

RESEARCH ARTICLE

The role of dynamic capabilities in circular economy implementation and performance of companies

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Abstract

Although most companies perceive that they might not be able to implement a circular economy (CE), some scholars perceive that companies may do so by developing dynamic capabilities (DCs). To empirically investigate the role of DCs in CE implementation, we analyzed a sample of 220 companies in Italy through partial least squares structural equation modeling (PLS-SEM). Our PLS-SEM analysis demonstrates that DCs and their underlying organizational activities significantly facilitate CE implementation, which consequently improves the overall performance of companies. Moreover, a circular dynamic environment (CDE) may stimulate companies towards CE implementation. This paper contributes to the literature in the following manner. First, this paper highlights how companies can identify and pursue CE opportunities. Second, this paper contributes to the debate on the role of a dynamic environment and how DCs leads to performance. Third, this paper presents the measurement scales of DCs and shows how to operationalize a hierarchical component model (HCM) in PLS-SEM.

KEYWORDS

circular dynamic environment, circular economy, corporate sustainability, dynamic capabilities, organizational performance, PLS-SEM

1 | INTRODUCTION

Circular economy (CE) has been seriously discussed by scholars and practitioners (Merli, Preziosi, & Acampora, 2018). They believe that CE is vital for sustainable development (Ghisellini, Cialani, & Ulgiati, 2016). Notably, the Ellen MacArthur Foundation (2013) points out that CE, being a straightforward strategy for corporate sustainability (Murray, Skene, & Haynes, 2017), can ultimately overcome global sustainability challenges by improving resource productivity. Hence, the EU and several national governments have been engaging companies for CE implementation (Korhonen, Honkasalo, & Seppälä, 2018). However, most companies perceive that they cannot transform their business operations, which are predominantly based on a linear economy, into a CE business model due to various barriers (Ormazabal, Prieto-Sandoval, Puga-Leal, & Jaca, 2018). In contrast, some scholars perceive that companies

may do so by developing dynamic capabilities (DCs) (Kabongo & Boiral, 2017; Khan, Daddi, & Iraldo, 2020).

Teece, Pisano, and Shuen (1997) define DCs as “*the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing [dynamic] environment*” (p. 516). They argue that DCs are processes and/or activities through which a company reconfigures its strategy and resources in order to accomplish a sustainable competitive advantage. Scholars and practitioners often remark that CE can provide a sustainable competitive advantage to companies. For instance, van der Heijden (2018) remarked that “*companies that can do more with less have a massive competitive advantage over those that have to scabble around for expensive resources – and pay for their own pollution*”. However, the transition towards a CE is not so simple rather a complex process that demands an organizational change (Ritzén & Sandström, 2017). Mousavi, Bossink, and van Vliet (2018) argue that the ability and willingness of a company to

implement an organizational change are dependent on its DCs. Hence, DCs are crucial for achieving CE (Khan et al., 2020).

The theory of dynamic capabilities (DCV) has been increasingly employed in the corporate sustainability studies (Annunziata, Pucci, Frey, & Zanni, 2018; Hofmann, Theyel, & Wood, 2012; Wu, He, & Duan, 2013). Somewhat surprisingly, DCV is still underused in environmental management studies (Daddi, Todaro, De Giacomo, & Frey, 2018). To date, only a few studies have employed DCV in the CE context (Kabongo & Boiral, 2017; Khan et al., 2020; Scarpellini, Valero-Gil, Moneva, & Andreaus, 2020). Although Kabongo and Boiral (2017) and Khan et al. (2020) show that DCs may facilitate CE implementation, insights of these case studies may not be generalized. Hence, the role of DCs for CE implementation needs to be further explored and thoroughly tested. Scholars argue that DCs involves substantial costs (Winter, 2003) thus companies would be hesitant to use DCs without having any compelling reason or knowing potential benefits (Wilden, Gudergan, Nielsen, & Lings, 2013). Here, we assume that companies might not be interested in developing DCs for CE objectives unless they are sure that this would consequently improve their overall performance (Gusmerotti, Testa, Corsini, Pretner, & Iraldo, 2019). However, to the best of our knowledge, the relationship between CE implementation and the overall performance of companies is not yet thoroughly tested.

To contribute to this knowledge gap, we investigate whether or not DCs and their underlying organizational activities facilitate CE implementation. If so, to what extent DCs and CE implementation improve the overall performance of companies. Furthermore, we assess whether or not a circular dynamic environment (CDE) influences CE implementation. This paper contributes to the literature of both DCV and CE in the following manner. Firstly, this paper empirically assesses the role of DCs in CE implementation using the partial least squares structural equation modeling (PLS-SEM). Accordingly, this paper highlights how companies can identify and pursue CE opportunities. Secondly, this paper responds to the research calls that demand more research on DCs for CE (Prieto-Sandoval, Jaca, Santos, Baumgartner, & Ormazabal, 2019) and corporate sustainability (Amui, Jabbour, de Sousa Jabbour, & Kannan, 2017). Thirdly, this paper investigates interrelationships of CDE and CE implementation along with DCs and the overall performance of companies. Thus, this paper simultaneously contributes to both ongoing debates in DCV research: (a) how DCs leads to improved performance, and (b) what is the role of a dynamic environment. Fourthly, this paper presents the measurement scales and shows the operationalization of DCs as a hierarchical component model (HCM) in PLS-SEM (Sarstedt, Hair, Cheah, Becker, & Ringle, 2019).

The rest of the paper proceeds as follows. Section 2 presents the theoretical framework and accordingly formulates the hypotheses. Section 3 describes how the constructs are operationalized, data is collected, and hypotheses are tested. Section 4 presents the results, whereas Section 5 discusses these results and underlying implications. Finally, Section 6 concludes the discussion, highlights the limitations and suggests some future research opportunities.

2 | THEORETICAL FRAMEWORK AND HYPOTHESES

DCs generate new knowledge, products, and processes that provide competitive advantages (Helfat et al., 2007). Scholars argue that DCs are an aggregation of organizational routines or activities (Winter, 2003) through which companies attain new resource configurations (Eisenhardt & Martin, 2000). Teece (2007) explicated that DCs can be classified into three dimensions as "(1) to sense and shape opportunities and threats, (2) to seize opportunities, and (3) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the firm's intangible and tangible assets" (p. 1319). These dimensions are generally known as "sensing", "seizing", and "reconfiguring". DCs are undergirded by "microfoundations", that is, "distinct skills, processes, and organizational activities" (Teece, 2007).

Hart (1995) pointed out that companies may encounter various unexpected challenges during their transition to corporate sustainability. Many scholars have substantiated the above statement. For instance, Ormazabal et al. (2018) found that companies are failing to adopt CE due to various barriers. Nevertheless, some scholars argue that both corporate sustainability and CE demand an organizational change (Ritzén & Sandström, 2017; Strauss, Lepoutre, & Wood, 2017). Hence, DCs are crucial for achieving both corporate sustainability and CE (Annunziata et al., 2018; Khan et al., 2020; Scarpellini, Marín-Vinuesa, Aranda-Usón, & Portillo-Tarragona, 2020). Put differently, DCs of a company determine its ability and willingness to implement the required changes for corporate sustainability (Mousavi et al., 2018). Scholars widely acknowledge that DCs are patterned activities that systematically solve problems (Amui et al., 2017). Wu et al. (2013) pointed out that "whether firms can overcome sustainability challenges lies in the development and application of their dynamic capabilities" (p. 257). Few scholars have recently substantiated the above statement (Kabongo & Boiral, 2017; Khan et al., 2020; Mousavi & Bossink, 2017).

Khan et al. (2020) pointed out that "sensing", "seizing", and "reconfiguring" can be referred to as a sequential process through which companies identify and pursue CE opportunities. They explicated that sensing is a set of activities that aim to identify new opportunities by scanning, learning, and interpretation. These activities usually involve knowing customer needs, analyzing market trends and competitors' actions, interpreting suppliers' feedback, and doing research and development (R&D) (Teece, 2007). We assume that those companies that have appropriate sensing capabilities are more likely to successfully identify CE opportunities. Khan et al. (2020) explicated that seizing is a set of activities, which usually involve planning and mobilization of resources, that aim to implement newly identified opportunities. They further explicated that reconfiguring is the ability of a company to reconfigure new resources, and/or to recombine its existing resource base (Helfat et al., 2007), in order to accomplish a newly identified opportunity (Khan et al., 2020). We assume that those companies that have appropriate seizing and reconfiguring capabilities are more likely to accomplish CE opportunities.



Even though corporate sustainability demands internalizing environmental and social concerns into business models which increase dynamism and add complexity (Arend, 2014), DCs are highly valuable in dealing with such complexities (Eikelenboom & de Jong, 2019). Indeed, scholars have a broad consensus on the significance of DCs for corporate sustainability (Amui et al., 2017). Prieto-Sandoval et al. (2019) used DCV to explore proactive environmental strategies for CE. They pointed out some DCs for CE implementation. Scarpellini, Valero-Gil, et al. (2020) investigated the cause-and-effect relationship between environmental capabilities and circular eco-innovation. They found a positive relationship between environmental capabilities and circular eco-innovation. Arend (2014) found a positive relationship between DCs and green activities. Some scholars have recently highlighted DCs as determinants or facilitators of CE. For instance, Kabongo and Boiral (2017) and Khan et al. (2020) show that DCs facilitate CE implementation. Hence, we may assume that there is a positive relation between DCs and CE implementation.

Scholars point out that a dynamic environment is an important contextual variable for DCV research. Dess and Beard (1984) referred a dynamic environment as “an external environment of a company where changes cannot be easily predicted”, whereas Wijbenga and van Witteloostuijn (2007) referred this concept as “the speed at which the preferences of customers and products or services of a company change”. A dynamic environment can be interpreted as the pace of changes and innovations in the industry and the unpredictability of customers' or competitors' actions. Scholars highlight that a dynamic environment forces a company to develop better DCs, which creates new or specific knowledge and nurtures creative thinking leading to innovativeness (Petrus, 2019). That is, DCs directly fight against a dynamic environment (Teece et al., 1997). Put differently, a dynamic environment drives a company to cultivate DCs (Li & Liu, 2014).

In the CE context, we argue that CDE is a driving force of both DCs and CE. We define CDE “as a momentum, that is, a push by customers, governments, and competitive intensity, towards CE”. Scholars highlight that disruptive events such as drastic market change or the introduction of a radically new technology may stimulate companies to develop and apply DCs in order to innovate circular products (Scarpellini, Valero-Gil, et al., 2020). Wilden et al. (2013) pointed out that a company may not require or put to use DCs unless that company faces some degree of competitive intensity. Some scholars argue that stakeholders' pressures positively affects the adoption of CE business models (Prieto-Sandoval et al., 2019). Scarpellini, Marín-Vinuesa, et al. (2020) found that stakeholders' pressures directly affect the environmental capabilities for CE. Furthermore, such environmental capabilities mediate the relationship between stakeholders' pressures and the circular scope of a company. Thus, we may hypothesize that DCs mediate the relation between CDE and CE implementation. We argue that the effects of DCs on CE implementation might be enhanced when a company would be facing an intense CDE. In light of the above discussion, we propose our first, second, and third hypotheses as following (see Figure 1):

Hypothesis 1 *Circular dynamic environment (CDE) is positively related to circular economy implementation level (CE).*

Hypothesis 2 *Dynamic capabilities (DCs) are positively related to circular economy implementation level (CE).*

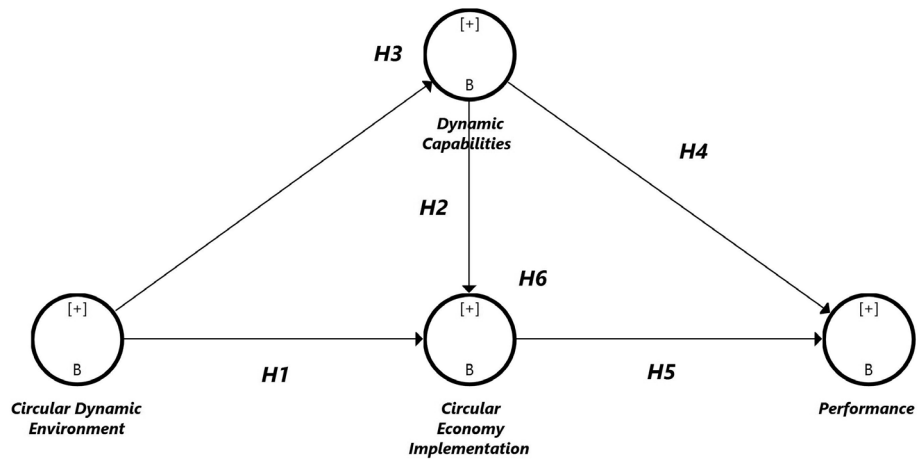
Hypothesis 3 *The relation between circular dynamic environment (CDE) and circular economy implementation level (CE) is mediated by dynamic capabilities (DCs).*

Scholars have been hotly debating on whether and how DCs lead to competitive advantage or improved performance. Teece et al. (1997) assumed that DCs directly impact the performance of a company. Eisenhardt and Martin (2000) reckoned that DCs do not necessarily lead to improved performance. They pointed out that competitive advantage or improved performance does not rely on DCs themselves, rather on the resource configurations created by DCs. Wilden et al. (2013) found that DCs alone does not lead to superior performance; the ability of a company to attain superior performance is contingent on a dynamic environment. That is, the context within which DCs are deployed affects performance. Schilke (2014) shows that a dynamic environment moderates the relation between DCs and competitive advantage. Also, Wilden et al. (2013) show that competitive intensity moderates the relation between DCs and performance. We expect that CDE positively moderates the relation between DCs and the performance of companies. Although some scholars found negative or insignificant effects (Protogerou, Caloghirou, & Lioukas, 2012; Wilden et al., 2013), most scholars generally agree that DCs positively affect the performance of companies (Drnevich & Kriauciunas, 2011; Pezeshkan, Fainshmidt, Nair, Lance Frazier, & Markowski, 2016).

There are plentiful empirical studies on the relation between DCs and performance. However, research on mediating mechanisms of DCs effects is very scarce (Zhou, Zhou, Feng, & Jiang, 2019). Wilden et al. (2013) suggest incorporating mediating mechanisms into the relation between DCs and performance. Zhou et al. (2019) hypothesized a mediating role of innovation between DCs and financial performance. They concluded that DCs facilitate different types of innovation that in turn improve the financial performance of a company. Scholars generally acknowledge that CE activities lead to improved environmental or financial performance of companies (Scarpellini, Marín-Vinuesa, et al., 2020). Notably, Zhu, Geng, and Lai (2010) contended that CE practices are positively related to the environmental and financial performance of a company. Thus, we may assume that there is a positive relation between CE implementation and the overall performance of companies. Furthermore, we hypothesize that CE acts as a mediator that determines the relation and stipulates the extent to which DCs influence on the overall performance of a company. In light of the above discussion, we propose our fourth, fifth, and sixth hypotheses as following (see Figure 1):

Hypothesis 4 *Dynamic capabilities (DCs) are positively related to overall performance (PER) of a company.*

FIGURE 1 Research model (Hypotheses)



Hypothesis 5 Circular economy implementation level (CE) is positively related to overall performance (PER) of a company.

Hypothesis 6 The relation between dynamic capabilities (DCs) and overall performance (PER) of a company is mediated by circular economy implementation level (CE).

3 | METHODOLOGY

3.1 | Questionnaire development

We followed the recommended guidelines to develop the questionnaire (Churchill, 1979). Firstly, we reviewed relevant literature to identify indicators related to the constructs in question. Preferably, we gathered indicators from empirical studies wherever it was possible. Otherwise, we created new indicators based on conceptual studies. Next, we drafted a trial questionnaire with selected indicators. Four academicians and practitioners carefully assessed the trial questionnaire which led to refinement of indicators wording and reduction of numbers of indicators. Then, we translated the questionnaire from English to Italian. We assumed that questionnaire in a native language may increase the response rate. Finally, we preliminary tested our questionnaire with some companies. The obtained data satisfied the psychometric properties described in Section 4.1. That is, the aforementioned step confirmed the suitability and validity of our questionnaire.

3.2 | Constructs and measures

We proposed a hierarchical component model (HCM) based on first-order and second-order constructs (Sarstedt et al., 2019). That is, we operationalized the main constructs of the present study with respective sub-constructs. We constructed circular dynamic environment (CDE) as a second-order construct with three first-order constructs, namely market turbulence (CDE-MT), technology turbulence (CDE-TT), and competitive intensity (CDE-CI). To measure the construct of

CDE, we adapted indicators from previous studies (Carter & Carter, 1998; Jaworski & Kohli, 1993; Narver, Slater, & MacLachlan, 2004). In the questionnaire, we asked companies to evaluate CDE indicators (see Table 1) on a Likert scale (1. *strongly disagree*, 2. *disagree*, 3. *undecided*, 4. *agree*, 5. *strongly agree*).

We constructed circular economy implementation level (CE) as a second-order construct with three first-order constructs, namely design and production (CE-DP), consumption and collection (CE-CC), and recycling and resourcing (CE-RR). Although the design, production, consumption, collection, recycling, and resourcing are distinct phases of the CE cycle, we combined adjacent phases for two reasons. First, to maintain the uniformity of our proposed HCM. Second, to avoid first-order constructs having only one indicator. We considered all phases of CE since different companies may have adopted different CE practices. To measure the construct of CE, we partly developed indicators and partly adapted from previous studies (Zhu et al., 2010). We asked companies whether they have been considering or implementing the listed CE practices (see Table 2) on a Likert scale (1. *not considering it*, 2. *planning to consider it*, 3. *considering it*, 4. *initiating implementation*, 5. *implementing successfully*) (Zhu et al., 2010).

We constructed dynamic capabilities (DCs) as a second-order construct with three first-order constructs, namely sensing (DC-SEN), seizing (DC-SEI), and reconfiguring (DC-REC). We mainly operationalized the constructs of DC-SEN, DC-SEI, and DC-REC by respective organizational activities (Winter, 2003). To measure the construct of DCs, we explored a large number of organizational activities pertinent to DC-SEN, DC-SEI, and DC-REC. We mainly developed indicators based on the insights from previous studies (Khan et al., 2020; Mousavi & Bossink, 2017; Teece, 2007) and adapted some indicators from other studies (Eurostat, 2014; Mousavi et al., 2018; Wilden et al., 2013; Wilden & Gudergan, 2015). For DC-SEN, we asked companies how frequently they engage in listed activities (see Table 3) to identify new opportunities in terms of new products or services on a Likert scale (1. *never*, 2. *rarely*, 3. *sometimes*, 4. *often*, 5. *regularly*). For DC-SEI, we asked companies to evaluate listed actions (see Table 3) that they might take once they have identified a new opportunity to produce new products or to deliver new services (1. *strongly disagree*, 2. *disagree*, 3. *undecided*, 4. *agree*,

**TABLE 1** Results of hierarchical measurement model (CDE)

Second-order constructs	First-order constructs	Indicator code	Indicators	Loadings	CR	AVE		
Circular dynamic environment (CDE) VIF = 1.392	Market turbulence (CDE-MT) Weights = 0.413 t-value = 17.636 VIF = 1.729	CDE-MT1	Customers are receptive to circular product ideas	0.926	0.926	0.863		
		CDE-MT2	Customers expect circular economy initiatives in the industry	0.932				
	Technology turbulence (CDE-TT) Weights = 0.429 t-value = 15.260 VIF = 2.166	CDE-TT1	Technological developments provide big opportunities for circular economy	0.904			0.895	0.810
		CDE-TT2	Many circular product ideas have been made possible through technological breakthroughs	0.896				
	Competitive intensity (CDE-CI) Weights = 0.316 t-value = 11.076 VIF = 1.874	CDE-CI1	Competition on circular ideas is intense in the industry	0.847			0.884	0.719
		CDE-CI2	Competitors have introduced circular products/services	0.906				
		CDE-CI3	Public organizations expect circular economy initiatives	0.787				

Abbreviations: AVE, average variance extracted, CR; composite reliability; VIF, variance inflation factor.

TABLE 2 Results of hierarchical measurement model (CE)

Second-order constructs	First-order constructs	Indicator code	Indicators	Loadings	CR	AVE		
Circular economy implementation level (CE) VIF = 1.271	Design and production stage (CE-DP) Weights = 0.461 t-value = 14.141 VIF = 2.297	CE-DP1	Designing products to be easily repaired / refurbished	0.680	0.881	0.554		
		CE-DP2	Designing products to be easily biodegradable / recyclable	0.768				
		CE-DP3	Utilizing biodegradable / recyclable packaging	0.785				
		CE-DP4	Using closed-loops in the production	0.752				
		CE-DP5	Increasing material and energy efficiency	0.804				
		CE-DP6	Transferring / selling bi-products to other organizations	0.666				
	Consumption and collection stage (CE-CC) Weights = 0.305 t-value = 8.933 VIF = 2.023	CE-CC1	Providing repairing / refurbishing services to customers	0.883			0.874	0.776
		CE-CC2	Collecting end-of-life products	0.879				
	Recycling and resourcing stage (CE-RR) Weights = 0.374 t-value = 13.278 VIF = 1.869	CE-RR1	Recycling own production waste	0.877			0.876	0.779
		CE-RR2	Reusing bi-products/recycled materials from other organizations	0.888				

Abbreviations: AVE, average variance extracted, CR; composite reliability; VIF, variance inflation factor.

5. *strongly agree*). For DC-REC, we asked companies to evaluate how well listed renewal actions (see Table 3) succeeded on a Likert scale (1. *poorly failed*, 2. *slightly succeeded*, 3. *fairly succeeded*, 4. *well succeeded*, 5. *perfectly succeeded*) to accomplish identified opportunities.

We constructed overall performance (PER) as a second-order construct with four first-order constructs, namely environmental

performance (PER-EN), financial performance (PER-FI), competitiveness (PER-CO), and corporate reputation (PER-CR). To measure the construct of PER, we mainly adapted indicators from previous studies (Bagur-Femenias, Llach, & del Mar Alonso-Almeida, 2013; Eurostat, 2014; Zhu et al., 2010). In connection to their CE initiatives, we asked companies to evaluate the improvement level (in last 5 years) of listed indicators (see Table 4) on a Likert scale (1. *not at all*,

TABLE 3 Results of hierarchical measurement model (DCs)

Second-order constructs	First-order constructs	Indicator code	Indicators	Loadings	CR	AVE
Dynamic capabilities (DCs) VIF = 1.478	Sensing (DC-SEN) Weights = 0.370 t-value = 9.661 VIF = 2.282	DC-SEN1	Identification of customer needs	0.776	0.920	0.536
		DC-SEN2	Tracking new market trends	0.831		
		DC-SEN3	Analyzing competitors' actions	0.653		
		DC-SEN4	Observing technological developments	0.807		
		DC-SEN5	Organizing brainstorming sessions	0.648		
		DC-SEN6	Involving customers / suppliers in the product development process	0.709		
		DC-SEN7	Undertaking R&D to create new knowledge for developing new products / processes	0.803		
		DC-SEN8	Undertaking R&D to try out new ideas having strategic / operational implication	0.777		
		DC-SEN9	Assessing potential environmental impacts of products / processes / services	0.617		
		DC-SEN10	Networking with public organizations / industrial associations / universities / others	0.660		
	Seizing (DC-SEI) Weights = 0.325 t-value = 7.928 VIF = 2.281	DC-SEI1	Formulation of a strategy	0.765	0.922	0.542
		DC-SEI2	Finding strategic partners	0.746		
		DC-SEI3	Planning investments	0.808		
		DC-SEI4	Capital budgeting	0.736		
		DC-SEI5	Planning requisite human resources	0.762		
		DC-SEI6	Redesigning / transforming business models	0.737		
		DC-SEI7	Restructuring of governance structure	0.659		
		DC-SEI8	Collaboration to acquire requisite knowledge / skills	0.662		
		DC-SEI9	Collaboration to acquire requisite raw materials / resources	0.743		
		DC-SEI10	Interdepartmental cooperation	0.735		
	Reconfiguring (DC-REC) Weights = 0.457 t-value = 14.326 VIF = 1.474	DC-REC1	Merger with or acquisition of another organization	0.656	0.939	0.607
		DC-REC2	Changed organizational structure	0.714		
		DC-REC3	Made slight modifications in existing technology / machinery	0.839		
		DC-REC4	Introduced new or significantly improved technology	0.826		
		DC-REC5	Acquisition of a new manufacturing plant	0.727		
		DC-REC6	Organized training to employees	0.826		
		DC-REC7	Acquisition of existing know-how	0.726		
		DC-REC8	Adopted new business practices for organizing procedures	0.834		
		DC-REC9	Adopted new methods of organizing external relations	0.812		
		DC-REC10	Adopted new or significantly improved logistics	0.807		

Abbreviations: AVE, average variance extracted, CR; composite reliability; R&D, research and development; VIF, variance inflation factor.

2. a little bit, 3. to some degree, 4. relatively significant, 5. significant). To operationalize the aforementioned constructs, we followed the recommended guidelines (Jarvis, MacKenzie, & Podsakoff, 2003). In short, we modeled first-order (*thinner circles*) and second-order (*thicker circles*) constructs respectively as reflective and formative measurement models commonly referred to as reflective-formative HCM (see Figure 2).

3.3 | Data collection and analysis

Italy is one of the largest economies in the world. The Italian manufacturing sector (second largest in the EU) is comprised of those industries (e.g., pulp and paper, leather, and textiles) that account for significant environmental impacts. Nevertheless, this sector has been putting efforts towards CE (Gusmerotti et al., 2019). Thus, this sector

**TABLE 4** Results of hierarchical measurement model (PER)

Second-order constructs	First-order constructs	Indicator code	Indicators	Loadings	CR	AVE
Performance (PER) VIF = 1.731	Objective - environmental (PER-EN) Weights = 0.323 t-value = 15.947 VIF = 1.683	PER-EN1	Reduced energy consumption	0.866	0.907	0.708
		PER-EN2	Reduced waste generation	0.853		
		PER-EN3	Reduced atmospheric pollution	0.821		
		PER-EN4	Decreased water consumption	0.826		
	Objective - financial (PER-FI) Weights = 0.247 t-value = 9.298 VIF = 1.516	PER-FI1	Decreased manufacturing / operational costs	0.866	0.897	0.689
		PER-FI2	Increased annual turnover	0.889		
		PER-FI3	Increased profit growth	0.888		
		PER-FI4	Increased market share	0.655		
	Subjective - competitiveness (PER-CO) Weights = 0.361 t-value = 14.332 VIF = 2.835	PER-CO1	Increased capability to introduce innovative products / services	0.845	0.921	0.744
		PER-CO2	Improved quality of products/services	0.875		
		PER-CO3	Improved brand value of products / services	0.914		
		PER-CO4	Increased accessibility to new markets	0.813		
	Subjective - corporate reputation (PER-CR) Weights = 0.304 t-value = 12.379 VIF = 2.357	PER-CR1	Improved corporate image among customers	0.785	0.900	0.691
		PER-CR2	Improved relationship with suppliers / local community / regulatory organization	0.854		
		PER-CR3	Increased satisfaction and support from investors/partners	0.841		
		PER-CR4	Increased satisfaction and loyalty of employees	0.844		

Abbreviations: AVE, average variance extracted, CR; composite reliability; VIF, variance inflation factor.

seems suitable for testing our proposed hypotheses. We compiled a list of 2,969 manufacturing companies registered in the Italian Chamber of Commerce and Industry. Then, we extracted their email addresses through the ORBIS database. In June 2019, we sent email invitations to those companies to participate in our online survey. We received data from 246 companies through SurveyMonkey. However, to ensure the reliability of our dataset, we followed very strict criteria of data screening. That is, we deleted observations with more than 15% missing values, retaining 220 observations in our dataset for further analysis (Hair, Hult, Ringle, & Sarstedt, 2017). The sample size of the present study comfortably meets the recommended rule of thumb, that is, 10 times to the number of indicators of the construct with the highest number of indicators (Hair, Sarstedt, Ringle, & Mena, 2012). Interestingly, the sample size of the present study is relatively high compared to the average sample size of previous studies who used PLS-SEM (Hair, Sarstedt, Pieper, & Ringle, 2012). It is worth noting that the majority of companies in our dataset are medium-sized companies that have high annual income too (Table A1).

To analyze our dataset, we employed structural equation modeling (SEM) since it is regarded as a very robust and powerful statistical tool in various disciplines (Hair, Sarstedt, Pieper, et al., 2012). To conduct SEM, two main approaches are known as covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). PLS-SEM is recommended when the research is exploratory, the focus is on predicting target constructs, the structural model is complex, and constructs are formatively measured (Hair, Ringle, & Sarstedt, 2011). For these reasons, we opted for PLS-SEM and used SmartPLS 3 software

(Ringle, Wende, & Becker, 2015). To measure our proposed HCM, we employed the embedded two-stage approach (mode B) instead of repeated indicators approach (Becker, Klein, & Wetzels, 2012). Although the repeated indicator approach can be easily applied in PLS-SEM, this approach is troublesome in HCM when reflective-formative or formative-formative constructs serve as dependent constructs in the structural model (Sarstedt et al., 2019). Simply put, the R^2 value becomes unity by default thus path coefficient tends to zero or nonsignificant. In contrast, the two-stage approach shows better results (Ringle, Sarstedt, & Straub, 2012). Chin (2010) recommends a two-step approach to examine and interpret PLS-SEM. Accordingly, firstly, we assessed the measurement model. For that, we applied the recommended settings by using a PLS algorithm with 300 iterations. Secondly, we assessed the structural model to examine our proposed hypotheses by using bootstrapping with 5,000 subsamples (Hair, Sarstedt, Ringle, et al., 2012). We carefully followed the recommended rules and guidelines while conducting PLS-SEM analysis and reporting the results (Chin, 2010; Hair, Risher, Sarstedt, & Ringle, 2019; Sarstedt et al., 2019).

4 | RESULTS

4.1 | Measurement model

First, we evaluated the reflective measurement model. For that, we assessed indicator reliability, internal consistency, convergent validity,

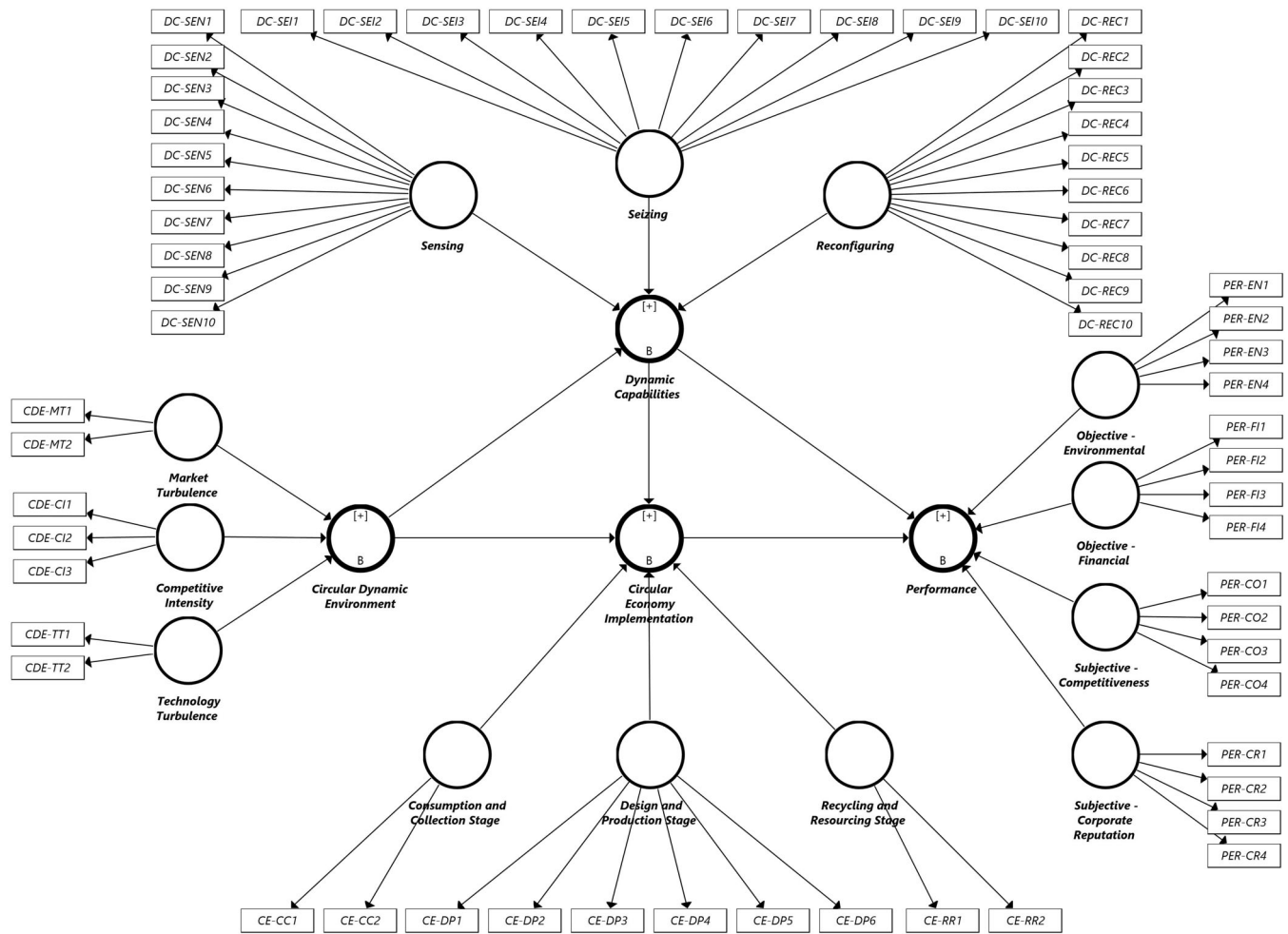


FIGURE 2 Hierarchical measurement model

and discriminant validity (Hair et al., 2019). According to Hair et al. (2011), indicator loadings should ideally be higher than 0.70. Nevertheless, indicator loadings between 0.40 and 0.70 are also acceptable if the average variance extracted (AVE) of the constructs is higher than 0.50 (Hair, Sarstedt, Ringle, et al., 2012). We found that all the indicator loadings were ranging between 0.617 and 0.932 (see Tables 1, 2, 3, and 4). Thus, the present study meets the criteria of indicator reliability.

For internal consistency, Cronbach's alpha (α) or composite reliability (CR) values should ideally be higher than 0.70 (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; Hair et al., 2011). Even though both Cronbach's α and CR are measures of internal consistency, Hair et al. (2019) point out that Cronbach's α is a less precise measure. Hence, CR should be preferably reported. We found that CR values were above the recommended cut-off values. That is, CR values were ranging between 0.874 and 0.939 (see Tables 1, 2, 3, and 4). Thus, we may conclude that the present study meets the criteria of internal consistency. For convergent validity, the AVE of each construct should be higher than 0.50 (Hair et al., 2011). We found that AVE values of all the constructs were ranging between 0.536 and 0.863 (see Tables 1, 2, 3, and 4). Thus, the present study meets the criteria of convergent validity.

To assess the discriminant validity, we tested the Fornell-Larcker criterion as well as the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion (Henseler, Ringle, & Sarstedt, 2015). The Fornell and Larcker criterion stipulates that the square root of the AVE of each construct should be greater than its correlation with other constructs (Chin, 2010). We found that the measurement model satisfied the Fornell-Larcker criterion (see Table 5). Henseler et al. (2015) pointed out that the Fornell-Larcker criterion may not be sufficient to assess discriminant validity. Therefore, the HTMT criterion should accompany the Fornell-Larcker criterion (Ali et al., 2018). According to Hair et al. (2019), the HTMT value should ideally be less than 0.90 for conceptually similar constructs. We found that the measurement model also satisfied the HTMT criterion (see Table 6). Thus, the present study meets the criteria of discriminant validity.

Next to the aforementioned steps, we evaluated the formative measurement model. That is, we further assessed the psychometric properties of first-order constructs since first-order constructs act as formative indicators for second-order constructs in our proposed HCM. We first checked the significance and relevance of second-order weights using bootstrapping. Afterward, we checked the variance inflation factor (VIF) of constructs and indicators. We found that

**TABLE 5** Discriminant validity (Fornell-Larcker criterion)

	CDE-CI	CDE-MT	CDE-TT	CE-CC	CE-DP	CE-RR	DC-REC	DC-SEI	DC-SEN	PER-CO	PER-CR	PER-EN	PER-FI
CDE-CI	0.848												
CDE-MT	0.544	0.929											
CDE-TT	0.662	0.626	0.900										
CE-CC	0.154	0.229	0.196	0.881									
CE-DP	0.190	0.338	0.245	0.673	0.744								
CE-RR	0.152	0.325	0.260	0.602	0.630	0.883							
DC-REC	0.301	0.337	0.405	0.286	0.428	0.352	0.779						
DC-SEI	0.282	0.337	0.386	0.165	0.215	0.129	0.480	0.736					
DC-SEN	0.226	0.345	0.359	0.229	0.312	0.188	0.496	0.729	0.732				
PER-CO	0.271	0.409	0.452	0.168	0.322	0.199	0.530	0.437	0.453	0.863			
PER-CR	0.281	0.424	0.408	0.197	0.273	0.267	0.472	0.371	0.368	0.749	0.832		
PER-EN	0.234	0.384	0.418	0.252	0.358	0.350	0.415	0.298	0.353	0.483	0.444	0.842	
PER-FI	0.336	0.263	0.347	0.198	0.245	0.220	0.295	0.285	0.268	0.475	0.375	0.522	0.830

Note: The diagonal values (in bold), that is, the square root of the AVEs of latent variables, are the highest in any column or row.

TABLE 6 Discriminant validity (HTMT criterion)

	CDE-CI	CDE-MT	CDE-TT	CE-CC	CE-DP	CE-RR	DC-REC	DC-SEI	DC-SEN	PER-CO	PER-CR	PER-EN	PER-FI
CDE-CI	—												
CDE-MT	0.661	—											
CDE-TT	0.845	0.778	—										
CE-CC	0.203	0.296	0.264	—									
CE-DP	0.234	0.402	0.302	0.874	—								
CE-RR	0.202	0.419	0.351	0.841	0.814	—							
DC-REC	0.350	0.381	0.476	0.350	0.483	0.428	—						
DC-SEI	0.334	0.384	0.461	0.202	0.245	0.165	0.516	—					
DC-SEN	0.275	0.397	0.434	0.282	0.358	0.232	0.535	0.805	—				
PER-CO	0.322	0.471	0.549	0.211	0.371	0.249	0.579	0.484	0.507	—			
PER-CR	0.339	0.503	0.506	0.251	0.319	0.339	0.528	0.423	0.419	0.859	—		
PER-EN	0.282	0.449	0.512	0.321	0.416	0.442	0.460	0.335	0.400	0.549	0.515	—	
PER-FI	0.417	0.321	0.440	0.258	0.292	0.288	0.326	0.331	0.316	0.551	0.443	0.607	—

Note: HTMT value less than 0.90 is a threshold limit for conceptually similar constructs (Hair et al., 2019).

t-values were greater than 1.96 while the VIF values of all the constructs were less than 3.0 (see Tables 1, 2, 3, and 4). That is, the significance confirmed and no potential multicollinearity existed (Hair et al., 2019). In short, the overall measurement model of the present study is appropriate. Hence, we may proceed to evaluate the structural model.

4.2 | Structural model

First, we assessed the structural model for collinearity issues. We found that the VIF values of all the constructs were less than 3.0 (see Tables 1, 2, 3, and 4). Thus, there was no multicollinearity problem (Hair et al., 2019). Next, we assessed the R^2 values, which indicate in-

TABLE 7 Hypothesis testing (Bootstrapping)

Hypotheses	Relationships	Type	Std Beta	SE	t-values	p values	f ²	q ²	95% CI LL	95% CI UL	Findings
Hypothesis 1	CDE → CE	Direct	0.177	0.072	2.474**	.013	0.029	0.028	0.058	0.296	Supported
–	CDE → CE → PER	Indirect	0.033	0.020	1.613	.107	–	–	0.005	0.070	Not supported
–	CDE → DCs	Direct	0.502	0.068	7.451***	.000	0.344	0.323	0.386	0.610	Supported
Hypothesis 2	DCs → CE	Direct	0.301	0.080	3.816***	.000	0.084	0.074	0.171	0.432	Supported
Hypothesis 3	CDE → DCs → CE	Indirect	0.154	0.053	2.920***	.004	–	–	0.074	0.245	Supported
–	CDE → DCs → CE → PER	Indirect	0.027	0.012	2.342**	.019	–	–	0.009	0.048	Supported
–	CDE → DCs → PER	Indirect	0.275	0.065	4.284***	.000	–	–	0.171	0.383	Supported
Hypothesis 4	DCs → PER	Direct	0.541	0.068	8.052***	.000	0.428	0.413	0.424	0.647	Supported
Hypothesis 5	CE → PER	Direct	0.178	0.062	2.895***	.004	0.046	0.035	0.074	0.276	Supported
Hypothesis 6	DCs → CE → PER	Indirect	0.052	0.020	2.695***	.007	–	–	0.021	0.087	Supported

Notes: The t-values of 1.65, 1.96, and 2.58 are respectively considered with the significance level of 10%, 5%, and 1% (two-tailed test). The f^2 values indicates the effect size as mentioned in brackets: 0.35 (large), 0.15 (medium), and 0.02 (small) (Cohen, 1988). The q^2 values indicates the predictive relevance as mentioned in brackets: 0.35 (large), 0.15 (medium), and 0.02 (small) (Henseler, Ringle, & Sinkovics, 2009).

Abbreviations: CDE, circular dynamic environment; CE, circular economy implementation; DCs, dynamic capabilities; PER, performance.

** $p < .05$.

*** $p < .01$.

sample predictive power, of the endogenous constructs. We found that the R^2 values of CE, DCs, and PER were equal to 0.180, 0.256, and 0.409 respectively. According to Cohen (1992), the standard R^2 values are 0.02 (small), 0.13 (medium), and 0.26 (large). However, in some disciplines or exploratory research, a lower R^2 value even 0.10 could be considered as a satisfactory value (Hair et al., 2019). Hence, the R^2 values in the present study are relatively high and acceptable. Afterward, we assessed the predictive relevance of the structural model through Stone-Geisser's Q^2 value using the blindfolding procedure (Ringle et al., 2015). The standard Q^2 values are 0 (small), 0.25 (medium), and 0.50 (large) (Hair et al., 2019). We found that the Q^2 values of CE, DCs, and PER were equal to 0.167, 0.244, and 0.392, respectively. Most importantly, we found that SRMR and NFI values were equal to 0.061 and 0.918, respectively. Thus, the present study meets the overall model fit criteria, that is, SRMR < 0.08 and NFI > 0.90, of PLS-SEM (Hair et al., 2017).

Finally, to test our proposed hypotheses, we computed the PLS algorithm with bootstrapping to assess path coefficients (standardized beta), significance levels, and t-values. We found that the direct effects of CDE and DCs on CE respectively had significant values of 0.177 ($p < .05$) and 0.301 ($p < .01$). That is, Hypotheses 1 and 2 were found to be empirically supported (see Table 7). Similarly, the direct effects of DCs and CE on PER respectively had significant values of 0.541 ($p < .01$) and 0.178 ($p < .01$). That is, Hypotheses 4 and 5 were found to be empirically supported (see Table 7). The indirect effects of CDE on CE and DCs on PER respectively had significant values of 0.154 ($p < .01$) and 0.052 ($p < .01$). We assessed the mediation effects of DCs and CE, proposed in the Hypotheses 3 and 6, as per the recent approach (Hair et al., 2017; Nitzi, Roldan, & Cepeda, 2016). We found that the relationship between CDE and CE was partially mediated by DCs. Similarly, the relationship between DCs and PER was partially

mediated by CE. That is, Hypotheses 3 and 6 were found to be empirically supported (see Table 8).

5 | DISCUSSION AND IMPLICATIONS

We investigated the role and the significance of DCs and their underlying organizational activities in CE implementation. Our PLS-SEM analysis demonstrates that DCs and their underlying organizational activities significantly facilitate CE implementation, which consequently improves the overall performance of companies (see Figures 3 and 4). This paper confirms and extends the findings of previous studies (Kabongo & Boiral, 2017; Khan et al., 2020). Amui et al. (2017) highlighted that further research on DCs may guide companies in transitioning towards a more sustainable industry. Indeed, our findings on the relation between CE implementation and overall performance may stimulate companies' interest in CE adoption. Furthermore, our findings on the relation between DCs and CE implementation might help companies in transforming their negative perceptions (if any) into strategic actions for CE implementation (Gusmerotti et al., 2019).

Our PLS-SEM analysis shows that DCs has a positive and significant relationship with the overall performance of companies. Our finding on the relation between DCs and performance is consistent with previous studies (Drnevich & Kriauciunas, 2011; Li & Liu, 2014). This paper extends that relation in the CE context and clarifies how DCs leads to improved performance. Protogerou et al. (2012) question whether DCs impact directly or indirectly on performance. Our PLS-SEM analysis shows that the relation between DCs and overall performance is mediated by CE implementation. That is, CE activities (or eco-innovation) act as a mechanism through which DCs influence overall performance (Zhou et al., 2019). This finding supports the

TABLE 8 Mediation effect analysis

Hypotheses	Relationships	Type	Std Beta	t values	p values	Significance	Conclusion
Hypothesis 3	CDE → CE	Direct	0.177	2.474**	.013	Yes	Complementary (partial mediation)
	CDE → DCs → CE	Indirect	0.154	2.920***	.004	Yes	
Hypothesis 6	DCs → PER	Direct	0.541	8.052***	.000	Yes	Complementary (partial mediation)
	DCs → CE → PER	Indirect	0.052	2.695***	.007	Yes	

Note: The t values of 1.65, 1.96, and 2.58 are respectively considered with the significance level of 10%, 5% and 1% (two-tailed test).

Abbreviations: CDE, circular dynamic environment; CE, circular economy implementation; DCs, dynamic capabilities; PER, performance.

**p < .05.

***p < .01.

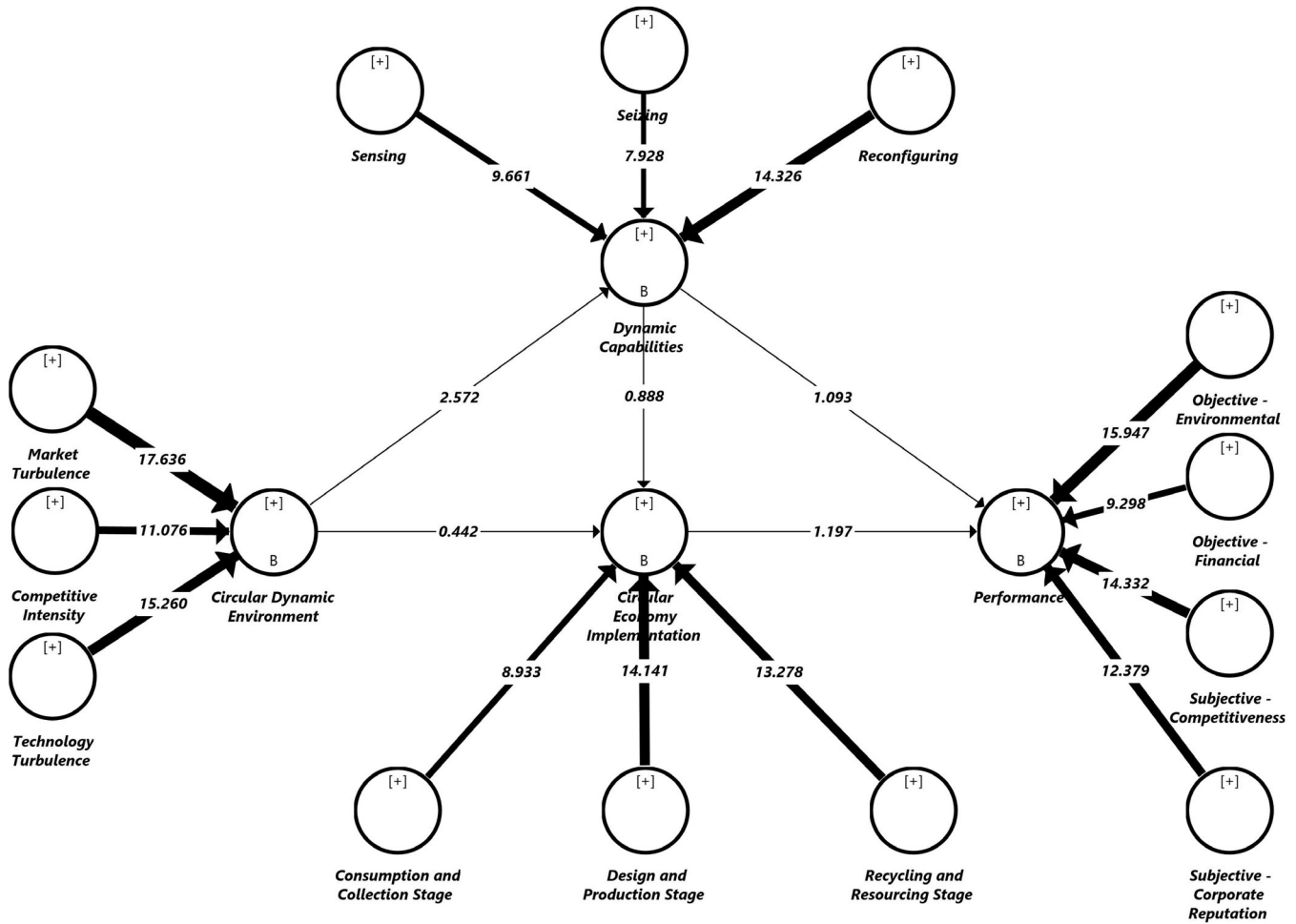


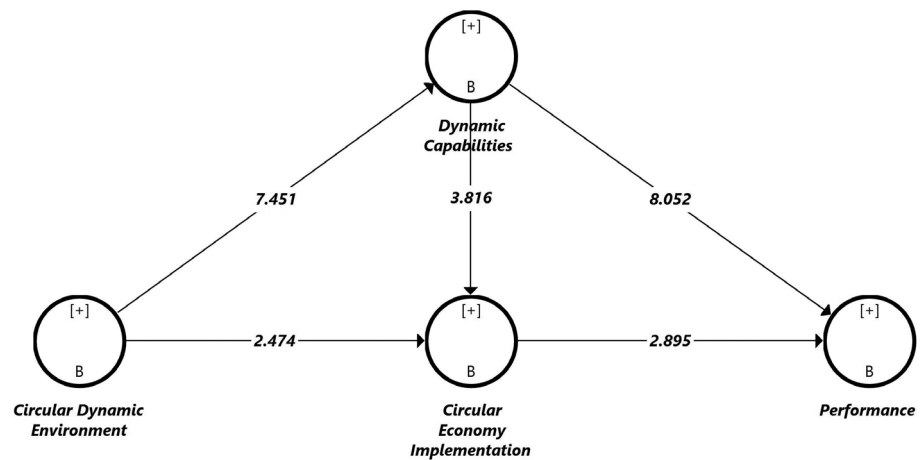
FIGURE 3 Summary of findings (First stage: Measurement model)

argument that DCs may not always directly produce companies' performance, rather DCs indirectly produce companies' performance (Pezeshkan et al., 2016). Furthermore, this finding reasserts that superior performance is not exclusively the outcome of DCs (Wilden et al., 2013). Protogerou et al. (2012) could not find a significant direct relation between DCs and performance. It is worth noting that we measured overall performance while most scholars usually measure only financial or market performance (Protogerou et al., 2012; Wilden & Gudergan, 2015; Zhou et al., 2019). This may be a reason

why we observed significant direct relation as well as significant indirect relation between DCs and overall performance.

Our PLS-SEM analysis shows that CE implementation has a positive and significant relationship with the overall performance of companies. Scarpellini, Valero-Gil, et al. (2020) measured eco-innovation being the crux of CE implementation. We operationalized CE implementation not just as an eco-innovation rather both product innovation and process innovation (Mousavi et al., 2018). Zhu et al. (2010) found that the adoption of CE practices improves environmental and

FIGURE 4 Summary of findings
(Second stage: Structural model)



financial performance. Our findings confirm that CE implementation does not only improve environmental and financial performance but also competitiveness and corporate reputation. This is an important finding and particularly valuable for companies aiming towards CE. We found that environmental performance was greatly improved due to the confluence of DCs and CE implementation. However, financial performance was least improved compared to environmental performance, competitiveness, and corporate reputation. An obvious reason for this is that return on investments takes time and depends on various factors too. Nevertheless, CE provides a long-term competitive advantage. Therefore, companies must strive for CE implementation.

Our PLS-SEM analysis shows that CDE has a positive and significant relationship with both DCs and CE implementation. Our finding on the relation between CDE and CE implementation implies that the ongoing momentum, that is, push by the EU and several national governments for CE (Korhonen et al., 2018), should be further accelerated. This paper contributes to the debate on whether a dynamic environment is a moderator or driver of DCs. Our finding on the relation between CDE and DCs confirms driving role which is consistent with previous studies (Li & Liu, 2014; Teece et al., 1997). Scarpellini, Marín-Vinuesa, et al. (2020) found that environmental capabilities mediate the relationship between stakeholders' pressures and the circular scope of a company. In this regard, our findings show that it is not just limited to environmental capabilities rather DCs as a whole mediate the relationship between CDE and CE implementation.

Our PLS-SEM analysis highlights the most important organizational activities through which companies can identify and pursue CE opportunities. We found that sensing activities in order of importance are DC-SEN2, DC-SEN4, DC-SEN7, DC-SEN8, and DC-SEN1 (see Table 3). Seizing activities in order of importance are DC-SEI3, DC-SEI1, DC-SEI5, DC-SEI2, and DC-SEI9 (see Table 3). Reconfiguring activities in order of importance are DC-REC3, DC-REC8, DC-REC4, DC-REC6, DC-REC9 (see Table 3). A significant barrier to eco-innovation is that companies are usually not able to identify new and profitable opportunities (Porter & Linde, 1995). In this regard, our finding suggests that a sensing activity, assessment of potential environmental impacts of products, can eliminate that barrier. This finding

implies that if a company has the capabilities or tool such as eco-management and audit scheme (EMAS) and life cycle assessment (LCA) then its probability to accomplish eco-innovation (Daddi, Magistrelli, Frey, & Iraldo, 2011) or sustainable innovation (Mousavi & Bossink, 2017) would be much higher than other companies. EMAS and LCA are dynamic (sensing) capabilities and essential tool to sense a CE opportunity (Khan et al., 2020). Indeed, the significance and effectiveness of LCA have been already proven in the CE context (Daddi, Nucci, & Iraldo, 2017). Therefore, companies must adopt LCA to discover CE opportunities.

Our findings demonstrate that all conventional sensing activities (Teece, 2007), that is, identification of customer needs, tracking new market trends, analyzing competitors' actions, observing technological developments, involving customers or suppliers, and undertaking R&D play a pivotal role in identifying new opportunities and gaining a competitive advantage. Therefore, companies aiming towards CE must incorporate these activities into their day-to-day operations. Our findings suggest that R&D is crucial for sensing a CE opportunity. Chakrabarty and Wang (2012) show that companies' R&D capabilities facilitate sustainability practices. It is understood that CE objectives demand new knowledge and skills. In this regard, our findings suggest that a seizing activity, collaboration with research institutions to acquire requisite knowledge and skills, is highly valuable and successful (De Marchi, 2012). Lastly, our findings indicate that companies should organize brainstorming sessions and do networking with other organizations to identify CE opportunities.

Our findings further demonstrate that the elements of strategic planning, that is, formulation of a strategy, finding strategic partners, planning investments, capital budgeting, and planning human resources, play a significant role in seizing identified CE opportunities. It is worth noting that the aforementioned activities usually involve risky-decisions. Daddi, Ceglia, Bianchi, and de Barcellos (2019) pointed out that top management might experience "paradoxical tensions" while taking CE decisions. Nevertheless, environmentally conscious top management is more likely to pursue CE (Gusmerotti et al., 2019). Therefore, the role of top management in strategic planning and/or CE decisions is quite pivotal. In this regard, our findings indirectly suggest that top management should be very competent



and hold a risk-taking ability. In short, companies aiming towards CE must be competent in strategic planning and/or possess strong seizing capabilities.

Our findings suggest that companies must have a strong capability for diverse collaborations to operationalize a CE business model. Indeed, most companies cannot achieve CE without having collaborations for requisite knowledge, skills, and recyclable materials. This statement is in line with previous studies that substantiated that tackling sustainability challenges essentially need collaborations (Hofmann et al., 2012). Some scholars pointed out that the allocation of resources and planning investments are key strategic decisions that ultimately determine a company's performance (Agarwal & Helfat, 2009). They emphasize on investments not only in R&D but also in acquisitions. Our results confirm that reconfiguring capabilities such as mergers or acquisitions and gaining technological competencies play an important role in CE implementation. Our findings reassert that reconfiguring capabilities strongly affects companies' performance (Girod & Whittington, 2017). It implies that companies can never achieve CE without having strong reconfiguring capabilities.

Mousavi et al. (2018) show that DCs, that is, sensing, seizing, and reconfiguring capabilities positively contribute to sustainable innovations, but sensing activities play the most prominent role. However, our findings show that reconfiguring activities play the most prominent role in CE implementation. Scholars perceive that measuring DCs is challenging since literature lacks generally accepted approaches (Zhou et al., 2019). Nevertheless, we attempted to overcome this issue and captured the measurement of the degree of DCs (Mousavi et al., 2018). In short, this paper demonstrates that DCs is not vague or fuzzy concept that cannot be measured, rather specific processes that can be explored theoretically as well as empirically.

6 | CONCLUSION

The main objective of this paper was to investigate the role and significance of DCs for CE implementation. We empirically demonstrated that DCs significantly facilitate CE implementation, which consequently improves the overall performance of companies. Therefore, we unequivocally suggest that companies must strive to develop and apply sensing, seizing, and reconfiguring capabilities in order to identify and accomplish CE opportunities. The top management of companies should clearly define CE objectives, allocate required human and financial resources, and involve all stakeholders for those CE objectives.

Despite profound merits, this paper contains some limitations. Although we took suggested measures to ensure the quality of the data. However, social desirability bias which is commonly found in surveys cannot be ruled out. Simply put, the respondents' perceptions may not coincide with the objective and rational reality. Furthermore, the overall performance of companies was measured with self-reported data which is another usual limitation of surveys. The survey was conducted in Italy and we got useful data from just

220 companies. Therefore, the findings of this paper can only be generalized to other countries with caution. Nevertheless, this paper suggests some future research opportunities. For instance, a similar study with a larger sample size may be replicated in other countries to get more valuable insights. It might be interesting to analyze the proposed hypotheses in different settings or by including other sectors. Although we perceive moderation occurs, future studies may investigate whether or not CDE moderates these relationships: (a) DCs and CE implementation, and (b) DCs and overall performance. Lastly, a retrospective longitudinal study on how DCs leads to CE implementation would be highly valuable.

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How to cite this article: Khan O, Daddi T, Iraldo F. The role of dynamic capabilities in circular economy implementation and performance of companies. *Corp Soc Responsib Environ Manag*. 2020;27:3018–3033. <https://doi.org/10.1002/csr.2020>



APPENDIX A

TABLE A1 Description of sample

Variable	Description	Number of companies
Number of employees	1–49	1
	50–249	109
	250–999	83
	1,000–4,999	24
	More than 5,000	3
Annual income	Less than 1,000,000 euro	23
	1,000,001–2,000,000 euro	11
	2,000,001–10,000,000 euro	16
	10,000,001–50,000,000 euro	81
	Higher than 50,000,000 euro	89
NACE activities	Manufacture of food products	18
	Manufacture of beverages	5
	Manufacture of textiles	12
	Manufacture of wearing apparel	7
	Manufacture of leather and related products	8
	Manufacture of wood and of products of wood and cork	2
	Manufacture of paper and paper products	6
	Printing and reproduction of recorded media	3
	Manufacture of coke and refined petroleum products	1
	Printing and reproduction of recorded media	12
	Manufacture of basic pharmaceutical products and pharmaceutical preparations	7
	Manufacture of rubber and plastic products	11
	Manufacture of other non-metallic mineral products	8
	Manufacture of basic metals	11
	Manufacture of fabricated metal products, except machinery and equipment	24
	Manufacture of computer, electronic and optical products	12
	Manufacture of electrical equipment	12
	Manufacture of machinery and equipment	23
	Manufacture of motor vehicles, trailers and semi-trailers	10
	Manufacture of other transport equipment	5
Manufacture of furniture	15	
Other manufacturing	8	