally, the "Little Giant" means small and medium-sized enterprises have boosted their production using cutting-edge technologies, contributed to the niche market, and kept the competitive advantage [71].

The sample was a subset of the population. The sample size was calculated using G*power Software version 3.1.9.7 [72,73]. "F Tests" were considered a test family, and the statistical test was "Linear multiple regression: Fixed model, R^2 deviation from zero". The effect size "F^2" was set as medium "0.15", and the number of predictors considered was "eight". The software had suggested a "160" sample size. In this study, the total sample size examined was 179, higher than the recommended sample size.

3.3. Data Collection Method

I5.0 is purely related to industry and manufacturing, with CEPs and SusP focused on the manufacturing industry. So, in this study, data were collected from the Chinese manufacturing industry through a survey using an online questionnaire method, which aligns with previous studies that have focused on the manufacturing industry [47,48]. In this study, with the support of a third party, 179 responses were collected from different experts in the manufacturing industry, which can be used for subsequent analysis.

3.4. Research Method

The partial least square–structure equation modeling (PLS-SEM) technique was employed to analyze the data using SmartPLS 4.1. There are two main reasons for choosing this method. First, the constructs I5.0 and its effect are at the exploratory stage, and there is no sufficient research conducted in this field. Second, PLS-SEM is not based on distribution assumptions and can work on a small sample size [70]. Additionally, PLS-SEM has been used to analyze measurement and structural models.

4. Results

This section presents the empirical results in both tabular and graphical form. The results are also interpreted and referenced where necessary.

4.1. Respondent's Profile

In this section, the respondents' demographic factors are elaborated on. In this study, the majority of the respondents have experience between 7 and 9 years, 37.43%, and the occupational level is skilled worker, 42.46%, and working, 34.08%, in electronics and electrical equipment in the manufacturing sector. The overall results are presented in Table 2.

Table 2. Respondents' profile.

Characteristics	Distribution	Frequency	Percentage
Experience	1–3 years	24	13.41
	4–6 years	42	23.46
	7–9 year	67	37.43
	Ten or above	46	25.70
Occupational Level	Entry level	33	18.44
	Skilled worker	76	42.46
	Supervisor	41	22.91
	Manager	29	16.20
Industry	Automobiles and Automotive Parts	41	22.91
	Machinery and Equipment	43	24.02
	Electronics and Electrical Equipment	61	34.08
	Textiles and Apparel	34	18.99

4.2. Measurement Model

In this section, the conceptual model is analyzed using the algorithm in SmartPLS 4.1 to examine the data's factor loadings, validity, reliability, and collinearity. The results are mentioned in Table 3.

Table 3. Factor loadings, reliability, validity, and average variance extract.

Variable	Item	Factor Loadings	VIF	Alpha	CR	AVE
Artificial Intelligence Capabilities (AICs)				0.884	0.920	0.743
	AIC1	0.880	2.689			
	AIC2	0.872	2.500			
	AIC3	0.816	1.930			
	AIC4	0.877	2.491			
Big Data Analytical Capabilities (BDACs)				0.86	0.905	0.705
	BDAC1	0.837	2.038			
	BDAC2	0.847	2.072			
	BDAC3	0.846	2.047			
	BDAC4	0.827	1.860			
Internet of Things Capabilities (IoTCs)				0.866	0.909	0.713
	IoTC1	0.827	1.910			
	IoTC2	0.848	2.181			
	IoTC3	0.838	1.994			
	IoTC4	0.865	2.208			
Machine Learning Capabilities (MLCs)				0.885	0.916	0.685
	MLC1	0.804	1.995			
	MLC2	0.833	2.391			
	MLC3	0.819	2.244			
	MLC4	0.858	2.435			
	MLC5	0.823	2.156			
Blockchain Technology Capabilities (BCTCs)				0.886	0.917	0.688
	BCT1	0.868	2.671			
	BCT2	0.820	2.088			
	BCT3	0.789	1.829			
	BCT4	0.856	2.547			
	BCT5	0.813	1.951			
Eco-Design (ED)				0.891	0.92	0.696
	ED1	0.837	2.238			
	ED2	0.837	2.19			
	ED3	0.849	2.452			
	ED4	0.844	2.39			
	ED5	0.804	1.926			

Table 3. *Cont.*

Variable	Item	Factor Loadings	VIF	Alpha	CR	AVE
Management System (MS)				0.905	0.927	0.679
	MS1	0.851	2.632			
	MS2	0.845	2.541			
	MS3	0.834	2.433			
	MS4	0.828	2.508			
	MS5	0.781	1.986			
	MS6	0.802	2.163			
Investment Recovery (IR)				0.883	0.914	0.681
	IR1	0.821	2.202			
	IR2	0.816	2.059			
	IR3	0.863	2.632			
	IR4	0.824	2.103			
	IR5	0.801	2.024			
Environmental Performance (EVP)				0.881	0.913	0.677
	EVP1	0.798	1.923			
	EVP2	0.812	1.968			
	EVP3	0.827	2.087			
	EVP4	0.866	2.594			
	EVP5	0.809	2.08			
Social Performance (SP)				0.895	0.923	0.705
	SP1	0.829	2.168			
	SP2	0.827	2.125			
	SP3	0.823	2.144			
	SP4	0.846	2.282			
	SP5	0.874	2.787			
Economic Performance (EP)				0.9	0.926	0.715
	EP1	0.869	2.792			
	EP2	0.829	2.136			
	EP3	0.823	2.13			
	EP4	0.855	2.483			
	EP5	0.851	2.436			

Table 3 indicates that all the factors possess factor loadings greater than 0.70, indicating that there are no items that need to be deleted [70,74]. The variance inflation factor (VIF) is lower than 5, indicating there is no collinearity issue [70,74]. The indicator's reliability using Cronbach Alpha and the composite reliability of each indicator is higher than 0.70, indicating that all items are reliable [70,74]. Additionally, the average variance extracted (AVE) values are higher than 0.50 [70,74], which indicates that no convergent validity issue was found in this study.

4.3. Discriminant Validity

This type of validity indicates that the research constructs are distinct. The discriminative validity was measured through the Fornell–Larcker criterion and Hetero-trait Mono-trait (HTMT) methods, Tables 4 and 5 represent the results, respectively.

The diagonal bold and italic values represent the square root of AVE values, which must be higher than the corresponding inter-correlational values [75]. In this study, all the diagonal values are higher than the inter-correlational values, showing no discriminant validity issue.

The HTMT is employed to assess the validity of the discriminant. The HTMT values must be less than 0.850 [76]. In Table 5, no value is higher than the HTMT threshold value, indicating no discriminant validity issue.

Table 4. Fornell–Larcker criterion method.

Construct	1	2	3	4	5	6	7	8	9	10	11
1. AICs	***0.862***										
2. BCTCs	0.721	***0.830***									
3. BDACs	0.716	0.574	***0.839***								
4. ED	0.644	0.613	0.62	***0.834***							
5. EP	0.667	0.619	0.628	0.672	***0.846***						
6. EVP	0.685	0.634	0.619	0.663	0.613	***0.823***					
7. IR	0.634	0.683	0.648	0.682	0.668	0.613	***0.825***				
8. IoTCs	0.682	0.587	0.640	0.685	0.678	0.623	0.681	***0.845***			
9. MLCs	0.701	0.669	0.64	0.700	0.621	0.678	0.656	0.684	***0.827***		
10. MS	0.672	0.592	0.634	0.694	0.728	0.614	0.620	0.617	0.711	***0.824***	
11. SP	0.659	0.705	0.605	0.694	0.565	0.728	0.665	0.53	0.673	0.681	***0.840***

Table 5. Hetero-trait Mono-trait (HTMT).

	1	2	3	4	5	6	7	8	9	10	11
1. AICs											
2. BCTCs	0.813										
3. BDACs	0.822	0.658									
4. ED	0.724	0.689	0.707								
5. EP	0.748	0.692	0.715	0.749							
6. EVP	0.774	0.716	0.711	0.746	0.688						
7. IR	0.715	0.772	0.741	0.769	0.747	0.692					
8. IoTCs	0.779	0.667	0.741	0.778	0.764	0.711	0.778				
9. MLCs	0.792	0.756	0.735	0.788	0.694	0.767	0.743	0.78			
10. MS	0.751	0.659	0.716	0.772	0.806	0.687	0.691	0.695	0.793		
11. SP	0.738	0.791	0.690	0.775	0.628	0.818	0.745	0.600	0.754	0.756	

4.4. Structural Model

The subsequent phase of structural equation modeling involves testing the structural model [70,74]. The hypotheses were tested in the structural model, and the results are mentioned in Table 6.

Table 6. Hypotheses, results, and decisions.

Hypothesis	β	t-stat.	*p*-Values	Decision
H_1: I5.0 → SusP	0.595	5.337	0.000	Supported
H_2: CEP × I5.0 → SusP	0.274	3.591	0.000	Supported
H_3: I5.0 → CEPs → SusP	0.473	5.079	0.000	Supported

Table 6 presents the hypotheses, coefficient (β) values, t-statistics, *p*-values, and decisions. The *p*-values are less than 0.05, which indicates that all the hypotheses have been accepted. Additionally, the structural model is mentioned in Figure 2.

4.5. Model Fit

The comprehensive model fit was analyzed using goodness of fit [77–79]. The goodness of fitness is mentioned in Table 7.

The results of the goodness of fit support the model fit. In addition, the model fit was evaluated using SmartPLS. The standard root mean square (SRMR) values are closer to zero, and the normed fit index (NFI) is closer to 1, indicating that the proposed model is fit [80,81].

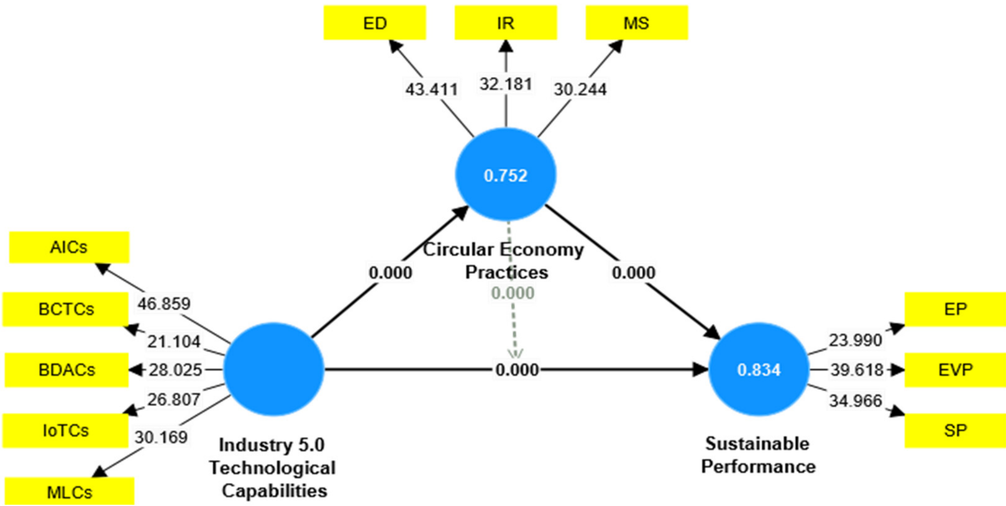

Figure 2. Path model for Industry 5.0, circular economy practices, and sustainable performance.

Table 7. Goodness of fit.

Construct	AVE		R Square
CEPs	0.777		0.752
SusP	0.757		0.834
	0.767		0.793
Goodness of Fit		0.779	

Note: SmartPLS model fit values are SRMR = 0.057 and NFI = 0.855.

5. Discussion and Conclusions

The Industrial Revolution has rapidly transformed organizations' thinking and operating styles. I5.0 has shifted the trend from adopting and utilizing advanced information technologies to becoming a more human-centric approach [82]. Without considering humans, organizations cannot achieve optimal financial benefits, gain a competitive advantage, protect the environment, and improve organizational processes [82].

The present study has identified five key I5.0 technological capabilities: AICs, BCTCs, BDACs, IoTCs, and MLCs, which were calculated by way of the second-order construct as I5.0 technological capabilities, CEPs were derived from ED, MS, and IR, and SusP was measured on the same pattern grounded on EVP, EP, and SP. AICs enable organizations to automate organizational tasks to be accomplished efficiently and accurately. Additionally, generative AI has a positive and significant impact on CEPs and sustainable supply chain performance [32]. BCTCs can maintain high security, reduce fraud, and streamline organizational processes. Additionally, blockchain has a positive effect on CEPs [44]. BDACs empower organizations to manage, retrieve, and visualize the results from big data to make data-driven decisions. Moreover, BDACs' positive impact on CEPs was found in the Indian [34] and Brazilian [35] manufacturing industries. IoTCs support organizations in tracking products and processes in real time using the internet. Moreover, the literature has found the positive impact of Industrial IoT on CE in Jordan SMEs [38]. MLCs use algorithms and models to predict the future using large amounts of data. This will enable organizations to make data-driven, accurate decisions. Additionally, the ML approach has been used for CE in the plastic industry [40].

The current study has focused on gaining a competitive advantage through the unique and specific capabilities required to work efficiently and smartly using advanced information technologies focused on I5.0. Organizations realize the importance of RBV theory, which posits that distinctive and non-imitable capabilities can give a competitive advantage [21,22]. In this study, RBV provided the foundation for developing the conceptual framework. Additionally, capabilities can create a difference in work efficiency. Organizations using advanced information technologies are far ahead of their competitors [21,22].

Data from the Chinese manufacturing industry was collected to analyze the conceptual framework empirically. From the hypothetical perspective, H_1 has established a direct and positive relationship between I5.0 technological capabilities and SusP. The results are aligned with the results found in the previous I4.0 literature [47,83]. H_2 has established the moderated effect of CEPs between I5.0 and SusP. The findings have supported the hypothesis. However, the direct moderated effect of CEPs between I5.0 capabilities and SusP was not found in the previous literature. However, the I4.0 literature has supported this relationship. H_3 has developed the mediating effect of CEPs between I5.0 and SusP. The results are in favor of the hypotheses. The same mediating relationship of CEPs with the technological perspective was found in the I4.0 literature [26,47].

The present study has concentrated on I5.0 capabilities, CEPs, and SusP, filling the literature gap. Because I5.0 is still emerging, and the scarcity of literature has not established this relationship. Moreover, most studies have only focused on I4.0, which is missing the human factor, and technologies cannot do anything. So, this study has highlighted and addressed this practical and theoretical gap. Moreover, organizations have focused on I5.0 technological capabilities to achieve better SusP regarding EP, EVP, and SP. Additionally, organizations with better technological capabilities facilitate them to adopt circular practices in their operations. This will establish a competitive advantage in achieving long-term SDGs.

5.1. Implications

This study has contributed to the knowledge because I5.0 is an emerging concept [3], and no sufficient literature has been published. So, the literature still lacks literature integrating the I5.0 technological capabilities to perform CEPs and achieve SusP. RBV has provided the foundation to develop the relationship, opening new horizons for the researchers to think from different perspectives and contribute to the literature.

The current research has provided the foundations that were beneficial for the manufacturing industry, managers, policymakers, and researchers. Specifically, I5.0 technological capabilities will enable managers to learn new techniques and implement new technologies in organizational processes. They will improve ED, MS, and IR as CEPs and automatically enhance organizational SusP regarding EVP, EP, and SP.

This study provides guidelines for policymakers because all the SDGs (17 goals) and targets (169 targets) were interlinked with the implementation of advanced information technologies to achieve sustainability [84]. More specifically, this study is helpful for policymakers to develop policies regarding SDG 8 on work and economic growth, specifically targeting 8.2 to achieve higher productivity through technological upgradation and innovation because this study has focused on I5.0, which is the revolution from I4.0. Target 8.4 focuses on improving resource efficiency with economic and environmental benefits, and I5.0 is considered more efficient as compared to I4.0. SDG 9, regarding industry, innovation, and infrastructure, specifically target 9.2, focuses on sustainable industrialization, and I5.0 is more concerned about sustainability. Target 9.4 focuses on upgrading infrastructure through technological and environmental perspectives, and I5.0 is upgraded and is more concerned with the environment. SDG 17 focuses on the partnerships to achieve the goals, specifically target 17.16, which focuses on sharing knowledge, expertise, and technological resources, and this study has focused on learning and developing new technological capabilities that align the current study with SDGs and their targets.

5.2. Limitations and Future Directions

In this study, only technological capabilities have been considered. To improve SusP, it is recommended that relational capabilities and learning capabilities be focused on in future studies. This study has focused only on five technological capabilities. Still, in future studies, researchers can consider the technologies and capabilities for specific operations like the Internet of Medical Things, humanoid robots, and industrial control systems. Additionally, this study has ignored the resilience, agility, and human–computer interaction factors that can be considered in future studies.

The current study used cross-sectional data, which was collected once. However, in future studies, longitudinal data can be collected and used for comparative analysis. Second, the data can be collected from different countries. This will also provide meaningful insights and comparisons of I5.0 technological capabilities, CEPs, and SusP among different countries, which will comprehensively generalize this new concept.

Author Contributions: Conceptualization, M.N.S. and A.R.; methodology, U.A.; software, M.N.S.; validation, U.A., A.R. and M.N.S.; formal analysis, U.A.; investigation, M.N.S.; resources, A.R.; data curation, U.A.; writing—original draft preparation, M.N.S.; writing—review and editing, U.A.; visualization, A.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the support action (CSA) ERA Chair BESIDE project financed by the European Union's Horizon Europe under grant agreement No. 951389, DOI10.3030/951389. We also acknowledge the financial support of FCT/MCTES, through national funds to CESAM (UIDP/50017/2020; UIDB/50017/2020 and LA/P/0094/2020).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: Data will be available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Artificial Intelligence Capabilities

- AI systems can perform complex tasks with high accuracy.
- I believe AI can analyze large datasets more efficiently than humans.
- AI technologies can make beneficial autonomous decisions.
- I trust AI capabilities in critical areas like manufacturing and supply chain.

Big Data Analytical Capabilities

- Big data analytics can process and analyze large amounts of data with high precision.
- I believe big data analytics provides valuable insights that traditional methods can't.
- Big data analytics can identify trends and patterns for strategic decision-making.
- I trust big data analytics to enhance efficiency and innovation in industries.

Internet of Things Capabilities

- IoT devices can collect and transmit data in real-time with high accuracy.
- I believe IoT technology can greatly improve daily operations in industries.
- IoT systems can provide better connectivity and automation for smart environments.
- I trust IoT to improve safety and security in smart manufacturing and industrial settings.

Machine Learning Capabilities

- Machine learning algorithms can improve performance over time without explicit programming.
- I believe machine learning can accurately predict outcomes using historical data.
- Machine learning models can find complex patterns in large datasets that humans can't see.
- I trust machine learning to automate decision-making in various industries.
- Machine learning can personalize services and products based on user data.

Blockchain Technological Capabilities

- Blockchain technology offers high security and transparency in transactions.
- I believe blockchain can prevent fraud and unauthorized access in digital transactions.

- Blockchain can ensure data integrity and immutability across networks.
- I trust blockchain to streamline and enhance supply chain management efficiency.
- Blockchain can enable trustless interactions by removing the need for intermediaries.

Management System

- Environmental TQM.
- Audit programs related to the environment
- Eco-labelling
- Pollution prevention program
- Internal performance evaluation system
- Our firm generates environmental reports for internal evaluation purposes.

Eco-Design

- Reduce consumption of materials and energy focus in design.
- 3R focus on product design
- Reduced use of hazardous products in design
- Waste minimization focus in process design
- Use environmental packaging by suppliers

Investment Recovery

- Sales of excess inventories/ materials
- Sell scrap and used materials at regular intervals
- Sale of excess capital equipment
- End-of-life products and materials are collected and recycled.
- Availability of recycling system.

Economic Performance

- Production costs
- Profits
- NPD costs
- Energy usage
- Inventory holding costs

Social Performance

- Working conditions
- Workplace safety
- Employee health
- Labor relations
- Satisfies employees

Environmental Performance

- Solid waste
- Liquid waste
- Gas emissions
- Energy consumption
- Consumption of hazardous and harmful product

References

1. Kraaijenbrink, J. What Is Industry 5.0 and How It Will Radically Change Your Business Strategy? *Forbes*, 27 May 2022.
2. Directorate-General for Research and Innovation (European Commission). Industry 5.0—Human-Centric, Sustainable and Resilient. Available online: https://op.europa.eu/en/publication-detail/-/publication/aed3280d-70fe-11eb-9ac9-01aa75ed71a1 (accessed on 25 June 2024).
3. Directorate-General for Research and Innovation (European Commission). Industry 5.0. What this Approach is Focused on, How it Will be Achieved and How it is Already Being Implemented. Available online: https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en (accessed on 31 October 2024).
4. Marketsandmarkets. Industry 5.0 Market. Available online: https://www.marketsandmarkets.com/Market-Reports/industry-5-market-35376359.html (accessed on 25 June 2024).

5. Schumpeter, J.A.; Swedberg, R. *The Theory of Economic Development*; Routledge: London, UK, 2021.
6. Zhang, M.; Qi, Y. Vertical network relationships, technological capabilities, and innovation performance: The moderating role of strategic flexibility. *Sustainability* **2023**, *15*, 11110. [CrossRef]
7. Reichert, F.M.; Zawislak, P.A. Technological capability and firm performance. *J. Technol. Manag. Innov.* **2014**, *9*, 20–35. [CrossRef]
8. Shafique, M.N.; Rashid, A.; Bajwa, I.S.; Kazmi, R.; Khurshid, M.M.; Tahir, W.A. Effect of IoT capabilities and energy consumption behavior on green supply chain integration. *Appl. Sci.* **2018**, *8*, 2481. [CrossRef]
9. Pereira, E.T.; Shafique, M.N. The Role of Artificial Intelligence in Supply Chain Agility: A Perspective of Humanitarian Supply Chain. *Eng. Econ.* **2024**, *35*, 77–89. [CrossRef]
10. Shafique, M.N.; Khurshid, M.M.; Rahman, H.; Khanna, A.; Gupta, D. The role of big data predictive analytics and radio frequency identification in the pharmaceutical industry. *IEEE Access* **2019**, *7*, 9013–9021. [CrossRef]
11. Shafique, M.N.; Yeo, S.F.; Tan, C.L. Roles of top management support and compatibility in big data predictive analytics for supply chain collaboration and supply chain performance. *Technol. Forecast. Soc. Change* **2024**, *199*, 123074. [CrossRef]
12. Parliament, E. Circular Economy: Definition, Importance and Benefits. Available online: https://www.europarl.europa.eu/topics/en/article/20151201STO05603/circular-economy-definition-importance-and-benefits (accessed on 25 June 2024).
13. United States Environmental Protection Agency. What is a Circular Economy? Available online: https://www.epa.gov/circulareconomy/what-circular-economy (accessed on 25 June 2024).
14. Puntillo, P. Circular economy business models: Towards achieving sustainable development goals in the waste management sector—Empirical evidence and theoretical implications. *Corp. Soc. Responsib. Environ. Manag.* **2023**, *30*, 941–954. [CrossRef]
15. Pan, X.; Wong, C.W.; Wong, C.Y.; Boon-itt, S.; Li, C. The influences of Circular Economy practices on manufacturing firm's performance: A meta-analytic structural equation modeling study. *Int. J. Product. Econ.* **2024**, *273*, 109267. [CrossRef]
16. Ronaghi, M.H. The influence of artificial intelligence adoption on circular economy practices in manufacturing industries. *Environ. Dev. Sustain.* **2023**, *25*, 14355–14380. [CrossRef]
17. Reza, M.N.H.; Jayashree, S.; Malarvizhi, C.A.; Gunasekaran, A.; Mohiuddin, M. Towards sustainable sustainability: Exploring the impact of antecedents on industry 4.0 and sustainable performance of organizations—An empirical investigation. *Ann. Oper. Res.* **2024**, 1–49. [CrossRef]
18. Farrukh Shahzad, M.; Liu, H.; Zahid, H. Industry 4.0 technologies and sustainable performance: Do green supply chain collaboration, circular economy practices, technological readiness and environmental dynamism matter? *J. Manuf. Technol. Manag.* **2024**. [CrossRef]
19. Tao, Z.; Chao, J. Unlocking new opportunities in the industry 4.0 era, exploring the critical impact of digital technology on sustainable performance and the mediating role of GSCM practices. *Innov. Green Dev.* **2024**, *3*, 100160. [CrossRef]
20. Zhou, J.; Shafique, M.N.; Adeel, A.; Nawaz, S.; Kumar, P. What is theoretical contribution? A narrative review. *Sarhad J. Manag. Sci.* **2017**, *3*, 261–271. [CrossRef]
21. Barney, J.B. Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *J. Manag.* **2001**, *27*, 643–650. [CrossRef]
22. Epelbaum, F.M.B.; Martinez, M.G. The technological evolution of food traceability systems and their impact on firm sustainable performance: A RBV approach. *Int. J. Product. Econ.* **2014**, *150*, 215–224. [CrossRef]
23. Barney, J. Firm resources and sustained competitive advantage. *J. Manag.* **1991**, *17*, 99–120. [CrossRef]
24. Barratt, M.; Oke, A. Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *J. Oper. Manag.* **2007**, *25*, 1217–1233. [CrossRef]
25. Liu, H.; Wei, S.; Ke, W.; Wei, K.K.; Hua, Z. The configuration between supply chain integration and information technology competency: A resource orchestration perspective. *J. Oper. Manag.* **2016**, *44*, 13–29. [CrossRef]
26. Karmaker, C.L.; Al Aziz, R.; Ahmed, T.; Misbauddin, S.; Moktadir, M.A. Impact of industry 4.0 technologies on sustainable supply chain performance: The mediating role of green supply chain management practices and circular economy. *J. Clean. Prod.* **2023**, *419*, 138249. [CrossRef]
27. Ghobakhloo, M.; Iranmanesh, M.; Fathi, M.; Rejeb, A.; Foroughi, B.; Nikbin, D. Beyond Industry 4.0: A systematic review of Industry 5.0 technologies and implications for social, environmental and economic sustainability. *Asia-Pac. J. Bus. Adm.* **2024**. [CrossRef]
28. Atif, S. Analysing the alignment between circular economy and industry 4.0 nexus with industry 5.0 era: An integrative systematic literature review. *Sustain. Dev.* **2023**, *31*, 2155–2175. [CrossRef]
29. Voulgaridis, K.; Lagkas, T.; Sarigiannidis, P. Towards industry 5.0 and digital circular economy: Current research and application trends. In Proceedings of the 2022 18th International Conference on Distributed Computing in Sensor Systems (DCOSS), Los Angeles, CA, USA, 30 May–1 June 2022; pp. 153–158.
30. Turner, C.; Oyekan, J.; Garn, W.; Duggan, C.; Abdou, K. Industry 5.0 and the circular economy: Utilizing LCA with intelligent products. *Sustainability* **2022**, *14*, 14847. [CrossRef]
31. Madanaguli, A.; Sjödin, D.; Parida, V.; Mikalef, P. Artificial intelligence capabilities for circular business models: Research synthesis and future agenda. *Technol. Forecast. Soc. Change* **2024**, *200*, 123189. [CrossRef]
32. Li, L.; Zhu, W.; Chen, L.; Liu, Y. Generative AI usage and sustainable supply chain performance: A practice-based view. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *192*, 103761. [CrossRef]

33. Awan, U.; Shamim, S.; Khan, Z.; Zia, N.U.; Shariq, S.M.; Khan, M.N. Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technol. Forecast. Soc. Change* **2021**, *168*, 120766. [CrossRef]
34. Sahoo, S.; Upadhyay, A.; Kumar, A. Circular economy practices and environmental performance: Analysing the role of big data analytics capability and responsible research and innovation. *Bus. Strategy Environ.* **2023**, *32*, 6029–6046. [CrossRef]
35. Guilhem, A.P.S.; Klein, L. Effects of big data capability on sustainable manufacturing and circular economy in Brazilian industries. *Rev. Bras. Gestão Negócios* **2024**, *26*, e20230152.
36. Cavalieri, A.; Reis, J.; Amorim, M. Circular economy and internet of things: Mapping science of case studies in manufacturing industry. *Sustainability* **2021**, *13*, 3299. [CrossRef]
37. Rejeb, A.; Suhaiza, Z.; Rejeb, K.; Seuring, S.; Treiblmaier, H. The Internet of Things and the circular economy: A systematic literature review and research agenda. *J. Clean. Prod.* **2022**, *350*, 131439. [CrossRef]
38. AL-Khatib, A.W. The impact of dynamic capabilities on circular economy: The mediating effect of the industrial Internet of things. *J. Manuf. Technol. Manag.* **2023**, *34*, 873–895. [CrossRef]
39. Noman, A.A.; Akter, U.H.; Pranto, T.H.; Haque, A. Machine learning and artificial intelligence in circular economy: A bibliometric analysis and systematic literature review. *Ann. Emerg. Technol. Comput. (AETiC)* **2022**, *6*, 13–40. [CrossRef]
40. Chen, X. Machine learning approach for a circular economy with waste recycling in smart cities. *Energy Rep.* **2022**, *8*, 3127–3140. [CrossRef]
41. Hoosain, M.S.; Paul, B.S.; Ramakrishna, S. The impact of 4IR digital technologies and circular thinking on the United Nations sustainable development goals. *Sustainability* **2020**, *12*, 10143. [CrossRef]
42. Böckel, A.; Nuzum, A.-K.; Weissbrod, I. Blockchain for the circular economy: Analysis of the research-practice gap. *Sustain. Prod. Consum.* **2021**, *25*, 525–539. [CrossRef]
43. Böhmecke-Schwafert, M.; Wehinger, M.; Teigland, R. Blockchain for the circular economy: Theorizing blockchain's role in the transition to a circular economy through an empirical investigation. *Bus. Strategy Environ.* **2022**, *31*, 3786–3801. [CrossRef]
44. Rehman Khan, S.A.; Yu, Z.; Sarwat, S.; Godil, D.I.; Amin, S.; Shujaat, S. The role of block chain technology in circular economy practices to improve organisational performance. *Int. J. Logist. Res. Appl.* **2022**, *25*, 605–622. [CrossRef]
45. Shafique, M.N.; Rashid, A.; Yeo, S.F.; Adeel, U. Transforming Supply Chains: Powering Circular Economy with Analytics, Integration and Flexibility Using Dual Theory and Deep Learning with PLS-SEM-ANN Analysis. *Sustainability* **2023**, *15*, 11979. [CrossRef]
46. Riggs, R.; Roldán, J.L.; Real, J.C.; Felipe, C.M. Opening the black box of big data sustainable value creation: The mediating role of supply chain management capabilities and circular economy practices. *Int. J. Phys. Distrib. Logist. Manag.* **2023**, *53*, 762–788. [CrossRef]
47. Edwin Cheng, T.; Kamble, S.S.; Belhadi, A.; Ndubisi, N.O.; Lai, K.-h.; Kharat, M.G. Linkages between big data analytics, circular economy, sustainable supply chain flexibility, and sustainable performance in manufacturing firms. *Int. J. Prod. Res.* **2022**, *60*, 6908–6922. [CrossRef]
48. Kamble, S.S.; Gunasekaran, A. Analysing the role of Industry 4.0 technologies and circular economy practices in improving sustainable performance in Indian manufacturing organisations. *Prod. Plan. Control* **2023**, *34*, 887–901. [CrossRef]
49. Yin, S.; Jia, F.; Chen, L.; Wang, Q. Circular economy practices and sustainable performance: A meta-analysis. *Resour. Conserv. Recycl.* **2023**, *190*, 106838. [CrossRef]
50. Le, T.T.; Behl, A.; Pereira, V. Establishing linkages between circular economy practices and sustainable performance: The moderating role of circular economy entrepreneurship. *Manag. Decis.* **2024**, *62*, 2340–2363. [CrossRef]
51. Mora-Contreras, R.; Torres-Guevara, L.E.; Mejia-Villa, A.; Ormazabal, M.; Prieto-Sandoval, V. Unraveling the effect of circular economy practices on companies' sustainability performance: Evidence from a literature review. *Sustain. Prod. Consum.* **2023**, *35*, 95–115. [CrossRef]
52. Chowdhury, S.; Dey, P.K.; Rodríguez-Espíndola, O.; Parkes, G.; Tuyet, N.T.A.; Long, D.D.; Ha, T.P. Impact of organisational factors on the circular economy practices and sustainable performance of small and medium-sized enterprises in Vietnam. *J. Bus. Res.* **2022**, *147*, 362–378. [CrossRef]
53. Malhotra, G. Impact of circular economy practices on supply chain capability, flexibility and sustainable supply chain performance. *Int. J. Logist. Manag.* **2023**, *35*, 1500–1521. [CrossRef]
54. Maldonado-Guzmán, G.; Garza-Reyes, J.A. Beyond lean manufacturing and sustainable performance: Are the circular economy practices worth pursuing? *Manag. Environ. Qual. Int. J.* **2023**, *34*, 1332–1351. [CrossRef]
55. Yavuz, O.; Uner, M.M.; Okumus, F.; Karatepe, O.M. Industry 4.0 technologies, sustainable operations practices and their impacts on sustainable performance. *J. Clean. Prod.* **2023**, *387*, 135951. [CrossRef]
56. Harikannan, N.; Vinodh, S.; Antony, J. Analysis of the relationship among Industry 4.0 technologies, sustainable manufacturing practices and organizational sustainable performance using structural equation modelling. *TQM J.* **2023**. [CrossRef]
57. Skalli, D.; Charkaoui, A.; Cherrafi, A.; Garza-Reyes, J.A.; Antony, J.; Shokri, A. Analyzing the integrated effect of circular economy, Lean Six Sigma, and Industry 4.0 on sustainable manufacturing performance from a practice-based view perspective. *Bus. Strategy Environ.* **2024**, *33*, 1208–1226. [CrossRef]
58. Bhagat, P.R.; Naz, F.; Magda, R. Role of Industry 4.0 Technologies in enhancing sustainable firm performance and green practices. *Acta Polytech. Hung.* **2022**, *19*, 229–248. [CrossRef]

59. Reza, M.N.H.; Malarvizhi, C.A.N.; Jayashree, S.; Mohiuddin, M. Industry 4.0–technological revolution and sustainable firm performance. In Proceedings of the 2021 Emerging Trends in Industry 4.0 (ETI 4.0), Raigarh, India, 19–21 May 2021; pp. 1–6.
60. Kamble, S.; Gunasekaran, A.; Dhone, N.C. Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. *Int. J. Prod. Res.* **2020**, *58*, 1319–1337. [CrossRef]
61. Pereira, E.T.; Shafique, M.N. The Implementation of Artificial Intelligence in Supply Chain. In Proceedings of the International Conference on Innovative Computing and Communication, Delhi, India, 17–18 February 2023; pp. 497–504.
62. Shafique, M.N.; Pereira, E.T. Leveraging the Synergy of Supply Chain Analytics, Visibility, Innovation, and Collaboration to Improve Environmental and Financial Performance: An Empirical Investigation. In Proceedings of the International Conference on Innovative Computing and Communication, Delhi, India, 19–20 February 2022; pp. 195–203.
63. Argyropoulou, M.; Garcia, E.; Nemati, S.; Spanaki, K. The effect of IoT capability on supply chain integration and firm performance: An empirical study in the UK retail industry. *J. Enterp. Inf. Manag.* **2024**, *37*, 875–902. [CrossRef]
64. Riggs, R.; Felipe, C.M.; Roldán, J.L.; Real, J.C. Information systems capabilities value creation through circular economy practices in uncertain environments: A conditional mediation model. *J. Bus. Res.* **2024**, *175*, 114526. [CrossRef]
65. Gupta, S.; Chen, H.; Hazen, B.T.; Kaur, S.; Gonzalez, E.D.S. Circular economy and big data analytics: A stakeholder perspective. *Technol. Forecast. Soc. Change* **2019**, *144*, 466–474. [CrossRef]
66. Jabbour, C.J.C.; de Sousa Jabbour, A.B.L.; Sarkis, J.; Godinho Filho, M. Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technol. Forecast. Soc. Change* **2019**, *144*, 546–552. [CrossRef]
67. Jiao, Z.; Ran, L.; Zhang, Y.; Li, Z.; Zhang, W. Data-driven approaches to integrated closed-loop sustainable supply chain design under multi-uncertainties. *J. Clean. Prod.* **2018**, *185*, 105–127. [CrossRef]
68. Zhu, Q.; Geng, Y.; Lai, K.-h. Circular economy practices among Chinese manufacturers varying in environmental-oriented supply chain cooperation and the performance implications. *J. Environ. Manag.* **2010**, *91*, 1324–1331. [CrossRef]
69. Belhadi, A.; Kamble, S.S.; Zkik, K.; Cherrafi, A.; Touriki, F.E. The integrated effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance of manufacturing companies: The case of North Africa. *J. Clean. Prod.* **2020**, *252*, 119903. [CrossRef]
70. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]
71. Xinhua. China's Manufacturing Sector Strives to Remain Competitive Amid Headwinds. Available online: http://english.scio.gov.cn/chinavoices/2024-03/11/content_117052667.htm (accessed on 25 June 2024).
72. Faul, F.; Erdfelder, E.; Lang, A.-G.; Buchner, A. G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* **2007**, *39*, 175–191. [CrossRef]
73. Faul, F.; Erdfelder, E.; Buchner, A.; Lang, A.-G. Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behav. Res. Methods* **2009**, *41*, 1149–1160. [CrossRef] [PubMed]
74. Hair, J.F.; Ringle, C.M.; Sarstedt, M. PLS-SEM: Indeed a silver bullet. *J. Mark. Theory Pract.* **2011**, *19*, 139–152. [CrossRef]
75. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
76. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
77. Hair Jr, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M.; Danks, N.P.; Ray, S. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*; Springer Nature: Berlin/Heidelberg, Germany, 2021.
78. Henseler, J.; Sarstedt, M. Goodness-of-fit indices for partial least squares path modeling. *Comput. Stat.* **2013**, *28*, 565–580. [CrossRef]
79. Tenenhaus, M.; Amato, S.; Esposito Vinzi, V. A global goodness-of-fit index for PLS structural equation modelling. In Proceedings of the XLII SIS Scientific Meeting, Bari, Italy, 9–11 June 2004; pp. 739–742.
80. Lohmöller, J.-B. *Latent Variable Path Modeling with Partial Least Squares*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013.
81. Hu, L.-t.; Bentler, P.M. Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychol. Methods* **1998**, *3*, 424. [CrossRef]
82. Alves, J.; Lima, T.M.; Gaspar, P.D. Is industry 5.0 a human-centred approach? a systematic review. *Processes* **2023**, *11*, 193. [CrossRef]
83. AL-Khatib, A.W. The impact of Industry 4.0 capabilities on operational performance: The mediating effect of supply chain ambidexterity. *TQM J.* **2023**. [CrossRef]
84. UNEP. Digitalization for Sustainability. Available online: https://www.unep.org/topics/digital-transformations/digitalization-sustainability (accessed on 31 October 2024).