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Digital-enabled dynamic capabilities for circular economy: The role of firm size

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ABSTRACT

Digital technologies are recognised to support the implementation of circular economy practices in the manufacturing sector. However, the mechanisms and contingencies explaining the relationship have not been properly consolidated, and there is unclear guidance on how to exploit digital technologies to implement the circular economy. Recently, discussions have focused on the possible mediating role of digital-enabled dynamic capabilities in this relationship, as well as moderators, such as firm size, that can impact it. To date, there is little empirical evidence from this standpoint. To improve our understanding of the relationships among digital technologies, circular economy practices, digital-enabled capabilities, and the moderating effect of firm size, this study conducted a quantitative empirical investigation involving 338 European manufacturing firms. We used partial least squares structural equation modelling and conditional mediation analysis to examine how the relationships among digital technologies, digital-enabled dynamic capabilities, and circular economy practices vary across firm sizes. The results show that digital technologies support the implementation of the circular economy both directly and via the mediated path of digital-enabled dynamic capabilities. However, the strength of this relationship varies according to firm size. Larger firms tend to leverage digital-enabled dynamic capabilities more effectively to implement circular economy practices. Lastly, the study suggests avenues for further research to enhance understanding of the role of digital-enabled dynamic capabilities in supporting the circular economy.

1. Introduction

The Anthropocene is marked by accelerating resource depletion, biodiversity loss, and climate change (Bonneuil and Fressoz, 2016). Industrial activity, while central to economic development, remains one of the primary drivers of these impacts due to its heavy reliance on finite natural resources and its generation of waste and emissions at scales that exceed planetary boundaries. The current industrial system has been shaped by a linear paradigm of extraction, production, consumption, and disposal, which has contributed significantly to the unprecedented environmental pressures (Sadiq et al., 2026; Vien, 2026). The circular economy (CE) has emerged as a compelling paradigm to challenge, contrast, and counteract the linear one (Chen and Dagestani, 2023; Franco and Giannoccaro, 2025) by seeking to decouple economic activity from resource depletion and environmental harm (Cagno et al., 2023). The CE paradigm represents not only an environmental necessity but also a strategic opportunity to reconfigure industry toward sustainable development (Kirchherr et al., 2017). The CE is central to global efforts to achieve climate-neutrality targets, and this has also been translated into European regulation, such as the EU Circular Economy Action Plan and the EU Taxonomy. Manufacturing firms are required to make a significant effort to foster the diffusion of CE, as they must reconsider their production and consumption modes entirely (Bianchini et al., 2019). However, the implementation of CE appears to be limited overall (Grafström and Aasma, 2021), highlighting the need for appropriate support to progress further towards the circular transition.

Digital technologies (DTs) can facilitate firms' transition towards the CE (Cannas et al., 2025b) and enable various CE strategies (Sadiq et al., 2026). DTs facilitate integrated, adapted, optimised, and interoperable production processes while also fostering connections among stakeholders and enhancing sustainability performance (Rodríguez-Espíndola et al., 2022; Upadhyay et al., 2021). The relationship between DTs

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adoption and CE implementation has been widely discussed in the literature, with recent reviews providing comprehensive summaries, e.g., Sánchez-García et al. (2024), Toth-Peter et al. (2023). Overall, it is widely accepted that DTs support manufacturing firms in embracing CE by implementing CE strategies and practices (Frank et al., 2025).

To move beyond a purely technological perspective, recent studies have increasingly called for closer examination of the mechanisms and contingencies shaping the relationship between DTs and CE implementation. Neri et al. (2025) attributed possible contrasting results to the mechanisms describing the relationship between DTs and CE, that is, to factors that moderate or mediate the relationship. Leveraging the dynamic capabilities (DCs) theory, Neri et al. (2025) focused on the mediating role of digital-enabled DCs. Specifically, while DTs are surely enablers for CE, their support can be mediated by changes in business processes, culture, and models enabled by DTs (Yu et al., 2021). While relevant, the role of digital-enabled DCs remains unclear. It deserves further exploration (Hoppe-Ludwig et al., 2025) to understand how they mediate the relationship between DTs and CE, ultimately supporting the implementation of CE in manufacturing firms. As for contingencies, previous research has underscored that both a digital and a circular divide, based on differences in size, might affect firms (Cagno et al., 2025; Ren, 2025). Specifically, smaller enterprises are usually seen as struggling to improve digitalisation and CE (Vien, 2026), with implications for their ability to generate digital-enabled DCs (AL-Khatib, 2023) and to exploit DCs for CE (Järvenpää et al., 2025). Despite the potential role of firm size as a moderator of the relationship between DTs and CE (Çetin et al., 2022; Huang et al., 2022; Soluk et al., 2023), it is often overlooked, again limiting the understanding of its role.

Despite the recognised enabling role of DTs, the mechanisms and contingencies underpinning their contribution to CE implementation are not yet fully consolidated (Frank et al., 2025; Kumar et al., 2025), with unclear guidance for practitioners on how to exploit DTs to implement CE. This limits the transition toward a more circular manufacturing sector, as hoped for by the political, industrial, and social discourse. More guidance could be provided by further exploring such mechanisms and contingencies, above all from an empirical perspective (Kumar et al., 2025; Neri et al., 2025). The present research aims to shed additional light on this point. To theorise mechanisms, this study draws on DCs theory, which explains how firms reconfigure resources and processes to respond to environmental changes and strategic challenges. This theoretical lens is particularly suitable for examining how DTs enable organisational capabilities that support the implementation of CE. Specifically, the study will analyse the role of digital-enabled DCs as a mediator of the relationship between DTs' adoption and CE implementation. Additionally, the study will examine the moderating effect of firm size, a relevant contingency to characterise the relationship further. This will be addressed by conducting a comprehensive empirical investigation of manufacturing firms and applying conditional mediation analysis to examine how the relationships between DTs and CE vary with the presence of digital-enabled DCs (as a mediator) and firm size (as a moderator).

The study contributes by empirically untangling the direct and indirect effects of DTs on CE through digital-enabled DCs. By employing a conditional mediation approach, this study further advances existing research by demonstrating that firm size significantly shapes this relationship and revealing that the mediating role of digital-enabled DCs is stronger in larger firms than in medium-sized ones.

The remainder of the paper is as follows: Section 2 introduces the theoretical and conceptual background; Section 3 presents the research hypotheses development; Section 4 describes the method employed for the empirical investigation; Section 5 reports the results; Section 6 discusses the results and implications of the study; Section 7 concludes the paper.

2. Theoretical and conceptual background

The section briefly introduces the main concepts and theory considered in the present research, aiming to provide a concise yet comprehensive overview to facilitate their understanding. CE represents the outcome of interest, DTs constitute the enabling factor, and DCs theory is used to explain the mediating mechanisms linking DTs to CE implementation.

2.1. Circular economy

The CE can be described as "*an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, recycling, and recovering materials in production/distribution and consumption processes […] to accomplish sustainable development*" (Kirchherr et al., 2017). While diverse definitions are present, and a consensus is elusive (Kirchherr et al., 2023; Ren, 2025), the literature largely agrees that CE is related to several strategies, also known as the Rs strategies (Ren, 2025; Vien, 2026), which help disclose the CE concept from a more tangible viewpoint (Cagno et al., 2021). Different frameworks of Rs strategies have been developed. The discourse primarily focused on the 3Rs (Reduce, Reuse, Recycle) model (Koksharov et al., 2019). The model soon evolved into the 6Rs model (Redesign, Reduce, Reuse, Remanufacture, Recycle, Recover) and then into the 9 (10)Rs model (Refuse, Redesign, Reduce, Reuse, Repair, Refurbish, Remanufacture, Repurpose, Recycle, Recover) (Potting et al., 2017; Rosa et al., 2020). The Rs strategies are also included in the butterfly diagram proposed by the Ellen MacArthur Foundation (2021). Following a cradle-to-cradle approach, the diagram highlights the difference between the biological and technical loops. As for the technical loop, activities such as reuse, refurbishment, and remanufacturing are strongly recommended (Cayzer et al., 2017).

The CE can be implemented at different levels from an industrial perspective, namely the micro (single firm), meso (industrial systems, such as industrial parks), and macro (regional and economy-based) (Kirchherr et al., 2017). All levels need to translate the Rs strategies into tangible, actionable efforts, namely circular economy practices (CEPs). CEPs are active initiatives resulting from decisions made by a decision-maker within the organisation (Masi et al., 2018) related to CE objectives, enabling firms to improve the related performance (Garza-Reyes et al., 2019). At the micro level, a variety of CEPs have been proposed in the literature (Leal et al., 2025), along with modalities to organise them. For example, Cagno et al. (2025) proposed a model of CEPs organised according to the Rs strategies; differently, Garza-Reyes et al. (2019) proposed a model of practices organised according to the depth of pervasiveness of the CE within the firm. Regardless of how they are organised, CEPs provide operational support to firms to better implement Rs strategies.

2.2. Digital technologies

Industry 4.0 is transforming the socioeconomic system, aiming to achieve higher levels of industrial automation and optimize industrial productivity and connectivity (Arcidiacono and Pieroni, 2018; Cannas et al., 2025a). The Industry 4.0 model includes various advanced enabling DTs (Cannas et al., 2025b), whose adoption shapes the aforementioned socioeconomic changes (Frank et al., 2025). In an era of rapid technological progress, the ability to innovate effectively is a critical competency and capacity (Urueña López, 2025). DTs can support firms through vertical integration, virtualisation, automation, traceability, flexibility, and energy management (Frank et al., 2019), and have been demonstrated to improve firms' performance (Ren, 2025). DTs comprise an array of interrelated technologies that integrate connectivity, distributed information, communication, and computing systems (Ren, 2025), and several distinct DTs can be identified. Rüßmann et al. (2015) proposed an extensive classification of DTs, including the following: the Internet of Things, big data analytics, cloud computing, horizontal system integration and vertical system integration, additive manufacturing, advanced robotics, simulation, cybersecurity and blockchain, and augmented reality. Additional DTs, such as artificial intelligence and computer-based technologies, can also be considered (Roberts et al., 2024; Xu, 2016). DTs can be exploited in different ways to generate value. According to Ren (2025), leveraging Gobble (2018) and Ancillai et al. (2023), a main distinction can be made between digitalisation, meaning the use of DTs to harvest value in new ways – i.e., applying DTs to improve existing business processes, and digital transformation, meaning DTs, besides enhancing operations, help reshaping value creation and capture mechanisms, influencing business models.

2.3. Dynamic capabilities theory

The present study is grounded in the DCs theory. The theory focuses on the renovation of a firm's routines, practices, procedures and assets for the firm to achieve sustainable competitive advantage and drive strategic transformations in turbulent environments characterised by rapid and unpredictable changes (Franco and Giannoccaro, 2025; Hoppe-Ludwig et al., 2025), such as the one connected to the implementation of CE and adoption of DTs (Lozada et al., 2025). DCs represent an organisation's capacity to renovate its resource base in a repeatable manner (Eisenhardt and Martin, 2000). The resource base includes tangible, intangible, and human assets, along with the capabilities that an organisation owns, controls, or is entitled to utilise (Schilke et al., 2018; Teece et al., 1997). Capabilities themselves are often viewed broadly as resources, suggesting that DCs can evolve or extend them (Fan and Liu, 2025). This renovation is based on three phases: sensing, seizing, and transforming (Teece, 2007, 2018): first, the opportunity is sensed; then, it is seized by adapting the business model; finally, aspects of the organisation's structure and culture are transformed. Leveraging Hoppe-Ludwig et al. (2025)'s description based on Teece (2007), the sensing phase focuses on identifying opportunities, and it thus relates to cognitive processes, such as scanning, learning, and interpreting, usually concentrated on markets, customers, suppliers, and competitors. The seizing phase involves transforming opportunities into competitive advantage and is thus related to the firm's ability to create new or innovate existing business models. The transforming phase focuses on maintaining the competitive advantage by transforming the intangible and tangible assets of firms.

Capabilities are often hard to identify within the organisation and are sustained by smaller mechanisms (Franco and Giannoccaro, 2025), known as microfoundations (Teece, 2007). Microfoundations lie in individuals, processes, and structures through which capabilities generate organisational phenomena, and they should be appropriately identified and studied to comprehensively understand and grasp the renovation of the resource base (Felin et al., 2012).

The DCs literature originally describes the sensing, seizing, and transforming as sequential phases of the capability renewal process (Teece, 2007); empirical research has often operationalised them as distinct but interrelated organisational capabilities, namely, stable, repeatable competencies that firms can develop and deploy to varying degrees, e.g., Franco and Giannoccaro (2025). Based on this, the present study treats sensing, seizing, and transforming as measurable capability dimensions that together constitute DCs. Accordingly, in the hypotheses and methods sections, these are referred to as DCs rather than phases, reflecting their operationalisation as constructs.

3. Hypotheses development

This section introduces the hypotheses that will subsequently be studied. Although the theory of DCs underpins the mediating mechanism, some of the hypotheses of the conditional mediation analysis are specified as a baseline to enable a comparison to be made between the direct, mediated and conditional relationships. Section 3.1 establishes the baseline direct relationship between the adoption of DTs and the implementation of CEPs. Section 3.2 explicitly draws on DCs theory to propose a mediation mechanism, suggesting that DTs contribute to CEPs by facilitating the development of digital-enabled DCs. According to this view, DTs strengthen the microfoundations of DCs, enabling firms to identify circular opportunities, allocate resources accordingly and reconfigure processes and asset bases. Section 3.3 incorporates firm size as a relevant contextual contingency, extending the DCs perspective by acknowledging that the development and exploitation of digital-enabled DCs are potentially shaped by firm size and thus relate to structural conditions, such as resource availability. Accordingly, a set of moderation and moderated mediation hypotheses is formulated to examine whether and how firm size conditions the relationships between DTs, CEPs and digital-enabled DCs, based on the previously established hypotheses. Taken together, the hypotheses articulated in this section form a conditional mediation framework enabling a systematic comparison of direct, mediated and size-contingent effects. This offers a theoretically grounded and nuanced understanding of how the adoption of DTs translates into the implementation of CEPs.

3.1. Digital technologies adoption and circular economy practices implementation

The literature largely agrees that adopting DTs can support the implementation of CE. The various mechanisms of this support have been discussed and reported in the literature (Ren, 2025). Overall, DTs can enhance abilities for real-time data collection and analysis, and for tracking and tracing resources (Liu et al., 2022; Ren, 2025). The support of DTs has also been related to specific CE strategies, such as reuse, remanufacturing, recycling, and refurbishment (Piedra-Muñoz et al., 2025; Virmani et al., 2025). The literature provides examples of support mechanisms offered by specific DTs for specific CE aspects – an overview is provided in Appendix A, based on the findings of Neri et al. (2025). Further, the debate also addresses the benefits of digital ecosystems for implementing the CE (Ertz et al., 2022). For example, the combination of additive manufacturing, automated robots, and artificial intelligence can improve the efficiency of activities and processes (Ghoreishi and Happonen, 2022). Selected contributions offer articulated evaluation, focusing on categories or groups of CE strategies and/or DTs. For example, Piedra-Muñoz et al. (2025) track the contribution of three categories of DTs, namely data collection, data integration, and data analysis, on CE strategies divided into narrowing, slowing, closing, and regenerating. They pinpoint the contributions of DTs' categories: data collection and data analysis contribute to all CE strategies, whereas data integration technologies predominantly contribute to narrowing and closing strategies. Additional granularity is offered by Neri et al. (2023a), who identify possible relationships among specific DTs and CEPs in manufacturing firms, followed by Cagno et al. (2025), who identify bundles of DTs that support the implementation of particular CEPs or bundles of CEPs.

Based on the above discussion and recent studies, e.g., Frank et al. (2025), it is evident and widely accepted that DTs can support manufacturing firms in embracing CE by implementing CE. We thus propose the following hypothesis:

H1. The adoption of DTs affects the implementation of CEPs in manufacturing firms.

However, the mechanisms and contingencies that provide depth of understanding of the relationship are not yet properly consolidated (Frank et al., 2025; Kumar et al., 2025). Following this, we will investigate the relationship further.

3.2. The mediating role of digital-enabled dynamic capabilities

From what has been discussed, DTs can support the implementation of CEPs. However, to realise the benefits of this relationship, the literature suggests that organisations should develop appropriate capabilities (Kumar et al., 2025) to exploit the potential of DTs (Sjödin et al., 2023). So, while the relationship between DTs and CE has mainly been considered as direct (Sharma et al., 2024), the investigation of transitivity paths - as defined by Godinho Filho et al. (2022), or mediators, may provide a more detailed characterisation of the relationship.

The literature has so far investigated diverse moderators of the relationship, such as supply chain integration, flexibility and risk management, traceability and collaboration, green logistics, and sustainable manufacturing – please refer to Neri et al. (2025) for a complete overview. Among the different mediators, DCs emerged as pivotal. The literature emphasises that DCs are needed for implementing CE (Coppola et al., 2023; Hoppe-Ludwig et al., 2025). Some of the DCs that support CE could be enabled by DTs (Elf et al., 2022; Hoppe-Ludwig et al., 2025) – the so-called digital-enabled DCs. From a DCs theory perspective (please refer to Section 2.3), the adoption of DTs may not create value in itself (Ren, 2025); rather, it can contribute to the implementation of CE by becoming embedded in organisational routines and decision-making processes. In this sense, DTs are linked to the microfoundations of DCs, enhancing firms' ability to identify opportunities, take advantage of them through informed strategic choices, and adapt existing processes and asset configurations accordingly. Therefore, DTs enable DCs by strengthening their microfoundations rather than directly driving CE outcomes.

The role of digital-enabled DCs has been studied in the literature. For example, Kristoffersen et al. (2021a, 2021b) emphasise that using data is crucial for developing the business analytics capabilities required for CE implementation; Santa-Maria et al. (2022), Khan et al. (2020a) and Belhadi et al. (2022) discuss the impact of technology on transforming and sensing capabilities. Chari et al. (2022) and Faisal (2023) state that DTs enable DCs relating to communication, resources, technology, collaboration, and knowledge, all of which facilitate CE; Quayson et al. (2023) focus on blockchain-enabled DCs for recycling, remanufacturing, and reuse strategies; Neri et al. (2023b) examine the digital-enabled DCs' microfoundations of sensing, seizing, and transforming aspects for implementing CEPs. All in all, DTs seem to foster and support business transformation, with several examples of digital-enabled microfoundations – e.g., Neri et al. (2023b) and Wilke and Kanbach (2026). Overall, DTs primarily support sensing through data generation and analytics, seizing through decision-support and coordination tools, and transforming through process integration and reconfiguration.

The literature suggests that DTs are surely enablers of CE. Still, without DCs, their power might be lower (A. N. Khan et al., 2025), and adopting DTs should also be studied in terms of modifying business processes and culture (Yu et al., 2021). It thus makes sense to focus on the related capabilities when aiming to understand the contribution of DTs to CE properly (Sjödin et al., 2023; van Eechoud and Ganzaroli, 2023). Despite this, the literature does not yet offer a complete overview or understanding of the relevance of digital-enabled DCs in supporting CE. While efforts are provided in the current literature, they tend to focus on a specific DT only, see for example Xu et al. (2025) who focus on green internet of things, or on a particular DC, as Kumar et al. (2025) who focus on supply chain integration and flexibility, based on literature data, and generally do not provide details on CEPs. Hence, while contributions are present, a comprehensive empirical overview is still missing. Using a transmittal approach (Rasoolimanesh et al., 2021), we developed a mediation hypothesis, proposing the following:

H2. Digital-enabled DCs mediate the relationship between the adoption of DTs and the implementation of CEPs in manufacturing firms.

To advance knowledge, and according to the DCs theory, we will focus on the three phases of sensing, seizing, and transforming. To the best of the authors' knowledge, the contribution by Sjödin et al. (2023) provides a similar investigation to the one proposed, focusing on digital-enabled DCs for circular business model innovation, but only on artificial intelligence.

3.3. The moderating role of firm size

The relationship between DTs and CE does not apply in the same way across different contingencies – i.e., contextual factors. Previous research has underlined that both a digital and a circular divide, based on differences in size, might affect firms. For example, Ren (2025) demonstrated it across micro, small, medium, and large firms, while Cagno et al. (2025) highlighted interesting differences between medium and large firms. Smaller firms are usually characterised by limited resources such as money, staff, and time (Negri et al., 2021). Due to the uneven distribution of resources (Ferasso et al., 2023), firm size emerges as a relevant contextual factor influencing firms' behaviour (Neri et al., 2021; Sousa and Voss, 2008). Specifically, small and medium-sized enterprises (SMEs) are often seen as struggling to improve their digitalisation and CE (Vien, 2026). The digital divide, i.e., differences in the ability to access, adopt, and use DTs (Gravili et al., 2018; Ngo et al., 2026), can be related to firm size. Smaller firms are usually recognised as slower to adopt DTs and to understand their opportunities and benefits (Horváth and Szabó, 2019; Prisco et al., 2022), and their adoption of DTs can be influenced by bias, bounded rationality, and path dependency (Pedota, 2023). Similarly, firm size is considered to influence digital proficiency (Lutfi et al., 2024). The circular divide can also be related to the firm size. Indeed, due to their inherent characteristics, SMEs may face greater challenges than larger firms when implementing CE (Howard et al., 2022), with larger firms generally showing a higher propensity to enhance resource quality, implement recycling initiatives, supply renewable goods and services, and establish more environmentally responsible management systems (Wang et al., 2018).

The presence of a digital and a circular divide based on firm size also appears to influence the relationship between DTs and CE, with firm size acting as a moderator (Ali and Johl, 2023). To the best of the authors' knowledge, no previous research has compared differences based on firms' size (e.g., small, medium, large) for the relationship between DTs and CE; however, Hernández et al. (2024), studying DTs for sustainability implementation, found that the relationship is stronger for larger enterprises.

Firm size is also associated with the capacity to develop DCs, with smaller enterprises lagging (Andren et al., 2003; Miyake and Nakano, 2007), and struggling to exploit them for disruptive innovations (Soluk et al., 2023). A technological capabilities asymmetry based on size appears to exist (Ngo et al., 2026), with larger firms achieving higher levels of capability than smaller ones (Huang et al., 2023). Indeed, smaller firms appear as less capable of generating digital-enabled DCs (AL-Khatib, 2023) and of exploiting DCs for CE (Järvenpää et al., 2025).

From the above discussion, larger firms seem to have greater resources to adopt DTs and are more likely to prioritise CE strategies. However, some discrepancies can be spotted in the literature. Although firm size is traditionally viewed as a key predictor of innovation, empirical evidence on this relationship remains ambiguous and contradictory, with studies reporting positive, negative, and non-significant effects (Leal-Rodríguez et al., 2015; Lee and Xia, 2006). The classic perspective holds that larger firms are better positioned to invest in research, development, and innovation due to their superior resource endowment. Conversely, other viewpoints emphasise the innovative prevalence of smaller firms due to their greater flexibility, versatility, and adaptability (De Jong and Marsili, 2006). The reduced institutional bureaucracy inherent in smaller organisations confers crucial structural flexibility and independence, fostering innovation. Moreover, smaller firms face pressure to innovate efficiently due to intense competition, shorter product life cycles, and rapid technological obsolescence (Laforet, 2013; Leal-Rodríguez et al., 2015). Further, the literature has identified different SMEs' behaviours regarding CE level (Holzer et al., 2021) and regarding approaches towards innovation connected to CE (Arroyabe et al., 2024).

Overall, firm size is a relevant moderator that can influence the adoption of DTs, the implementation of CEPs, and the presence and exploitation of digital-enabled DCs. However, discrepancies seem to emerge. Given the exploratory nature of the present study, and the differences and inconsistencies present in the literature, the following hypotheses are formulated, which consider the moderating effect of the firm size, following the indication of Memon et al. (2019) for the institution of a moderating variable:

H3. Firm size moderates the relationship between DTs and digital-enabled DCs.

H4. Firm size moderates the relationship between digital-enabled DCs and CEPs.

H5. Firm size moderates the relationship between DTs and CEPs.

H6. Firm size moderates the mediated relationship between DTs and CEPs.

The conceptual framework for the developed hypotheses is reported in Fig. 1.

4. Methods

We conducted a survey to quantitatively examine the relationships among DTs, CEPs, and digital-enabled DCs. The survey was based on the verification of a priori hypotheses through the operationalisation of variables and measures (Park et al., 2020).

4.1. Data collection

We developed a closed-ended question survey to collect responses and analyse the relationships between the variables of interest. The survey was developed in English. The questions and terminology were evaluated by two professionals and a market research company manager, resulting in refinements to the wording and items. The survey was subsequently made available in multiple languages. Large and medium-sized European manufacturing firms were selected as targets due to their relevance to CE and digitalisation (European Commission, 2023a, 2023b). The focus on medium and large firms is justified, given that they are expected to have higher adoption of DTs (Cagno et al., 2024) and CE (Mishra et al., 2024) compared to smaller ones – see also Ren (2025). Italy, the UK, Spain, and Portugal were selected as target countries. The reason is twofold: i) they are relevant economies with different levels of digitalisation and environmental impact in their manufacturing sectors. For instance, concerning the CE implementation, Italy and the UK show a high level of implementation, Spain a medium one, and Portugal a low one (Claudio-Quiroga and Poza, 2024); regarding the environmental impact, Italy and Portugal are showing progress, but challenges remain, Spain is showing a slower progress, while the UK is remaining off track (European Environment Agency, 2025; Office for Environmental Protection, 2026); in terms of business digitalisation level, Italy is ranked quite low, Portugal and Spain show an overall higher level, and the UK is recognised as a leaderboard (European Commission, 2025; Eurostat, 2025); ii) given the prior point, they were selected as countries of interest for the funded research project to which the present paper is tied. General managers, production managers, and sustainability/environmental managers were identified as the key informants to target. An external research company distributed the survey among large and medium-sized manufacturing firms in the selected countries, addressing the identified key informants.

We received 353 anonymised filled questionnaires. We performed data screening, deleting observations with more than 7% missing values, to ensure the dataset's reliability with very acceptable levels of statistical power. The final dataset comprises 338 answers: 127 (38%) from large firms and 211 (62%) from medium firms. Additional information on the surveyed firms is reported in Table 1. This sample size is deemed sufficient, as 100 observations are adequate to achieve acceptable statistical power in PLS-SEM models (Reinartz et al., 2009), and it exceeds the minimum sample size required by our model specification (Faul et al., 2009).

4.2. Model design and variables

The proposed model is a hierarchical component model (HCM) based

Table 1
Description of the sample.

		Medium enterprises	Large enterprises
Sector	Food and beverage	19%	19%
	Metalworking	21%	24%
	Paper	10%	8%
	Pharma and chemical	6%	20%
	Plastic	14%	10%
	Textile and apparel	20%	9%
	Others	10%	10%
Production technology	Assembly	7%	17%
	Fabrication	67%	55%
	Process	26%	28%
Country	Italy	74%	25%
	Portugal	9%	23%
	Spain	10%	21%
	The UK	7%	31%

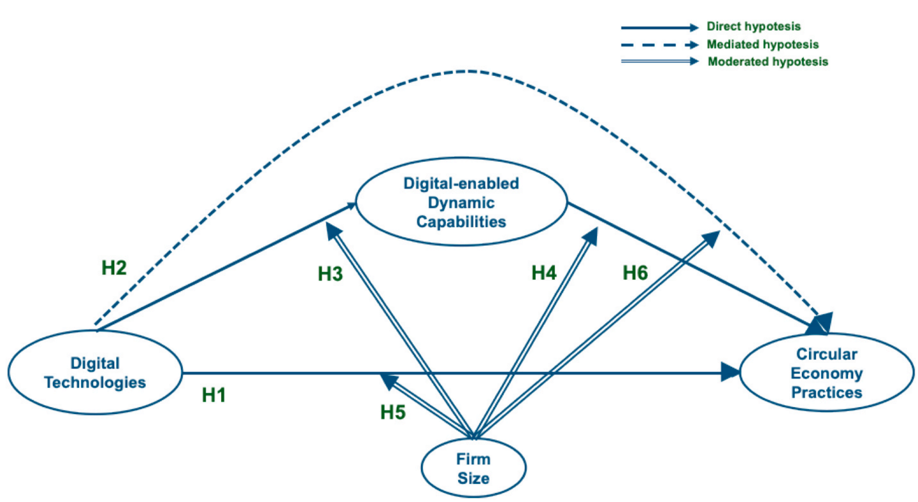

Fig. 1. The conceptual framework of the study.

on second-order constructs (Sarstedt et al., 2016). We operationalised three primary constructs based on the variables considered in this research, namely DTs, CEPs, and digital-enabled DCs (hereafter referred to as DCs), along with their respective sub-constructs. When developing the constructs, we aimed to be comprehensive while limiting the number of items to be tested.

DTs were constructed as a second-order reflective construct, comprising seven first-order reflective constructs, namely *computer-based technology (CBT)*, *Internet of Things (IOT)*, *autonomous robots (ROB)*, *big data analytics and artificial intelligence (BDA_AI)*, *cloud computing (CLO)*, *vertical systems integration (VSI)*, and *blockchain and cybersecurity (CYB)*. Based on the DTs considered in previous studies (Cagno et al., 2025), we selected these technology families as they were identified as the most widely implemented in previous research (Marcon et al., 2022; Neri et al., 2023a). Conversely, we did not include horizontal system integration, simulation, additive manufacturing, or augmented reality as these technologies were not widely adopted in previous studies (Cagno et al., 2025; Cimini et al., 2021). Big data analytics and artificial intelligence were included in the same construct as they are often considered together (Kamyab et al., 2023; Thayyib et al., 2023) and are both critical for making data practical and actionable (Zamani et al., 2023). To measure DTs, we adapted indicators from previous studies (Table 2). We adopted a 5-point Likert-like scale to assess the level of DTs use in the firms (*1: Not planned to use; 5: Advanced use*).

CEPs are constructed as a second-order reflective construct comprising five first-order reflective constructs, namely *recycle and recover (REC)*, *remanufacture and repurpose (REM)*, *refurbish, repair and reuse (REF)*, *rethink (RET) and reduce (RED)*. The considered practices relate to the 10Rs framework proposed by Kirchherr et al. (2017), except for the refuse strategy. We aggregate strategies and subsequently practices based on their aims and intrinsic nature. Recycle and recover both relate to the practical application of materials; remanufacture and repurpose both relate to the reuse of discharged parts in a new product; refurbish, repair and reuse all entail extending the life of a product or component for use by the same or a new customer (Kirchherr et al., 2017). As in Cagno et al. (2025), we thus organised and aggregated CEPs according to Rs strategies. To measure CEPs, we adapted indicators from previous studies (Table 3). We adopted a 5-point Likert-like scale to assess the level of CEP implementation in the firms (*1: Not implemented and not interested in implementing; 5: Implemented for more than 3 years*).

DCs were constructed from three first-order reflective constructs, namely *sensing capability (SENS)*, *seizing capability (SEIZ)*, and *transformative capability (TRANS)*. The division of the three phases is considered indeed appropriate for analysing DCs in the context of CE (Franco and Giannoccaro, 2025). To measure DCs, we adapted indicators from previous studies (Table 4). We adopted a 5-point Likert-like scale to determine the extent to which the use of DTs enables the firm's DCs. (*1= Decrease; 5=Increase*).

In this study, sensing, seizing, and transforming are used to inform the operationalisation of digital-enabled DCs; however, they are analysed as a higher-order construct capturing firms' overall capability to reconfigure resources through DTs. Similarly, while DTs and CEPs are operationalised through multiple dimensions, they are analysed as aggregate constructs.

4.3. Data analysis

We used partial least squares structural equation modelling (PLS-SEM), a variance-based method well-suited to testing complex hypothesised relationships and multidimensional constructs (Hair et al., 2011; Wright et al., 2012), to analyse our dataset. The study adopts a composite measurement model with a reflective design approximation (Mode A). Following the two-step approach recommended by Sarstedt et al. (2016), we first assessed the measurement model using a PLS algorithm with 300 iterations, followed by evaluation of the structural

Table 2
First-order constructs and indicators for the second-order construct DTs.

First-Order Construct		Indicator		
Name	Description	Code	Description	Supporting Reference
Computer-Based Technology	Combination of computer-related hardware or software such as social networks, and e-commerce.	CBT1	Firm's Website	Schindler et al. (2017)
		CBT2	Social networks	Yao et al. (2023)
		CBT3	E-commerce channel	Schindler et al. (2017)
		CBT4	CAD; CAM; CIM; CAT	Werner Dankwort et al. (2004)
Internet of Things	Interconnected systems, monitored or remotely controlled, allowing to transfer real-time data.	IOT1	RFID and smart devices	Kandil et al. (2024)
Big Data Analytics and Artificial Intelligence	Systems using technologies to gather and/or use data to predict, recommend or decide the best action.	BDA_AI1	Tools for analytics	Huynh et al. (2023)
		BDA_AI2	Tool for knowledge discovery	Cannas et al. (2023)
Cloud Computing	Online services to access software, computing power, storage capacity etc.	CLO1	Store of files	Al Hadwer et al. (2021)
		CLO2	Host of database	Al Hadwer et al. (2021)
		CLO3	Integrated systems in the cloud	Ali et al. (2020)
Vertical Systems Integration	Systems for sharing and integrating of all aspects of the manufacturing execution system within the organization.	VSI1	DCS (Distributed Control Systems); MES (Manufacturing Execution System); PDM (Product Data Management);	Moeuf et al. (2018)
		VSI2	MRP (Manufacturing Resource Planning)	Rana and Rathore (2023)
		VSI3	ERP (Enterprise Resource Planning)	Moeuf et al. (2018)
		VSI4	CRM (Customer Relationship Management)	Pereira Pessôa and Jauregui Becker (2020)
Advance Robotics	Autonomous industrial robots to perform repetitive tasks and cooperate with humans.	ROB1	Autonomous industrial robots for production process	Fragapane et al. (2020)
		ROB2	Autonomous industrial robots for internal logistics	Pereira Pessôa and Jauregui Becker (2020)
Cybersecurity and Blockchain	Systems managing the security of digital communication in a large,	CYB1	Vulnerability and threat management tools	Admass et al. (2024)

(*continued on next page*)

Table 2 (*continued*)

First-Order Construct		Indicator		
Name	Description	Code	Description	Supporting Reference
	integrated inter- and intracompany manner.	CYB2	Distributed digital ledger	Magrini et al. (2021)

model. Statistical analyses were conducted using SmartPLS v.3.2.9 (Henseler et al., 2009); RStudio 2022.12.0 Build 353 was used for endogeneity assessments with Gaussian copulas.

5. Results

5.1. Measurement model

To confirm the robustness of the model, we conducted a comprehensive assessment of the indicators' reliability, internal consistency, and convergent and discriminant validity across the complete sample and samples of large and medium firms, as recommended by Hair et al. (2019). The detailed outcomes of these evaluations are presented in Tables 5–8. Most of the factorial loadings of the constructs measuring the items are >0.7, as recommended (Hair et al., 2011), although some values > 0.4 are also acceptable (Hair et al., 2012). All composite reliabilities (CRs) exceed 0.7, indicating the model's internal consistency (Hair et al., 2021) and indicating that the items consistently measure the same underlying concept. Convergent validity was established (AVE>0.5) (Hair et al., 2017a), indicating that the majority of variance in the scale is accounted for by the construct itself, not by measurement error. Operationally, the results suggest that the measurement model is sound and that the latent construct scores can be confidently used in the assessment and interpretation of the structural model relationships.

Discriminant validity was assessed using Fornell-Larcker and HTMT criteria: the emboldened numbers on the diagonal in Table 8 represent the square roots of the AVEs for each construct. These values were greater than the correlation values in the rows and columns, thus establishing discriminant validity. The HTMT criterion is more rigorous than the Fornell-Larcker approach. All HTMT values were <0.90, further confirming discriminant validity (Hair et al., 2019) and indicating that each construct is empirically distinct from the others, demonstrating

Table 3
First-order constructs and indicators for the second-order construct CEPs.

First-Order Construct		Indicator		
Name	Description	Code	Description	Supporting Reference
Recovery and recycle	Waste is used as a source of energy or valuable biochemical compound, or it is reprocessed into products, materials, or substances for the original or other purposes.	REC1	Internal recover	Iacovidou et al. (2017)
		REC2	Recover of another firm's waste	Iacovidou et al. (2017)
		REC3	Internal recycling of waste material/scraps	Iacovidou et al. (2017)
		REC4	Waste material/scraps recycled by another firm	Iacovidou et al. (2017)
Remanufacturing and repurpose	Parts of a discharged product are used in another product or for an alternative purpose.	REM1	Reuse of parts of a discharged product	Coughlan et al. (2018)
		REM2	Design for disassembly	Vanegas et al. (2018)
		REM3	Design for remanufacturing	Bjørnbet et al. (2021)
Refurbish, repair and reuse	Old products are restored, brought up to date and made available for re-sale.	REF1	Sale of refurbished products	Coughlan et al. (2018)
		REF2	Sale reconditioned products	Coughlan et al. (2018)
		REF3	Design for refurbishment	Huynh et al. (2023)
Reduce	The use of resources is reduced.	RED1	Reduction in resources used for the production	Garcia-Ortega et al. (2023)
		RED2	Reduction in resources used for the packaging	Kamble and Gunasekaran (2021)
		RED3	Design for consumption reduction/waste minimization	Garcia-Ortega et al. (2023)
Rethink	The use of products is made more intensive, including the re-elaboration/re-conceptualization of ideas, processes, concepts, and uses.	RET1	Design for durability	Bjørnbet et al. (2021)
		RET2	Design for quality	Dokter et al. (2021)
		RET3	Design for manufacturing and assembly	Dokter et al. (2021)
		RET4	Design for supply chain	Dokter et al. (2021)

Table 4
First-order constructs and indicators for the second-order construct DCs.

First-Order Construct		Indicator		
Name	Description	Code	Practice	Supporting Reference
Sensing Capability	Identification of new opportunities.	SENS1	Identification of customers' needs	Witschel et al. (2019)
		SENS2	R&D activities	Prieto-Sandoval et al. (2018)
		SENS3	Knowledge of critical aspects of the production process	Tortora et al. (2021)
		SENS4	Tight control of the production process	Gao and Sarwar (2022)
		SENS5	Audit	Khan et al. (2020b)
Seizing Capability	Exploitation of new knowledge.	SEIZ1	Data management	Gao and Sarwar (2022)
		SEIZ2	Knowledge management	Witschel et al. (2019)
		SEIZ3	Interdepartmental collaboration	Khan et al. (2020b)
		SEIZ4	Learn from competitors and partners	Khan et al. (2020a)
		SEIZ5	Change in the management's mentality	Annarelli et al. (2021)
Transforming Capability	Development of new markets and processes.	TRAN1	Product management along the supply chain	Annarelli et al. (2021)
		TRAN2	New business practices	Prieto-Sandoval et al. (2018)

Table 5
Results of measurement model: DTs.

	Total sample (N = 338)			Large firms (N = 127)			Medium firms (N = 211)		
Construct/*dimension*/indicator	Loadings/VIF	CR	AVE	Loadings/VIF	CR	AVE	Loadings/VIF	CR	AVE
DTs	(VIF = 1.000)	0.919	0.62		0.914	0.602		0.922	0.63
Computer Based Technologies	0.768 (VIF = 1.883)			0.81 (VIF = 2.155)			0.728 (VIF = 1.691)		
CBT1	0.807			0.837			0.915		
CBT2	0.825			0.842			0.917		
CBT3	0.625			0.731			0.915		
CBT4	0.665			0.744			0.917		
Internet of Things	0.741 (VIF = 1.882)			0.744 (VIF = 1.967)			0.742 (VIF = 2.019)		
IOT1	1			1			1		
Advance Robotics	0.789 (VIF = 2.385)			0.728 (VIF = 2.036)			0.833 (VIF = 2.674)		
ROB1	0.903			0.888			0.911		
ROB2	0.926			0.934			0.916		
Big Data Analytics and Artificial Intelligence	0.778 (VIF = 2.067)			0.748 (VIF = 2.228)			0.795 VIF = 2.028		
BDA_AI1	0.948			0.955			0.921		
BDA_AI2	0.953			0.947			0.913		
Cloud Computing	0.785 (VIF = 2.142)			0.769 (VIF = 2.057)			0.793 (VIF = 2.456)		
CLO1	0.921			0.924			0.919		
CLO2	0.913			0.925			0.901		
CLO3	0.901			0.874			0.918		
Vertical Systems Integration	0.856 (VIF = 2.684)			0.826 (VIF = 2.325)			0.878 (VIF = 2.953)		
VSI1	0.876			0.909			0.853		
VSI2	0.842			0.927			0.787		
VSI3	0.873			0.939			0.820		
VSI4	0.856			0.901			0.821		
Cybersecurity	0.789 (VIF = 2.176)			0.746 (VIF = 1.825)			0.878 (VIF = 2.695)		
CYB1	0.896			0.915			0.877		
CYB2	0.898			0.917			0.880		

Table 6
Results of measurement model: CEPs.

	Total sample (N = 338)			Large firms (N = 127)			Medium firms (N = 211)		
Construct/*dimension*/indicator	Loadings/VIF	CR	AVE	Loadings/VIF	CR	AVE	Loadings/VIF	CR	AVE
CEPs	(VIF = 1.836)	0.861	0.557		0.887	0.662		0.884	0.579
Recycle and recover	0.814 (VIF = 1.726)			0.786 (VIF = 2.159)			0.653 (VIF = 1.597)		
REC1	0.791			0.784			0.804		
REC2	0.645			0.638			0.649		
REC3	0.77			0.759			0.782		
REC4	0.698			0.788			0.629		
Remanufacture and repurpose	0.808 (VIF = 2.129)			0.761 (VIF = 2.011)			0.692 (VIF = 1.716)		
REM1	0.806			0.879			0.762		
REM2	0.929			0.925			0.913		
REM3	0.921			0.938			0.934		
Refurbish, repair and reuse	0.679 (VIF = 1.621)			0.654 (VIF = 1.684)			0.631 (VIF = 1.543)		
REF1	0.942			0.954			0.937		
REF2	0.942			0,926			0.953		
REF3	0.927			0.911			0.931		
Rethink	0.817 (VIF = 2.06)			0.852 (VIF = 2.168)			0.884 (VIF = 2.063)		
RET1	0.781			0.814			0.780		
RET2	0.796			0.910			0.723		
RET3	0.889			0.899			0.881		
RET4	0.832			0.869			0.809		
Reduce	0.785 (VIF = 1.646)			0.851 (VIF = 2.198)			0.792 (VIF = 1.474)		
RED1	0.942			0.952			0.933		
RED2	0.943			0.935			0.946		
RED3	0.914			0.897			0.922		

that they are unique and separate concepts in the model.

5.2. Structural model

Examining the structural model reveals the latent form of the association between the variables. We used standard criteria to estimate the model's predictive ability and to establish relationships. To ensure unbiased regression results, we checked for collinearity using the variance inflation factor (VIF). The VIF values for all the antecedent constructs were <3.0 (Table 5, Table 6, Table 7), indicating the absence of collinearity issues (Hair et al., 2019) and that the structural model estimates are reliable.

To assess the statistical significance of the structural path coefficients, we employed a bootstrapping procedure with 5,000 resamples (Hair et al., 2012). The results (Table 9) indicate that DTs have a significant direct impact on CEPs, thus supporting H1. Additionally, the direct influence of DTs on DCs and the effect of DCs on CEPs are both statistically significant. The reported R^2 values in Table 9 reflect the explanatory power of the endogenous constructs and align with Chin (1998) guidelines for model quality, suggesting the independent variables are relevant and substantial predictors. The calculated Cohen's f^2 values are all >0.02, confirming that each variable is a critical

Table 7
Results of measurement model: DCs.

	Total sample (N = 338)			Large firms (N = 127)			Medium firms (N = 211)		
Construct/indicator	Loadings	CR	AVE	Loadings/VIF	CR	AVE	Loadings/VIF	CR	AVE
DCs	(VIF = 1.836)	0.925	0.805		0.932	0.821		0.918	0.788
Sensing capabilities	0.926 (VIF = 2.866)			0.94 (VIF = 3.474)			0.912 (VIF = 2.504)		
SENS1	0.785			0.853			0.749		
SENS2	0.818			0.873			0.781		
SENS3	0.622			0.851			0.470		
SENS4	0.796			0.826			0.794		
SENS5	0.849			0.873			0.815		
Seizing capabilities	0.916 (VIF = 2.684)			0.914 (VIF = 2.711)			0.922 (VIF = 2.714)		
SEIZ1	0.83			0.839			0.831		
SEIZ2	0.87			0.910			0.858		
SEIZ3	0.759			0.845			0.713		
SEIZ4	0.78			0.850			0.724		
SEIZ5	0.816			0.856			0.780		
Transforming Capabilities	0.847 (VIF = 2.282)			0.728 (VIF = 2.364)			0.833 (VIF = 1.933)		
TRAN1	0.884			0.908			0.862		
TRAN2	0.895			0.924			0.872		

Table 8
Results of measurement model: discriminant validity.

	Fornell-Larcker criterion				HTMT			
Total sample (N = 338)		DTs	DCs	CEPs		DTs	DCs	CEPs
	DTs	**0.787**			DTs			
	DCs	0.675	**0.897**		DCs	0.746		
	CEPs	0.656	0.494	**0.746**	CEPs	0.708	0.506	
Large firms (N = 127)		DTs	DCs	CEPs		DTs	DCs	CEPs
	DTs	**0.748**			DTs			
	DCs	0.667	**0.906**		DCs	0.729		
	CEPs	0.625	0.513	**0.749**	CEPs	0.714	0.529	
Medium firms (N = 211)		DTs	DCs	CEPs		DTs	DCs	CEPs
	DTs	**0.743**			DTs			
	DCs	0.692	**0.897**		DCs	0.766		
	CEPs	0.649	0.448	**0.687**	CEPs	0.722	0.496	

Table 9
Effects on endogenous variables.

Effects on endogenous variables	Direct effect	t-Value	Percentile bootstrap 95%	p-value	Explained variance	f^2
DCs ($R^2 = 0.455/Q^2 = 0.449$)						
DTs	0.675***	20.718	[0.623; 0.731] Sig.	0.000	0.455	0.836
CEPs ($R^2 = 0.435/Q^2 = 0.424$)						
DTs	0.593***	12.027	[0.512; 0.674] Sig.	0.000	0.389	0.339
DCs	0.094*	1.788	[0.018; 0.185] Sig.	0.046	0.046	0.021

Sig. denotes a significant direct effect at 0.05; **Non-sig.** denotes a non-significant direct effect at 0.05. Bootstrapping based on n = 5000 subsamples. *p < .05; **p < .01; ***p < .001. t(0.05; 4999) = 1.960; t(0.01; 4999) = 2.577; t (0.001; 4999) = 3.292. ns: not significant (based on t (4999), two-tailed test).

antecedent of its respective dependent construct (Roldán and Sánchez-Franco, 2012). The DTs–DCs relationship is particularly substantial ($f^2 = 0.836$). The cross-validated redundancy index Q^2 for all endogenous reflective constructs is greater than zero, confirming the model's satisfactory predictive relevance. Given the results of the structural model examination, the structural relationships can be interpreted with confidence.

5.3. Mediation analysis

To evaluate the mediating role of DCs, we tested the mediation hypothesis using a bootstrapping approach (Nitzl et al., 2016). The results confirmed that DCs significantly mediate the DTs-CEPs relationship, thus supporting H2. Including the indirect contribution of DCs, the total overall effect is 0.656 (Table 10). The proportion of the total effect explained by the indirect pathway (VAF index) is moderate (9.6%).

Table 10
Direct and indirect effects of digital technologies on circular economy practices.

Total effect		Indirect effect		
Coefficient	t-value	Coefficient	Bootstrap 95% Percentile	VAF
0.656***	23.643	0.063	[0.001; 0.126] Sig	9.6%

Sig. denotes a significant direct effect at 0.05; **Non-sig.** denotes a non-significant direct effect at 0.05. Bootstrapping based on n = 5000 subsamples. *p < .05; **p < .01; ***p < .001. t(0.05; 4999) = 1.960; t(0.01; 4999) = 2.577; t (0.001; 4999) = 3.292. Non-Sig.: not significant (based on t(4999), two-tailed test).

5.4. Conditional mediation analysis

To explore how the mediated effects of DTs on CEPs vary based on firm size, we conducted a conditional mediation analysis using the procedure described by Cheah et al. (2023, 2021). Moderated mediation occurs when the strength or significance of the mediation pathway varies across levels of the moderator, providing a more nuanced understanding of the underlying mechanisms (Karazsia et al., 2013). We performed a multigroup analysis (MGA) with firm size as the moderator, categorising firms as either large or medium. To ensure the validity of this comparison, we first tested for measurement invariance using the Measurement Invariance of Composite Models (MICOM) procedure (Henseler et al., 2016). This step confirms that the constructs are interpreted consistently across groups, thereby addressing potential differences in cultural values, scale interpretation, or response styles that could introduce systematic bias (Hair et al., 2017b). Our analysis revealed complete measurement invariance for the CEPs construct, whereas DTs and DCs exhibited partial invariance (Table 11). This partial measurement invariance suggests that any differences in model estimates across groups reflect genuine variation rather than measurement error, thereby supporting the reliability of our multigroup analysis.

We applied the permutation test to groups to determine whether the strength of relationships differs between group-based estimates, and whether these differences are statistically significant (Chin and Dibbern, 2010). A p-value of 0.047 (Table 12) suggests a significant difference (0.126) in the mediated effect between large and medium firms (H6 supported). The mediated effect was substantial for large firms (the 90% PBCI excludes zero), but not for medium firms. Notably, a difference of 0.19 emerged between large and medium firms for the relationship between DCs and CEPs (H4 supported), and a difference of −0.185 emerged between large and medium firms for the relationship between DTs and CEPs (H5 supported). In contrast, the difference is not significant for the relationship between DTs and DCs (H3 not supported) (Table 12).

5.5. Gaussian copulas

To address potential endogeneity concerns, we employed a Gaussian copula analysis following the approach outlined by Hult et al. (2018). First, we assessed the distribution of the standardised composite scores for DTs, DCs, and CEPs using the Kolmogorov–Smirnov test with Lilliefors correction. As none of the constructs exhibited normally distributed scores (p-value <0.05), the use of Gaussian copulas for endogeneity testing was justified. However, none of the copulas were statistically significant, suggesting that endogeneity is not an issue in this model and further supporting the reliability of the estimated structural relationships (see Appendix B).

6. Discussion

6.1. Digital-enabled dynamic capabilities for circular economy and the role of firm size

Through our analysis, we confirmed that the adoption of DTs is associated with the implementation of CEPs (H1 supported). This aligns with previous literature and, as outlined in section 3.1, is overall expected. However, as we tried to understand precisely how the relationship works, we found conflicting insights. For instance, autonomous robots facilitate disassembly practices for Sarc et al. (2019) but not for Masi et al. (2018). We therefore need to identify the mechanisms and contingencies that can influence the relationship. Regarding mechanisms, we focused on the presence of a transitive path, which may explain the conflicting insights (Neri et al., 2025). We addressed the role of digital-enabled DCs as mediators of the relationships between DTs and CE. Our analysis revealed a transitive path, confirming the propositions of Neri et al. (2023b) and Bag et al. (2024) that DTs enable DCs, which in turn can support the implementation of CEPs (H2/ce:cross--ref> supported). However, given previous findings from other studies, we would have expected the transitive path to be stronger. In our investigation, the proportion of the total effect explained by the indirect pathway is moderate (9.6%); Kumar et al. (2025) however, review literature on the mediating effect of supply chain integration and flexibility, finding that between 19% and 35% of the total effect is due to mediation, with percentages varying based on countries' characteristics. Our results suggest that the implementation of CEPs may be more closely related to DTs themselves than to the business transformations resulting from their adoption. This observation contrasts with previous evidence, e.g., (Liu et al., 2022; Neri et al., 2023a), emphasising that DTs are adopted primarily for production and efficiency reasons, with firms realising their potential for CE only at a later stage. Additionally, Sánchez-García et al. (2024) stressed that to properly integrate DTs, adapting established methods and developing new skills are necessary, and that despite adopting DTs, complete alignment with CE is not achieved.

The analysis of contingencies, specifically the conditional mediation analysis, provides further insights, shedding light on possible reasons for the contrasting results. When firm size is considered as a moderator of the mediated relationship, the transitive path takes on a different valence depending on the group considered. Indeed, the transitive path appears stronger for large firms than for medium ones. This suggests that, compared to medium-sized firms, the implementation of CEPs in larger firms is generally associated with the presence of digital-enabled DCs. This is a relevant result because it highlights that firm size influences the ability to generate and exploit DCs (Huang et al., 2023), supporting the capabilities asymmetries described by Ngo et al. (2026). However, this consideration is still partial. Indeed, smaller firms might lag in generating digital-enabled DCs (AL-Khatib, 2023), in exploiting DCs for CE (Järvenpää et al., 2025), or in both. Specifically, while a difference in the transitive path exists between medium and larger firms, we need to explore further whether this difference already begins in the generation of digital-enabled DCs or is explicitly focused on their exploitation. Firm size does not appear to be a strong moderator of the ability to generate digital-enabled DCs from DTs adoption. The results do not support the formulated hypotheses and contrast the widespread notion that smaller firms might face more difficulties in generating digital-enabled DCs. Nonetheless, the evidence Garbellano and Da Veiga (2019) regarding the possible generation of digital-enabled DCs from Industry 4.0 adoption in SMEs is backed. However, if digital-enabled DCs are generated in the same way in both groups, they are exploited differently. Firm size appears to influence firms' ability to exploit

Table 11
Results of the measurement invariance of composite models (MICOM) procedure.

	Step 1	Step 2			Step 3a				Step 3 b				
	Configural Invariance	Compositional Invariance			Equal variances				Equal means				
		Original Correlation	5%	Partial Measurement Invariance established	Variance-Original Difference (LA-ME)	5%	95%	Equal	Mean-Original Difference (LA-ME)	5%	95%	Equal	Full Measurement Invariance Established
CEPs	Yes	0.994	0.992	Yes	0.178	−0.274	0.239	Yes	−0.158	−0.209	0.176	Yes	Yes
DTs	Yes	0.999	0.999	Yes	0.265	−0.229	0.229	No	−0.295	−0.199	0.185	No	No
DCs	Yes	1	0.999	Yes	0.486	−0.3	0.276	No	−0.091	−0.186	0.181	Yes	No

Table 12
Differences in mediated effects between large and medium firms.

	Large (n = 127)				Medium (n = 211)				Large-medium	
Direct effect	Path	t-value	p-value	PBCI (90%)	Path	t-value	p-value	PBCI (90%)	Difference	Permutation p-value
H3: DTs → DCs	0.663	12.773	0*	[0.576; 0.747]	0.691	16.943*	0	[0.62; 0.759]	−0.028 ns	0.3262
H4: DCs → CEPs	0.191	2.334	0.01*	[0.052; 0.326]	0.001 ns	0.017*	0.493	[-0.118; 0.128]	0.19*	0.0422
H5: DTs → CEPs	0.499	6.124	0*	[0.365; 0.631]	0.684	11.276*	0	[0.583; 0.785]	−0.185*	0.0278
Mediated effect	**Path**	**t-value**	**p-value**	**PBCI (90%)**	**Path**	**t-value**	**p-value**	**PBCI (90%)**	**Difference**	**Permutation p-value**
H6: DTs → DCs → CEPs	0.127	2.2	0.014*	[0.035; 0.225]	0.001 ns	0.017	0.493	[-0.083; 0.089]	0.126*	0.047

digital-enabled DCs, with larger firms being better able to utilise them to support CEPs implementation. This result partly confirms the findings of Soluk et al. (2023), who noted the presence of DCs in SMEs but emphasised their inability to exploit them for disruptive innovation, and of Arroyabe et al. (2024), who asserted that DTs could lead to innovation in SMEs only through informed decision-making in the context of priority-setting. Overall, the findings suggest that, although both large and medium-sized firms enable DCs through DTs adoption, larger firms can leverage these capabilities more effectively to implement CEPs. The scale advantage of large firms probably benefits the most resource-intensive phase, the transformation of the organisation to integrate CEPs, more than the initial phases of sensing or seizing opportunities.

6.2. Paving the way for a future research agenda

Based on the results of the conditional mediation analysis performed and current trends in research and practice, we identify and discuss knowledge limitations and future research streams to further examine the relationship between the adoption of DTs and the implementation of CEPs.

Future direction n.1. Do DTs enable DCs equally, and do digital-enabled DCs support *the implementation of CEPs in the same way?* Previous research has shown that DTs and DCs can make distinct contributions (Neri et al., 2023b), yet empirical analyses are scarce. It would be essential to examine the different phases of DCs (sensing, seizing, and transforming) to determine whether DTs equally enable them, whether they are equally exploited, and whether they contribute similarly to the implementation of CEPs. For example, Pedota (2023) notes that SMEs typically have lower seizing capability. Similarly, Kanda et al. (2025) stress that sensing and seizing capabilities are only related to awareness and competencies, whereas only the reconfiguration capability can lead to circular ecosystems. In our analysis, the sensing, seizing, and transforming phases are used to inform the operationalisation of digital-enabled DCs, but DCs were analysed as a higher-order construct. To fully grasp business transformations, it would be essential to explore the microfoundations and to understand the similarities and differences among diverse firms, an aspect currently mostly overlooked by the literature.

Future direction n.2. Does the exploitation of digital-enabled DCs lead to higher performance from the implementation of SMEs? From our results, it emerged that the direct relationship between DTs and CE is stronger than the mediated one: the digital-enabled DCs do not appear as a prerequisite for CE implementation; rather, they might help firms understand how to make their CEPs more impactful. Indeed, the business transformations resulting from DCs have the potential to create new business models, but, based also on our results, we cannot assume they will lead to higher performance. Previous studies have suggested a positive effect of DCs on performance (Marrucci et al., 2022; Ortiz-Avram et al., 2024), while others note that the impact on performance can be more substantial when digital-enabled DCs drive business transformation (Yoshikuni et al., 2025). More investigation is needed on the topic, and previous research (Li et al., 2022; Mai et al., 2026) suggested that contextual factors can influence a general positive effect of DTs, CE, and digital-enabled DCs on firms' performance.

Future direction n.3. Do other contextual factors moderate the relationship between DTs, DCs, and CEPs? The literature recognised several contextual factors beyond firm size, such as country, sector, and how digitalisation and CE are perceived and addressed within firms (Kumar et al., 2025; Neri et al., 2025), which were not considered by the present study. As contextual factors have been shown to influence a firm's innovation and CE behaviour (Sadiq et al., 2026), further analyses employing a conditional mediation model are required to shed light on their roles. For instance, in smaller enterprises, the positive relationship between DTs, digital-enabled DCs, and CEPs might be mediated by the availability of organisational slack (e.g., underutilised human capital and dedicated budgets for digitalisation), suggesting that resource scarcity is the fundamental constraint on the development of these capabilities.

Future direction n.4. Does a country's institutional framework influence the level of DTs and CEPs adoption and implementation? Does it affect the presence and importance of digital-enabled DCs? When discussing differences based on country, it is impossible to avoid considering its institutional framework. Digitalisation and CE implementation are both tied to formal institutions (Yin et al., 2024), and government support is fundamental to fostering them (Sánchez-García et al., 2024). It is also interesting to consider the impact of informal institutions, such as customers (M. I. Khan et al., 2025), on the emergence of isomorphism in this context. While institutional theory has already been applied to the study of CE implementation (Karuppiah et al., 2024a), it would be beneficial to examine the relationship between DTs and CE.

6.3. Contributions of the study

6.3.1. Theoretical contribution

The present research advances the theory of digital-enabled DCs by empirically investigating their mediating role in the intricate relationship between DTs and CEPs. It responds to calls from previous studies for further empirical research on the topic (Kumar et al., 2025; Neri et al., 2025). A key contribution lies in the study's comprehensive scope. Unlike previous research, which often focused on specific DTs or individual DCs, this study investigated a broad spectrum of DTs while considering all three critical DCs phases (sensing, seizing, and transforming). For example, Pattanayak et al. (2024) focused solely on blockchain technology and Oliveira-Dias et al. (2023) limited their scope to cloud computing, big data analytics, and the Internet of Things. Similarly, research has focused on specific capabilities, such as analytical capabilities (Karuppiah et al., 2024b) and artificial intelligence capabilities (Sjödin et al., 2023).

Furthermore, unlike previous studies, e.g., Bag et al. (2024) and Sjödin et al. (2023), which explored connections between DCs and broader concepts such as circular business models or digital CE innovation, this study uniquely investigates the impact of digital-enabled DCs across a wide range of CEPs. Finally, this study makes a significant contribution by employing a mediated-moderated analysis. By incorporating firm size as a crucial moderating factor, the research provides valuable insights into how the relationship between DTs, digital-enabled DCs, and CEPs varies across firms of different sizes. This advances current knowledge and provides a deeper understanding of the relationship between DTs adoption and CEPs implementation.

Further, the study, reasoning from current knowledge limitations, proposed future research directions to be investigated to analyse in more detail the mechanisms and contingencies characterising the relationship between the adoption of DTs and the implementation of CE.

6.3.2. Practical contribution

The present research offers practical implications, proposing ways to leverage DTs to enhance competitiveness and transition towards CE.

As DCs are essential for reconfiguring businesses to stay competitive in a volatile, rapidly changing environment, manufacturing firms should make the most of DTs by understanding how they can support the grasp of market dynamics and the reconfiguration of current systems. They should also consider how these transformations could be exploited for CE purposes. In doing so, firms must acknowledge and address potential asymmetries related to firm size. Smaller firms may face difficulties in developing and utilising digital-enabled DCs due to resource constraints and limited access to expertise. As collaboration among stakeholders can facilitate DCs for CE (Khan et al., 2020a), smaller firms are encouraged to establish fruitful partnerships with stakeholders. This could enable firms to adopt DTs and implement CEPs beyond their own boundaries by leveraging horizontal system integration or industrial symbiosis, for example. Cultivating internal awareness and capabilities is crucial. Firms must invest in developing internal expertise in areas such as DTs and sustainable production and consumption. Additionally, raising employees' understanding of the principles of the CE is essential for driving internal change and encouraging engagement.

Awareness of (and the conditions for the proper exploitation of) DCs should not only come from firms. Policymakers are advised to support the implementation of CEPs by adopting DTs and providing adequate, consistent informational and economic instruments. They should also develop regulations that favour the digital transformation of the manufacturing sector. As for our results, support should be tailored to the specific characteristics and needs of firms. This could include facilitating interaction between firms and external consultants.

Eventually, improving the effectiveness of digital-enabled DCs in driving the CE requires an integrated approach that addresses both policy and operations. More in detail, it would be highly beneficial to establish regional enablers, such as shared digital hubs and industrial symbiosis systems within clusters, which would help overcome systemic barriers, such as fragmented data governance and financing risks, especially for smaller firms (Rissola and Sörvik, 2018). At the operational level, a three-phase capability-building roadmap could be proposed, tailored to firm size: smaller firms should focus on resource mobilisation and low-cost solutions for sensing and seizing capabilities, whereas larger firms should prioritise integrating complex systems and organisational renewal to achieve systemic impact and scale up CEPs.

7. Conclusions

This study examines the relationship between DTs and CEPs. Unlike previous literature, we used conditional mediation analysis to estimate and evaluate the mediating effect of digital-enabled DCs and the moderating effect of firm size.

An extensive empirical investigation was conducted in manufacturing firms, and the results were analysed using PLS-SEM. Our findings reveal that the adoption of DTs influences the implementation of CEPs, both directly and via digital-enabled DCs. Although the mediated path was weaker than expected, conditional mediation analysis revealed that firm size significantly moderates the transitive path, which appears stronger in large firms than in medium-sized ones. Larger firms are more likely to associate CEPs implementation with the exploitation of digital-enabled DCs. This study provides interesting insights for practitioners, policymakers, and academics to foster support for the adoption of DTs to facilitate CE implementation and offers future research directions.

Despite its contributions, this study is subject to several limitations that should be acknowledged and further justify the future research directions outlined in the previous section. While some limitations have already been discussed in Section 6.2 in terms of current knowledge limitations paving the way for future research streams, in the following, the focus is on limitations related to the sample and the method employed. Our empirical analysis focuses on large and medium-sized firms and is restricted to specific geographical contexts. This might limit the generalizability of the findings. Small firms may face different constraints in terms of resources, digital maturity, and organisational structure, which could significantly affect their ability to adopt DTs, develop and exploit digital-enabled DCs, and implement CEPs. Extending the analysis to a broader range of firm sizes and geographical contexts is a valuable avenue for future research. Further, our study adopts a cross-sectional design, which limits our ability to capture the dynamic and evolutionary nature of the relationships between DTs and CE. Future research could benefit from longitudinal designs based on multiple waves of panel data (Erdem et al., 2025). Such an approach would enable a more precise estimation of how changes in DTs adoption over time influence the emergence, reconfiguration, and persistence of DCs. Finally, our firm-level focus does not fully reflect the systemic and inter-organisational nature of many CEPs, nor the contexts in which the benefits of DTs materialise only when multiple organisations along the value chain adopt them. Future research adopting an ecosystem or value-chain perspective could also contribute to understanding strategic alignment among actors, governance mechanisms, data-sharing arrangements, and power asymmetries within ecosystems (Urueña et al., 2024). Overall, the limitations point to opportunities for future research to deepen our understanding of the relationship between DTs and CE across firms, institutions, and ecosystems.

CRediT authorship contribution statement

Alberto Urueña: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Alessandra Neri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Enrico Cagno:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **Ebru Susur:** Writing – review & editing, Validation, Methodology, Investigation.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

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Appendix A

Overview of the support provided by individual DTs to CE implementation.

Digital technology	Brief description of use	Supporting reference	Circular economy aspects supported	Supporting reference	How the digital technology supports the circular economy
Internet of things	It facilitates interaction, cooperation, data collection and exchange.	Rejeb et al. (2022)	Different strategies, such as recovery, recycling, repair, remanufacture and reuse	Carlos et al. (2024)	It provides real-time data on asset condition and location, enabling predictive maintenance (repair), accurate tracking for product recovery, and immediate feedback for resource efficiency.
			Practices related to resource efficiency, such as reducing resource and energy consumption	Awan et al. (2021)	
			Raised awareness of circular opportunities	Ghoreishi and Happonen (2022)	
Big data analytics	It enhances data processing and decision-making through data-driven insights.	Carlos et al. (2024)	Different strategies, such as remanufacturing, reuse, recycling, and resource efficiency	Hallioui et al. (2022)	It facilitates pattern recognition and optimization, allowing firms to predict material flows, improve reverse logistics, and identify the most valuable CE strategies across the product lifecycle.
			Control on parameters for energy production, helping reduce related emissions	Neri et al. (2023a)	
			Collection and analysis of data on the production processes	Neri et al. (2023a)	
Artificial intelligence	It improves process quality through data analysis.	Chuah et al. (2016)	Circular design and lifecycle thinking	Awan et al. (2022)	It enables automated decision-making and complex design optimization, allowing for smart sorting in waste management and predicting resource demand to minimize consumption and waste.
			Waste management, resource efficiency and optimization of processes	Laskurain-Iturbe et al. (2021)	
Cloud computing	It enables data storage and sharing and can promote traceability.	Gebhardt et al. (2022)	Different strategies, such as reuse, remanufacturing and recycling	Sharma et al. (2023)	It provides the shared infrastructure for data storage and processing, which is essential for collaborative CE models (e.g., product-as-a-service) and real-time data access across the value chain.
Cybersecurity and blockchain	They ensure transparency, traceability and cyber-environment protection.	Carlos et al. (2024)	Renovation of supply chains and business models	Prakash and Ambedkar (2023)	It ensures immutable traceability and transparency of materials and transactions, building the necessary trust and verifiable history for high-value recovery, repair, and circular supply chain integrity.
Additive manufacturing	It enables producing items by layering material, also allowing the creation of complex parts not feasible with traditional methods.	Guo and Leu (2013)	Circular design	Sauerwein et al. (2019)	It allows for on-demand, localized production and repair of custom parts, drastically reducing material waste, inventory needs, and logistics impacts.
			Reduced waste	Burmaoglu et al. (2022)	
			Use of recovered materials	de Mattos Nascimento et al. (2022)	
			Support to testing activities, reducing the environmental impact of shipping prototypes	Neri et al. (2023b)	
Simulation	It allows the testing and optimization of systems before implementing physical changes.	Rosa et al. (2020)	Disassembly and maintenance	Charnley et al. (2019)	It creates virtual environments to test and optimize complex CE processes (e.g., disassembly sequences, remanufacturing flows) before physical implementation, saving time and resources.
			Remanufacture	Khan et al. (2021)	
			Circular supply chain	Romagnoli et al. (2023)	
			Logistics practices	Neri et al. (2023a)	
Autonomous robots	They facilitate the automation of production and logistics processes.	Fragapane et al. (2020)	Recycling and recovery	Laskurain-Iturbe et al. (2021)	It automates labor-intensive and complex tasks like sorting, disassembly, and precise material handling, improving the efficiency and purity of recycling and recovery processes.
			Disassembly	Kayikci et al. (2022a)	
			Resource-efficiency and circular design practices	De Marchi and Di Maria (2020)	
Horizontal and vertical systems integration	They enable an automated value chain between and within firms	Pérez-Lara et al. (2020)	Several stages of the life cycle of a product, such as dematerialization, recycling and end-of-life	Chauhan et al. (2022)	It creates seamless data flow between different stages of the value chain and production, which is essential for coordinating cross-functional CE initiatives and reducing dematerialization efforts.
	The systems can be divided into levels, i.e., vertical (within the firm) and horizontal (among firms).	Blichfeldt and Faullant (2021)	Control of production related issues (vertical)	Dev et al. (2020)	

(continued on next page)

(*continued*)

Digital technology	Brief description of use	Supporting reference	Circular economy aspects supported	Supporting reference	How the digital technology supports the circular economy
			Coordination along the value chain and with other value chains (horizontal)	Neri et al. (2023b)	
Augmented reality	It employs digital tools to access virtual space superimposed on physical space	Abari et al. (2017)	Virtualisation strategies - ref. ReSOLVE framework (Ellen MacArthur Foundation, 2015)	Bressanelli et al. (2022)	It enhances CE implementation by providing real-time, context-aware visualization and guidance during design, manufacturing, maintenance, and disassembly processes, enabling more precise material use, easier component separation, reuse, and reallocation.
			Disassembly	Kayikci et al. (2022b)	
			Resource efficiency and recycling	Oyinlola et al. (2022)	

Appendix B

Gaussian copula results on CEPs.

	Original model		Gaussian copula model one (copula added DT)		Gaussian copula model two (copula added DC)		Gaussian copula model three (copula added DT, DC)	
Variable	Value	p-value	Value	p-value	Value	p-value	Value	p-value
DTs	0.600	0.000	0.676	0	0.600	0	0.671	0
DCs	0.100	0.069	0.101	0.066	0.131	0.109	0.113	0.180
C_{DTS}			-0.070^{ns}	0.310			-0.065^{ns}	0.371
C_{DCs}					-0.025^{ns}	0.610	-0.010^{ns}	0.854

Data availability

The authors do not have permission to share data.

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