INDUSTRY 4.0 TECHNOLOGIES AND CIRCULAR ECONOMY: THE MEDIATING ROLE OF SUPPLY CHAIN INTEGRATION

ABSTRACT

There is a great expectation that Industry 4.0 technologies will enable better circular economy (CE) results at firms. However, it is unclear how these technologies might contribute to CE. We hypothesize that Industry 4.0 technologies are positively related to the level of integration among actors along the supply chain (supply chain integration), which, in turn, explains superior CE results. By employing partial least square structural equation models on original survey data based on a sample of more than 1,200 Italian manufacturing firms and almost 200 adopters, we find that disentangling for the type of technologies is essential to understanding both the direct and indirect role of technologies toward CE. Smart manufacturing technologies have a stronger impact on CE outcomes than data processing technologies, and the mediating effect of supply chain integration is verified for the former but not for the latter type of technologies, questioning the possibility for those technologies to support sustained CE performance.

Keywords: circular economy; big data; robots; data processing technologies; smart manufacturing; supply chain integration

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1. Introduction

Digital technologies have received much attention from scholars and practitioners since the introduction of the German policy initiative "Industry 4.0" (Thoben, Wiesner & Wuest, 2017), paving the way for a completely new approach to value creation (Reinhard, Jesper, & Stefan, 2016; Roblek, Meško, & Krapež, 2016). Robotics, big data, and additive manufacturing are just some of the most well-known technologies that are considered under the umbrella term "Industry 4.0"— a new technological infrastructure, interconnected set of cyber-physical systems, and advanced data management solutions enabling new manufacturing processes, value chain organizations, and strategy development paths. Such technologies promise to reshape value creation, boosting productivity and the optimization of production processes (e.g., Mittal et al., 2018; Zheng et al., 2018), traceability, along the supply chain (e.g., Xie et al., 2016), and allowing great opportunities for innovation and the development of service-based business models (e.g., Manyika et al., 2015; Ceipek et al., 2020).

An increasing number of practitioner and scholarly articles advocate the potential of those technologies to achieve better sustainability results, especially in terms of circular economy (CE) (Chen et al., 2015; Kohtala & Hyysalo, 2015; Kumar, Singh, & Lamba, 2018; Massaro, Secinaro, Dal Mas, Brescia & Calandra, 2021). CE has been described as a new sustainable paradigm that might enhance value creation by minimizing the use of natural resources and the creation of waste to conserve the natural capital (Geissdoerfer, Savaget, Bocken, & Hultink, 2017; Hopkinson, Zils, Hawkins, & Roper, 2018; Webster & MacArthur, 2017). This extends resources' lifespan and includes strategies such as reuse, repairing, refurbishing, remanufacturing, recycling, and reducing the overall negative effects of production activities on the environment (Mac Arthur, Zumwinkel & Stuchtey, 2015; Ghisellini, Cialani, & Ulgiati, 2016; de Sousa Jabbour, Jabbour, Godinho Filho & Roubaud, 2018).

While there is quite an expectation of the positive role of such new technologies in boosting firms' capacity to achieve CE strategies (Lacy & Rutqvist, 2016), the contrary might also hold. For example, digital technologies such as robotics, 3D printing, and augmented reality may create barriers to the implementation of environmental initiatives due to conflicts that arise between economic results (i.e., flexibility and customization) and sustainability. Moreover, possible trade-offs might occur in the relationship between digitalization and CE. Indeed, digitalization might increase resource efficiency but also energy usage and waste emission (Chen et al., 2020; SUI and REJESKI, 2002; The shift project, 2019). Furthermore, very little is known regarding the mechanisms that might drive a positive relationship to take place. Indeed, to understand the mechanisms that enable Industry 4.0 technologies (I4.0 techs) to increase CE requires the need of investigating "the path toward sustainable operations' management and the achievement of CE strategies" (de Sousa Jabbour et al., 2018: 278). This research suggests that the path from I4.0 techs to CE involves firms' ability to collaborate and integrate activities within and outside their boundaries, i.e., to increase their supply chain integration (SCI) (De Angelis, Howard & Miemczyk, 2018; Rosa, Sassanelli, Urbinati, Chiaroni & Terzi, 2020). Indeed, to effectively close the loops and fully grasp CE potential, firms need to extensively integrate and collaborate both within the firm and across their supply chains to access, develop, and cross-fertilize complementary resources and capabilities and restructure their supply chain (Ataseven & Nair, 2017; Wiengarten & Longoni; 2015; Kang, Yang, Park & Huo, 2018). Closing the loops requires firms to modify their innovation and production systems by pooling knowledge and competences spanning across departments (*internal integration)*. Furthermore, to extend the product lifecycle, end-of-life product recovery, product refurbishing, or remanufacturing, firms must further engage with customers (*customer integration*) (Bakker, Wang, Huisman, & Den Hollander, 2014). Similarly, CE requires stronger cooperation with suppliers to ensure the supply of recycled or recyclable materials and reduce waste along the entire chain (*supplier integration*) (e.g., Hofstetter et al., 2021). Due to their ability to collect, process, and integrate a huge amount of data and optimize production processes (e.g., Schuh et al. 2019), I4.0 techs might indeed enable better communication, coordination, and cooperation mechanisms within and outside the organization, boosting process and product monitoring, and tracking input acquisition from suppliers or product use at the customer level, which in turn will support CE strategies.

Based on original firm-level data, we investigate the mediating role of SCI between I4.0 techs and CE—distinguishing between two types of digital technologies, i.e., data processing and smart manufacturing technologies. Our study sheds light on the role of CE in the new Industry 4.0 technological scenario in multiple ways. First, we extend the literature addressing the potential of I4.0 techs for CE by providing quantitative evidence of a impact on CE, reporting on the presence of a direct and indirect effect, via SCI. Second, we further the understanding of the differences among I4.0 techs for circularity, as our results indicate that the mediating effect of SCI holds only for smart manufacturing but not for data processing technologies. Third, we highlight that unintended impacts of I4.0 techs may cast doubt on the possibility to enhance CE in a long-term perspective. We argue that the improved automatization of information sharing and coordination due to digitalization, though having positive environmental implications, may raise challenges and potentially negative effects for circularity as relational interactions among internal and external actors are likely minimized, suggesting that knowledge that can not be codified in algorithms have less chances to be shared. The emergent analysis provides important insights for managers by detailing how such technologies should be implemented to achieve the highest CE results, and for policy makers aiming at understanding how to spur CE results in manufacturing industries.

2. Literature review

2.1. Defining the circular economy

CE has developed as a new economic paradigm with a particular focus on the waste cycle, being defined as "a strategy that emerges to oppose the traditional open-ended system, aiming to face the challenge of resource scarcity and waste disposal in a win-win approach with economic and value perspective" (Homrich et al., 2018: 534). It is an industrial system that is restorative by design in the sense that it preserves and enhances natural capital, optimizes resource yields, and minimizes system risks by managing finite stocks and renewable flows (Webster & MacArthur, 2017). More specifically, the European Environment Agency (2016) defined the five key characteristics of CE as follows:

1. Less input and use of natural resources (i.e., minimized and optimized exploitation of raw materials, energy, and natural resources for efficiency)
2. Increased share of renewable and recyclable resources and energy (replacing non-renewable resources with renewable, recyclable, and recycled ones, closing material loops, and sourcing sustainably)
3. Reduced emissions throughout the full material cycle
4. Fewer material losses/residuals (minimizing waste and dissipative losses of valuable resources)
5. Retaining the value of products, components, and materials in the economy (extending product lifetime, supporting the reuse of components, and high-quality recycling)

An effective transition toward CE requires a systemic perspective that takes into consideration the entire supply chain, as no actor in isolation might have the resources and capabilities to shift from linear to circular production systems (Batista, Bourlakis, Liu, Smart & Sohal, 2018; Fehrer & Wieland, 2021). Specifically, the entire supply chain of the firm—from suppliers to final customers—as well as the whole business and natural ecosystem should be revised, as there is a need for an integrated approach to the production, selection, and use of resources as inputs as well as outputs (products) (Geissdoerfer et al., 2017; Ghisellini et al., 2016). Existing research has acknowledged that supply chain management should provide an organizational infrastructure that enables firms to sustain the new paradigm shift to CE. However, past literature scarcely sheds light on the constituent features of such infrastructure (Bressamelli, Perona & Saccani, 2019). We argue that it is important to investigate the supply chain infrastructure sustaining CE. In particular, we focus on supply chain integration that, by enabling both an *external* coordination of processes, activities, perceptions with key partners such as customers and suppliers, and *internal* coordination among departments, plays a fundamental role in complementing and supporting CE (Genovese, Acquaye, Figueroa & Koh, 2017; Frishammar & Parida, 2019).

2.2 Circular economy and the importance of SCI

SCI refers to the strategic collaboration among all the actors involved in the value-added activities that provide products, information, and services to the final customer, including product design, procurement, manufacturing, assembly, warehouse management, sales, and distribution (Alfalla-Luque et al., 2013). Overall, SCI helps information sharing, processes streamlining, and an alignment of interests along the supply chain, thus leading to superior supply chain performance and, more generally, to operational and financial performance (Cao & Zhang, 2011; Ataseven & Nair, 2017). High SCI requires that both internal and external processes are integrated and flow seamlessly to attain customers' needs in the most effective way (Flynn, Huo & Zhao, 2010). The extent to which a firm is *internally* integrated depends on its ability to overcome functional silos and foster collaboration among different actors across functions and departments (Schoenherr & Swink, 2012). The extent to which a firm is *externally* integrated depends on its ability to develop close relationships with suppliers and customers by coordinating processes and practices (Frohlich & Westbrook, 2001).

By fostering internal integration, SCI enhances CE because it develops closer linkages among different firms' activities, such as design, production, and delivery (De los Rios & Charnley, 2017). Ensuring these activities be coherent and aligned is important to develop CE. Take the case of new product development activities as an example: the effective development of new CE products needs a broad understanding of operations activities, user expectations and behaviors, and business model functioning (De los Rios & Charnley, 2017), indicating that the R&D, operations, and marketing departments should be closely integrated. In their analysis of how CE business models are designed and developed, Frishammar and Parida (2019) reported that achieving sufficient internal alignment was a key challenge in many of the case studies analyzed.

By fostering external integration with suppliers, SCI enables firms to share environmental planning, collaborate to reduce or prevent pollution, define joint environmental goal setting, and implement shared purchasing policies and practices (Bowen et al., 2001; Vachon & Klassen, 2008) that, in turn, are likely to strengthen CE. Moreover, by fostering external integration with customers, SCI enables firms to respond to customers' environmental concerns, exchange information about greener customers' purchasing behavior, and jointly develop greener products, with positive effects on environmental performance (Wong et al., 2018). In general, SCI with external partners, especially suppliers or customers, is peculiarly important to ensure the development and implementation of new products or processes that reduce environmental impacts, as complementary resources and capabilities are needed to tackle such important challenges (e.g., Cainelli, De Marchi & Grandinetti, 2015; De Marchi, 2012; Kesidou & Demirel, 2012). Developing the capability 'to leverage other actors' resources and knowledge' (Choi & Hwang, 2015, p. 89) is particularly important in the case of firms aiming at achieving CE results, for example, as clients might be involved in the collection of post-usage waste, and/or suppliers might be essential to provide circular raw materials (De Marchi, Di Maria, & Micelli, 2013; Webster & MacArthur, 2017). This is in line with studies that focus on the barriers to the implementation of CE and report that a lack of collaboration in the supply chain plays a prominent role (Farooque, Zhang, & Liu, 2019; Fehrer & Wieland, 2021).

Overall, the extant literature suggests that internal- and external-to-the-firm SCI is key to ensuring a transition toward CE. Accordingly, our first hypothesis is as follows:

H1: Supply chain integration is positively associated with CE

2.3 Industry 4.0 technologies as enablers of SCI

Ensuring the effectiveness of such integration along the supply chain, however, is not straightforward. Firms need to develop a shared understanding of sustainability issues, involve SC partners to co-develop innovative solutions, and develop an open and collaborative infrastructure to ensure effective information sharing, the integration of operational activities, and logistical synchronization (Fehrer & Wieland, 2021; Herczeg, Akkerman, & Hauschild, 2018; Mishra et al., 2019). Important transformations in firms' activities and routines need to be implemented, which might be enabled and eased by the implementation of technologies.

Past research investigating the relationship between technological advancements and supply chain management (Cagliano, Caniato & Spina, 2005; Devaraj, Krajewski & Wei, 2007) have suggested that information and communication technologies enable SCI (Devaraj et al., 2007; Prajogo & Olhager, 2012). Considering how I4.0 techs differ from prior technological advancements (Loebbecke & Picot, 2018), we expect this relation to be even stronger. Compared to traditional technologies, I4.0 techs mostly draw on artificial intelligence, which equips machineries with self-learning systems, implying greater automatization, and ubiquitous computing systems—which use sensors and other devices to connect objects, individuals, and machineries in the physical environment, implying greater flow of data (Cascio & Montealegre, 2016). As a consequence, these technologies not only transform how products are produced and how information flows, but also how work activities are coordinated, and how information is generated and used within and across the boundaries of firms (Grote & Parker, 2020; Waschull et al., 2020).

The umbrella term Industry 4.0 groups different technologies, distinguished by the resources needed to develop them, the activities in which they are implemented, and even the impact on CE outcomes (Osterrieder et al. 2020; Culot et al. 2020; Stentoft & Rajkumar, 2020; De Marchi & Di Maria, 2020). Following prior literature (Frank, Dalenogare & Ayala, 2019; Stentoft & Rajkumar, 2020), we distinguish between I4.0 techs in two groups based on their objective: data processing technologies and smart manufacturing technologies. This classification is useful in the context of SCI because data processing technologies mostly sustain the transformation of information flows in SCs, whereas smart manufacturing technologies mostly sustain the production flows.

Smart manufacturing technologies include technologies aiming at increasing automatization that is, advanced robotics, cyber-physical systems, 3D printing, 3D scanning, and augmented reality. Positive impacts of the application of such technologies include achieving vertical and horizontal integration (Zheng et al., 2018), both at the firm and the supply chain level. Smart manufacturing opens opportunities for distributed manufacturing processes, reducing the distance between supply, production, and use, as well as increasing the level of product customization (Weller, Kleer, & Piller, 2015). This is particularly the case for the engagement of customers, who become makers and have a larger role in the innovation processes of firms. Through 3D printing, for example, the firm may be particularly interested in collaborating with customers to involve them in product development so that customers can become the drivers and main actors in production (Bogers, Hadar, & Bilberg, 2016; Petrick & Simpson, 2014). In this perspective, relying on smart manufacturing technologies enables a high level of integration within the organization and toward customers and suppliers (Simonette et al., 2008), Nee et al., 2018). Therefore, we hypothesize that:

H2: The implementation of smart-manufacturing technologies is positively associated with SCI.

Data processing technologies include big data, cloud computing, simulation, automatic analysis and data visualization, artificial intelligence, and IoT (Internet of Things) solutions, which are conceived as base technologies because of their fundamental support in terms of interconnectivity and intelligence provided to the whole manufacturing system (Frank et al., 2019). They enable the production, collection, and analysis of huge amounts of data at different points of the value chain, having important implications for supply chain management in terms of higher performances and changed practices (Haddud, De Souza, Khare & Lee, 2017; Ivanov, Dologui & Sokolov, 2019; Schniederjans, Curado & Khalajhedayati, 2020). In particular, they increase firms' control over internal as well as external processes and relationships with actors in the value chain, partners in the business ecosystem, and consumers (Adner, 2006; Huberty, 2015). In the SC context, such technologies might support the development of trust between firms and their suppliers, improve transparency and traceability (Mahyuni et al., 2020), reduce risks, increase control, and favor adaptive learning (Ivanov et al., 2019), so as to engage and interact with customers (Tan & Zhan, 2017). Through investments in data processing technologies, the firm can expand its opportunities of collaboration with customers for product development as well as the design of advanced business models rooted in servitization (Opresnik & Taisch, 2015; Chierici, Mazzucchelli, Garcia-Perez & Vrontis, 2019).
Similarly, the literature suggests that such technologies might support deeper interaction and integration within the firm and across different functions, for example, in critical activities, such as the development of new products (Tan & Zhan, 2017). Investing in data processing technologies and implementing them in the different aspects of operations—from physical production in the factory and suppliers to data management connected with those extended manufacturing processes—may enhance cooperation among workers due to increased connectivity. Accordingly, we formulate a third research hypothesis as follows:

H3: The implementation of data processing technologies is positively associated with SCI.

2.4 The mediating effect of SCI in the relationship between Industry 4.0 technologies and CE

Based on the arguments presented above, we suggest that the relationship between digital technologies (i.e., data processing technologies and smart manufacturing technologies) and CE is mediated by SCI. It is worth investigating the mediation analysis because the adoption of smart manufacturing or data processing technologies sustains integration along the supply chain, thus facilitating the collaborative dimension that is fundamental for the achievement of CE goals in terms of better control in the use of resources, resource allocation, optimization, etc. (Despeisse et al., 2017; Liu et al., 2019). For example, through 3D printing, the firm and its customers interact to share product ideas and requirements on a collaborative basis. Thus, benefits may also be achieved from a CE perspective, in terms of improved use of resources and manufacturing location (Despeisse et al., 2017; Garmulewicz, Holweg, Veldhuis & Yang, 2018). Similarly, studies on human–robot collaboration emphasize the consequences on the CE side of such collaborative forms of production, where the collaboration between workers and machines in the factory allows enhanced disassembly processes and closing-the-loop dynamics (Liu et al., 2019). From this point of view, SCI is required to both fully exploit smart manufacturing technologies (robots and automation) within the firm and facilitate the broader achievement of CE goals. In the context of data processing technologies, recent empirical research suggests that big data analytics might positively impact CE performance by enabling better decision-making, which allows firms to implement CE supply chain practices and increase integration and coordination along the supply chain (Del Giudice, Chierici, Mazzucchelli & Fiano, 2021). In summary, we hypothesize that companies that adopt smart manufacturing technologies or data processing technologies can therefore achieve CE thanks to the enhanced SCI. Figure 1 outlines the theoretical model that guides the present research.

H4a: SCI positively mediates the relationship between smart manufacturing technologies and CE.
H4b: SCI positively mediates the relationship between data processing technologies and CE.

Figure 1 around here
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3. Methodology

3.1 Sample and survey design

To investigate the mediating role of SCI in Industry 4.0 and the CE nexus, we opted for a quantitative method, which allows us to quantify such a relationship by comparing across different technologies and capturing the level of CE implemented by firms. Considering that no data exists that allow us to investigate both technological investments and sustainability results at the firm level, we opted for an original survey, which has been developed based on existing scales.

The survey was conducted on Italian manufacturing firms between May and December 2017. The sample was identified following a mixed methods sampling strategy combining cluster sampling and purposive sampling techniques (Teddlie & Yu, 2007). Specifically, we initially clustered manufacturing firms with an annual turnover above 1 million Euros[1] located in North Italy (Veneto, Friuli-Venezia-Giulia, Trentino-Alto-Adige, Lombardia, Piemonte, Emilia Romagna), a highly industrialized area that has a major impact on Italian gross domestic product (GDP), with a population accounting for more than 52% of the total Italian manufacturing firms (ISTAT, 2020). We focused on the "Made in Italy" industries, including automotive, rubber and plastics, electronic appliances, lightning, furniture, eyewear, jewelry, sport equipment, and textile and clothing, because they record a high level of innovation (Di Maria & Micelli, 2012) and play a critical role in exports among Italian firms (ICE, 2020). As such, these industries are likely to play a relevant role in the adoption of innovative initiatives, such as the "National Plan for Industry 4.0" promoted by the Italian Government in 2016, and are more likely to be under pressure from stakeholders to adopt sustainability initiatives such as CE (Galeazzo & Klassen, 2015). As a result, a total population of 7,694 manufacturing firms was identified, drawing from the AIDA national database

[1] The decision of including firms with an annual turnover of more than 1 Million Euro allows us to select firms that have a stable structural organization. We ignored this threshold if firms belonged to industries such as eyewear, lightning, jewelry and sport equipment, given the strong presence of important districts characterized by small firms (Becattini et al., 2009).

(developed by Bureau Van Dijk, a Moody's analytics company that collates information on 200,000 Italian firms).

A questionnaire was submitted to entrepreneurs, chief operation officers or managers with responsibility for the manufacturing and technological processes of these firms using a computer assisted web interview (CAWI) methodology[2], which is appropriate for large samples. A total of 1,229 firms agreed to participate and completed the questionnaire, corresponding to a 16% response rate, in line with recent studies in the environmental and social sustainability literature (e.g., Daddi, Iraldo, Testa & De Giacomo, 2019; Demirel & Kesidou, 2019).

A second stage of clustering targeting a sample of 1,229 firms involved the selection of those firms that confirmed the adoption of at least one of the following I4.0 techs: (1) Robotics, (2) Additive manufacturing (AM), (3) Big data/Cloud, (4) 3D Scanner, (5) Augmented reality (AR), and (6) Internet of Things (IoT) and Smart products. Following Almada-Lobo (2015), these technologies are the most relevant in triggering the transformation of traditional manufacturing firms into Smart Factories and, more than others, fit the strategic needs of manufacturing firms both in B2C and B2B markets (Sanders, Elangeswaran & Wulfsberg, 2016). Furthermore, they are the technologies considered in a recent governmental initiative (National Plan for Industry 4.0), aimed at spurring the adoption of 4.0 technologies among Italian firms. From the initial sample, we ended up with 189 usable questionnaires.

Common method variance (CMV) may emerge from different sources, such as the use of single respondents for dependent and independent variables and item characteristics (Podsakoff, MacKenzie, Lee & Podsakoff, 2003). We addressed the CMV issue in the survey design and survey administration. Specifically, the survey was designed using different response formats and was administered to respondents who were well-acquainted with all the topics the questionnaire required, thus avoiding response bias due to scarce knowledge of these topics. As CMV might depend on other sources that are difficult to detect, we also conducted post-hoc analyses. Specifically, two statistical procedures were used to empirically check the lack of CMV. First, we used the marker technique developed by Lindell and Whitney (2001). According to this technique, after including a theoretically uncorrelated marker variable in the questionnaire, we assessed whether there was a significant correlation between the marker variable and the variables of interest. As an example, we correlated items associated with collaboration with items of other constructs of the database, hence showing that respondents did not tend to answer all questions in the same way. Second, we conducted the Harman one-factor test (Podsakoff et al., 2003), showing that the items loaded on different factors in the exploratory factor analysis (EFA).

Non-response bias was tested by comparing early respondents (from May to July) and late respondents (October-December) using a two-tails *t* statistics test on the variables of interest (Armstrong & Overton, 1977). No statistically different results emerged, thus suggesting that non-response bias did not apply to our sample.

3.2 Measures

The dependent variable, CE, was assessed using seven items measured on a 5-point Likert scale. An analysis of the literature suggests a paucity of measures for assessing CE (Centobelli, Cerchione, Chiaroni, Del Vecchio & Urbinati, 2020; Rosa et al., 2020; Sassanelli, Rosa, Rocca &

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[2] If not available online, the research team contacted the firm's personnel by phone to ask, when possible, to have the email address of the key respondents.

Terzi, 2019). We adopted the definition by the European Environment Agency (EEA, 2016) (see Section 2.1) and generated seven items to represent the characteristics of CE listed, as reported in Appendix 1[3]. Such a measure enables us to capture the extent to which firms implement CE either achieving savings across several dimensions—that is, savings in the input used, reducing production waste, and re-using wastes in the production process—or achieving important ones across a few of them—that is, using renewable, recyclable or recycled inputs for the majority of products realized and drastically reducing process-related emissions.

SCI was measured on a 5-point Likert scale using five items adapted from previously validated scales (Koufteros, Cheng, & Lai, 2007; Flynn et al., 2010). The instrument captures the extent to which the parties involved in the flow of goods are integrated, thus assessing external relationships between suppliers and customers, as well as internal relationships within the focal firm. Externally, it assesses the interactions of the focal firm with suppliers and customers along the supply chain. Internally, it assesses the extent to which operators collaborate within and across different departments.

Two formative variables were created to assess the extent to which firms have implemented data processing vs. smart manufacturing digital technologies in their value chains. Following Jarvis et al. (2003), we modeled our constructs as formative variables because the different technologies are not interchangeable and are not manifestations of the same construct; rather, they represent different types of digital technologies that greatly differ from each other (for example, additive manufacturing vs. artificial intelligence). In line with Stentoft and Rajkumar (2020), we distinguish between *data processing technologies*, comprising i) big data, ii) cloud computing and IoT, and iii) RFID and sensors in the product, and *smart manufacturing technologies*, including iv) robotics in production, v) additive manufacture, vi) 3D scanner, and vii) augmented reality. Each technology was a summated index that ranged between 1 and 7, based on the extent to which managers indicated the technology was applied (yes/no) along the following seven activities of the value chain: (1) new product development (NPD), (2) prototyping, (3) production, (4) production management, (5) logistics and supply chain management, (6) marketing/commercial processes, and (7) post-service.

Lastly, three variables, namely *firm size*, *export* and *industry type*, were included as control variables to mitigate influences from firms and industry's characteristics. *Firm size* was measured as the natural logarithm of the number of employees. By including firm size, we accounted for the minor risk of larger firms investing in CE because of the extra financial resources and organizational slack that they have compared to smaller firms (Bansal, 2005). *Export* was a dichotomous variable that took the value 1 if a firm's percent of export on turnover was more than (or equal to) 50%, 0 otherwise. As firms operating in multiple markets are more exposed to pressures from external stakeholders (Galeazzo & Klassen, 2015), they might be more prone towards CE. *Industry type* accounted for the difference between high-tech and low-tech industries. It took a value of 1 if the firm belonged to a high-tech industry, 0 otherwise, according to the Eurostat classification (Eurostat, 2018). As innovation and CE are strongly associated (De Jesus et al., 2018), we controlled for industry type to rule out that firms in high-tech industries, which are generally more innovative than firms in low-tech industries and show a higher propensity to invest in CE.

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[3] Experts on sustainability were asked to review the items to check for ambiguity and appropriateness. The items were modified based on their feedback. The construct was then validated by conducting a test on 74 managers, thus demonstrating face and content validity.

The mean, standard deviation, and correlations of all the variables are presented in Table 1.

Table 1 around here

3.3 Measure reliability and validity

For all reflective constructs, reliability, and validity were tested. Following Gerbing and Anderson's (1998) two-step method, we first assessed the unidimensionality of the constructs using an exploratory factor analysis (EFA) and then assessed their reliability. First, an EFA with varimax rotation was conducted to calculate the number of factors and the common factor loading values for all items. As the survey item CE01 (see Table 2) had a loading value lower than the recommended threshold of 0.5 (Hair et al., 2010), it was removed from the analysis. After that, a new EFA was conducted. All survey items loaded well on the expected factors with values greater than 0.53, thus showing unidimensionality. Second, reliability was assessed using Cronbach's alpha. The alphas were well above the minimum limit of 0.70 (Hair et al., 2010). Moreover, the corrected item-total correlations were between the recommended range of 0.3 and 0.8 (Nunnally & Bernstein, 1994), indicating that each item had good correlations with the other items and together measured the same construct with no issues of multicollinearity. The alpha coefficients did not change significantly if an item was deleted, indicating that all items had to be retained.

All relevant tests for assessing convergent and discriminant validity were performed. Convergent validity was confirmed by finding that the items loaded significantly onto the respective latent variables ($p < 0.001$) with values greater than 0.5. Moreover, based on Fornell and Larker's (1981) recommendation of calculating the average variance extracted (AVE), we found that the AVE estimates exceeded the cutoff value of 0.5. Composite reliability (CR) was higher than 0.7, as recommended by Hair et al. (2010). As for discriminant validity, we compared constrained and unconstrained models, showing that the hypothesized model better fit the data. As a further test, we found that the square root of the AVE estimates was higher than the correlation between the two constructs, as shown in Table 1. Table 2 reports item loadings, Cronbach's alphas, CR, and AVE of all the constructs.

Regarding the formative constructs, when conventional procedures to test reliability and construct validity are not applicable (Diamantopoulos & Winklhofer 2001), multicollinearity and nomological validity should be assessed. Multicollinearity was not an issue for our constructs because the variance inflation factors (VIF), which ranged between 1.01 and 1.14, were far below the cut-off value of 3.3 (Diamantopoulos & Siguaw 2006). Nomological validity was tested by regressing theoretically related antecedents (e.g., motivations to adopt digital technologies) to the formative constructs. For example, we found that smart manufacturing technologies were significantly positively associated with reshoring, in line with Stentoft and Rajkumar (2020), and that data processing technologies were significantly positively associated with improving customer service, in line with previous literature (Spiess et al., 2019). Therefore, we concluded that the measures related to digital technologies are reliable and valid constructs.

Table 2 around here

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4. Results

The hypotheses were tested using partial least squares structural equation models (PLS-SEM). The PLS-SEM method has been widely applied in the social sciences because it allows the estimation of complex relationships between reflective and formative constructs (Hair, Black, Babin, & Anderson, 2010). Compared to the covariance-based SEM, this method is appropriate for this study because it does not draw on distributional assumptions, showing higher robustness with nonnormal data, and it has greater statistical power, which is useful for investigating less developed theory, as in our case (Hair, Risher, Sarstedt & Ringle, 2019).

Table 3 reports the PLS-SEM results, including the standardized path coefficients and the p-values. The analysis suggests that both smart manufacturing and data processing technologies were directly and positively associated with CE, suggesting that I4.0 techs were apt to the premises, even if the magnitude of the coefficient of the first was larger than the second. Furthermore, SCI was found to be significantly and positively associated with CE, confirming H1. However, differently from what was expected and suggested by the literature, only smart manufacturing technologies were positively associated with SCI (H2), whereas data processing technologies were not (H3)[4].

To test the presence of a mediation effect of SCI, we ran the bias-corrected bootstrapping analysis for mediation (Rungtusanatham, Miller & Boyer, 2014), the Sobel test, and the Monte Carlo simulation with level of confidence at 95% and 20,000 repetitions using data from the SEM model (MCMAM; MacKinnon, Lockwood & Williams, 2004). From the bias-corrected bootstrapping analysis, we observed that the indirect effect through smart manufacturing technologies was 0.191, with the 95% confidence interval ranging from 0.081 and 0.301. This result indicates that the confidence interval for smart manufacturing technologies does not include zero, thus supporting H4a. Accordingly, we found support for the hypothesis that the more smart manufacturing technologies are adopted across firms' activities, the higher the CE performance of firms. Such a relationship was mediated by SCI: adopting smart manufacturing technologies improved a firm's integration along the supply chain and, thus, its ability to enhance processes and products toward the CE framework. CE measure captured resource savings as well as different resource management processes in production and product management (i.e., using renewable, recyclable, or recycled inputs).

On the contrary, H4b, focused on data processing technologies, was not supported. The bias-corrected bootstrapping analysis suggested that the indirect effect through data processing technologies was 0.063, with the 95% confidence interval ranging from -0.037 and 0.163 – the confidence interval (CI) for data processing technologies includes zero. The more data-processing technologies adopted within the firms, the higher the CE performance of the firm; however, such a relationship was not mediated by the level of SCI within the firm and between the firm and its SC partners.

Two additional approaches to testing mediation effects were taken to further validate the results. The Sobel test for data-processing technologies confirmed the lack of a mediation effect of SCI in the relationship between data processing technology and CE ($p = 0.223$). The Sobel test for smart manufacturing technologies confirmed the presence of a mediation effect of SCI on the relationship between smart manufacturing technology and CE ($p = 0.001$). Lastly,

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[4] To test the robustness of these findings and address the criticisms of some scholars on PLS-SEM (Rönkkö, McIntosh, Antonakis & Edwards, 2014), we performed covariance-based SEM using single-item indicators (summated indexes) for the set of variables related to digital technologies. Similar results emerged from the SEM analysis, supporting the PLS-SEM findings.

we performed the MCMAM test. The confidence intervals resulting from the MCMAM provided additional support for our results.

Table 3 and Figure 2 around here
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5. Discussions and conclusions

The paper offers an original perspective on the relationship between Industry 4.0 technologies (I4.0 techs) and CE (Chen et al., 2015; Kohtala & Hyysalo, 2015; Kumar et al., 2018; Massaro et al., 2021) by investigating the mediating role of supply chain integration (SCI). The results, based on the analysis of original survey data on Italian manufacturing firms, show a positive relationship between the wide adoption of these technologies within firms' activities (i.e., new product development, production, logistics, marketing) and the ability to tackle several of the aspects needed to achieve a circular production process. Results also suggest that the mediation of SCI reinforces such a positive relationship. Differently from what was expected, however, the mediating role of SCI holds only in the context of smart manufacturing technologies, but not data processing technologies—suggesting the type of I4.0 techs is an important contingency in understanding the mediation role of SCI. Overall, these findings push further the theoretical debate related to CE in the new Industry 4.0 technological scenario by entering the 'black box' of the mechanisms that allow firms to reap the potential of Industry 4.0 to improve CE.

This research contributes to the existing literature and opens up new questions regarding the boundary conditions that need to be considered when the implementation of new digital technologies and CE are at stakes. First, our findings confirm the positive link between the adoption of I4.0 techs and CE results, as suggested by prior research (Kumar et al., 2018; Rosa et al., 2020; Massaro et al., 2021). The direct effect of both data processing technologies and smart manufacturing technologies on CE demonstrates that the digitalization of both the flow of materials and the flow of information allows firms to achieve CE. Referring to data processing technologies, our findings corroborate past literature emphasizing the data-driven view of CE (Ranta, Aarikka-Stenroos & Väisänen, 2021). These digital technologies are mostly responsible for changing the flow of information within firms, which has a central role in CE: collecting and mastering data in relation to the flows of materials, resources, and waste, as well as the users' behavior about product use, is the new frontier for a real, positive transition to the CE paradigm (Ellen MacArthur Foundation, 2019). They help firms optimize resource management at each point in the production process, taking a lead role in waste reduction for CE (Ranta et al., 2021). Regarding smart manufacturing technologies, our findings support previous research showing that digital technologies that determine a change in the flow of materials positively sustain CE implementation processes and the achievement of CE results through better management of resources (i.e., resource savings, energy efficiency) (Rosa et al., 2020; Massaro et al., 2021).

Second, and more interestingly, we suggest that understanding the I4.0 techs–CE link also needs to consider their indirect, mediated effect on the organization of a firm's activities, both within the firm and with the entire supply chain. An important barrier to achieving CE is related to a lack of cooperation and joint effort toward convergent goals within and outside the organization (Farooque et al., 2019; Fehrer & Wieland, 2021). To close, narrow, or slow the loops, firms need to revisit their production processes and product portfolio in ways that require acquiring and integrating knowledge from different domains, thus enhancing collaboration with supply chain partners and among the firm's departments (Farooque et al., 2019; Fehrer & Wieland, 2021). By adopting I4.0 techs, firms may smooth such processes and overcome organizational boundaries to develop a more complex CE approach.

Third, connected to the previous point, we contribute to the literature linking Industry 4.0 and CE by demonstrating that, to fully grasp how I4.0 techs support achieving CE, we should distinguish across I4.0 techs types, in line with contributions pointing to the fact that this umbrella term group technologies are quite diverse, for example, in terms of resources needed and application potential (Osterrieder et al. 2020; Culot et al. 2020; Stentoft & Rajkumar, 2020). Smart manufacturing technologies unleash their full potential when they are enabled to contribute to the integration with supply chain partners—suppliers and customers—as well as within the organization (Ardito et al., 2019; Ben-Daya et al., 2019), with both a direct and an indirect effect, mediated by SCI. By enhancing SCI, smart manufacturing technologies foster their contribution to the scope of circularity in its complex and multifaced characteristics and dimensions (Homrich et al. 2018; Moraga et al. 2019). On the contrary, obtaining CE results *via* data processing technologies is less likely to occur through the mediating role of SCI. Our evidence is consistent with studies on blockchains that highlight that data processing technologies allow new forms of coordination, no longer based on relational mechanisms but on automated processes (Lumineau et al., 2021). Accordingly, this interpretation of our results suggests an unintended result of I4.0s adoption, as it partially substitutes for the role of SCI because they are automating it. This might be explained by considering the different elements characterizing SCI within the Industry 4.0 scenario (Schuh et al., 2014), namely i) information sharing, ii) cooperation, and iii) coordination. Thus, leveraging data processing technologies may reduce the need for the different dimensions of SCI because of technologically supported information sharing and less cooperation and coordination due to the more explicit goal orientation of the actors involved.

The lack of a mediating role of SCI might also cast doubts on achieving sustainability results in the long run. It could indeed compromise the ability of companies to fully leverage the advantages of data exploitation across the supply chain (Jabbour, de Sousa Jabbour, Sarkis & Godinho Filho, 2019; Ranta et al., 2021; Kache & Seuring, 2017), which is necessary for implementing innovative strategies to reuse, repair, refurbish, remanufacture, or recycle resources. In other words, considering the evidence in the literature suggesting collaboration is essential for CE to be fully enacted (De Marchi, 2012; Cainelli et al., 2015), we might interpret this result as a lower ability of data processing technologies to provide support for the introduction of circular improvements in the medium- and long-run. If collaboration is a peculiar trait and requisite of CE dynamics, then it becomes relevant to enter into those collaborative mechanisms and understand how digitalization and specific technologies more precisely have a role in such a context. Our finding suggests that collaboration is not always needed. Nevertheless, without collaboration, it is possible that firms may not capture the innovative aspects that the literature highlights when there is collaboration, thus not fully exploiting the potentialities of digitalization for sustainability goals.

While providing new and relevant contributions to the literature, which might allow for a more informed decision-making process for managers and policy makers interested in exploiting the relationship between Industry 4.0 and CE, this study has important limitations, mostly related to the nature of the data analyzed. A main limitation is related to the fact that we focused on only one point in time; it would be interesting to investigate the extent to which such a relationship might change when the firm becomes more experienced with those technologies. A panel analysis might also allow for further inference of causality among the variables considered. It also seems necessary for future research to expand the current analysis by considering specific technologies and activities within the value chain. Additional research could also explore the variety of actors with which a firm can collaborate and its implications for CE achievement. A further limitation of the current paper is that we adopted a subjective measure of CE performance, and one that might not fully capture CE activities. This problem is particularly relevant considering the potential divergence between sustainability practices and outcomes, which Halme et al. (2020, p. 1211) call a 'means-ends decoupling'. Further research should verify our evidence by adopting an objective measure of CE performance. Finally, we acknowledge the limitations of the analysis driven by the one-country focus. Further research could expand our analysis to different empirical contexts, for example, by studying firms located in different countries, to verify if institutional or cultural issues impact how firms use I4.0 techs.

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FIGURES

Figure 1. The theoretical model

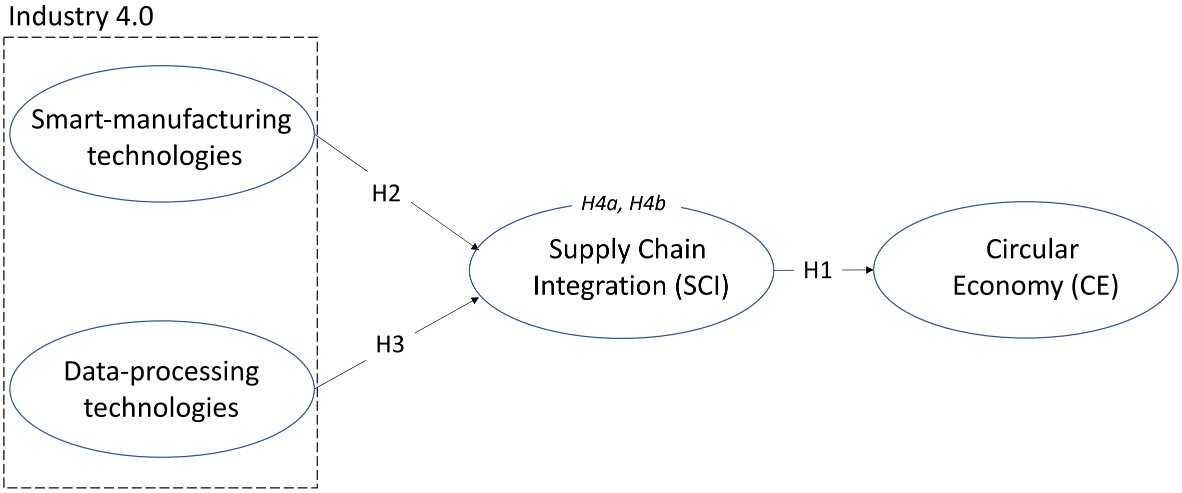
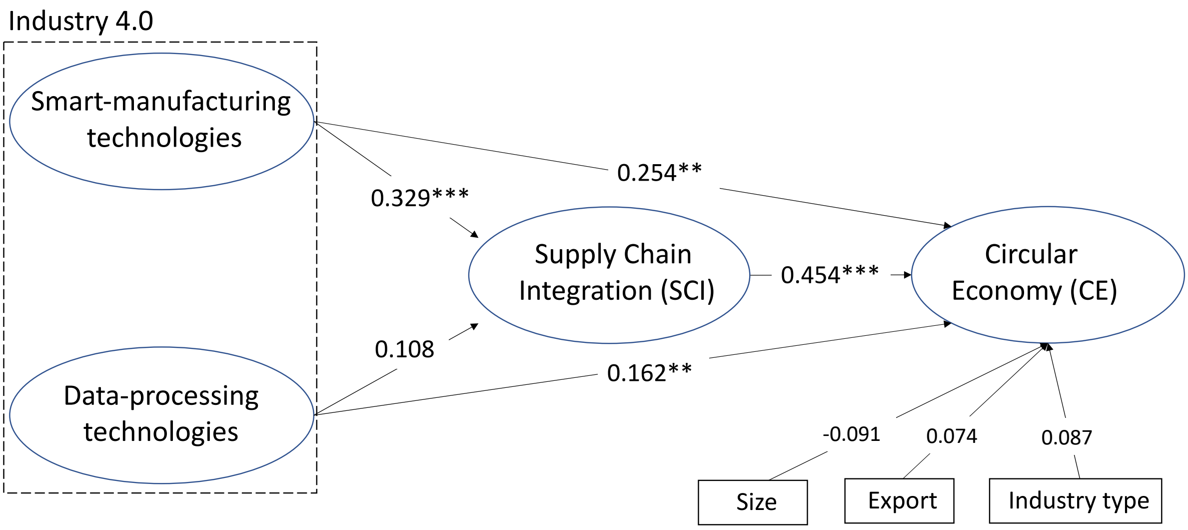


Figure 2. PLS-SEM model with direct effects



TABLES

Table 1. Mean, standard deviation, correlations

	Mean	S.D	1	2	3	4	5	6	7
1. Data processing technologies	1.02	1.81	1						
2. Smart manufacturing technologies	1.69	2.18	0.272	1					
3. SCI	2.21	0.95	0.197	0.358	0.71				

4. Circular Economy	2.07	0.88	0.306	0.447	0.581	0.76			
5. Size	3.41	1.08	0.198	0.192	0.093	0.039	1		
6. Industry type	0.556	0.50	-0.020	0.087	0.084	0.138	0.005	1	
7. Export	0.561	0.50	0.070	-0.046	0.077	0.093	0.093	-0.0734	1

Note. The square root of AVE of the reflective constructs (circular economy and collaboration capability) is shown on the diagonal. Inter-construct correlations are shown off the diagonal.

Table 2. Loadings, Cronbach's alphas (Alpha), construct reliability (CR) and average variance extracted of the reflective constructs

Construct	**Item**	**Loadings**	**Alpha**	**CR**	**AVE**
Circular Economy			0.86	0.89	0.58
	CE01. Reduction of inputs used (including energy or materials) (dropped)	-			
	CE02. Adoption of more sustainable inputs (e.g., recycled or recyclable materials)	0.622			
	CE03. Move towards greener suppliers	0.831			
	CE04. Use of waste from other sectors/firms as inputs	0.763			
	CE05. Reduction of process-related environmental impacts (e.g., on air or water)	0.795			
	CE06. Reduction of production waste	0.687			
	CE07. Use of firm's waste in the production process	0.858			
Supply Chain Integration			0.75	0.83	0.50
	SCI01. There is collaboration between production department and suppliers	0.589			
	SCI02. There is collaboration among shop-floor workers	0.762			
	SCI03. There is collaboration between production department and other firm's departments	0.706			
	SCI04. Customers have an active role in new product development	0.721			

SCI05. Customers have an active role in the production process	0.739

Table 3. Results for data processing technologies and smart manufacturing technologies

Path	**PLS result**	**P-values**	**SEM result †**	**P-values**
Data processing technologies -> Circular Economy	0.162**	0.046	0.121	0.126
Smart manufacturing technologies -> Circular Economy	0.254**	0.005	0.014	0.876
Data processing technologies -> SCI	0.108	0.152	0.150	0.126
Smart manufacturing technologies -> SCI	0.329***	0.001	0.334***	0.001
SCI -> Circular Economy	0.454***	0.000	0.742***	0.000
Size -> Circular Economy	-0.091	0.133	-0.083	0.265
Export -> Circular Economy	0.074	0.240	0.037	0.611
Industry type -> Circular Economy	0.087	0.188	0.157**	0.035

†, Fit indices: Chi-square/df=1.12, RMSEA=0.026; CFI=0.982; TLI=0.997.

Appendix 1. Items adopted to identify the dependent variable

Key characteristics of the CE (EEA)	CE items included in the survey
1. Less input and use of natural resources	i. Reduction of inputs used (including energy or materials)
2. Increased share of renewable and recyclable resources and energy	ii. Adoption of more sustainable inputs (e.g., recycled or recyclable materials)
	iii. Move towards greener suppliers
3. Keeping the value of products, components and materials in the economy	iv. Use of waste from other sectors/firms as inputs
4. Reduced emissions	v. Reduction of process-related environmental impacts (e.g., on air or water)
5. Fewer material losses/residuals	vi. Reduction of production waste
	vii. Use of firm's waste in the production process