RESEARCH ARTICLE

A framework of digital technologies for the circular economy: Digital functions and mechanisms

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Abstract

Digital technology is regarded as providing a promising means of moving production
and consumption towards the circular economy. However, it is still unclear which
functions of digital technologies are most useful to improving circularity, and how
these functions could be used to enhance different circular economy strategies. This
paper aims to address this knowledge gap by conducting a systematic literature
review. After examining 174 papers, creating 782 original codes and 259 second-
round codes, the study identifies 13 critical functions of digital technologies which
are most relevant to circular economy strategies. The paper then proposes a frame-
work which reveals seven mechanisms of how these digital functions can enhance
different circular economy strategies. The framework also reveals which combina-
tions of the digital functions and circular economy strategies have already been stud-
ied extensively as well as where there may be gaps. This indicates which digital
functions are more mature in terms of possible implementation for circular economy
as well as what missing links there are in the empirical and theoretical research. The
study advances the synergies between digital technologies and the circular economy
paradigm through the lens of digital functions. The proposed framework and mecha-
nisms build a theoretical foundation for future research, and we highlight five
research areas for further studies. This study also provides a structured way for man-
agers to explore the appropriate digital functions for their CE strategies, so as to
identify required digital technologies and new value creation through digital
functions.

KEYWORDS

circular economy, digital function, digital sustainability, digital technology, digital
transformation, digitalisation, Industry 4.0, sustainable development

1 | INTRODUCTION

As global consumption of materials and annual waste generation are
expected to double by 2050, the transition to a more sustainable

production and economic system is a vital requirement (European
Commission, 2020). The circular economy (CE) has been widely
recognised as a promising paradigm for decoupling economic
growth from resource extraction and environmental destruction

(Franzo et al., 2021). It has gained increasing attention from governments, practitioners, and researchers (Korhonen et al., 2018; McDowall et al., 2017). It addresses the creation of a resource-effective and resource-efficient economic system mainly through intentionally narrowing, slowing and closing material- and energy-flows (Pieroni et al., 2019; World Economic Forum, 2016).

At the same time, emerging digital technology (DT), such as the internet of things (IoT), big data analytics (BDA), artificial intelligence (AI), and 3D-printing, has been radically changing the way products are made, delivered, sold, and consumed (Lasi et al., 2014). Known as Industry 4.0, the new industrial stage not only changes the manner of production but also causes versatile organizational transformation (Vaidya et al., 2018). With the emerging technologies, devices can communicate with other devices and services over the internet to achieve a diversity of goals (Whitmore et al., 2015), such as automated manufacturing, home automation, and smart waste management.

There is an increasing interest in the potential of DT in moving production and consumption towards CE (Awan et al., 2021). Implementing DTs is considered a promising means to overcome barriers to the CE transition (Rosa et al., 2020; World Economic Forum, 2016). It can provide CE opportunities for the manufacturing industry, such as retrofitting equipment, increasing workers' efficiency and motivation, building a smart factory based on resource efficiency, and designing closed-loop manufacturing process chains (Stock & Seliger, 2016).

Current research provides insights into the interactions between DT and CE from various perspectives. Some articles have developed frameworks linking specific DTs to various CE strategies (Ingemarsdotter et al., 2019; Kristoffersen et al., 2020; Nobre & Tavares, 2020a; Okorie et al., 2018; Rosa et al., 2020). Others link DTs to other concepts, such as lean manufacturing (Chen et al., 2020; Ciliberto et al., 2021) and sustainable development (Furstenau et al., 2020; Liu et al., 2020; Sun et al., 2021) and then link these concepts to CE. Awan et al. (2021) focus on IoT tools and implementation practices, while another stream looks at the implementation challenges (Liu et al., 2021; Lobo et al., 2022).

Despite the growing interest, the theoretical understanding of the mechanism whereby DT can be used to implement CE strategies is still inadequate and underdeveloped (Cagno et al., 2021). While some research focuses on one or a limited set of DTs, such as IoT and BDA (Ingemarsdotter et al., 2019; Mboli et al., 2020; Nobre & Tavares, 2020a; Reuter, 2016), other research focuses on a specific situation, such as supply chain management, remanufacturing, and recycling (Kerin & Pham, 2020; Sarc, 2021; Yadav et al., 2020). Kristoffersen et al. (2020) proposed a smart CE framework for exploiting IoT- and BDA-based business analysis for CE implementation and innovation. It focuses on data and business analytics but did not address the possibilities of AI and automation (Ellen MacArthur Foundation, 2019; Fraga-Lamas et al., 2021; Lutje et al., 2020). Therefore, the mechanisms of DTs enabling CE strategies still need further development. It needs not only to provide a holistic, strategic CE transformation view, but also to investigate how the combination of DTs enable CE from an operative perspective (Cagno et al., 2021).

The combined adoption of different DTs can achieve various functions. Existing studies, however, have not clarified which functions would be most helpful to improving CE. Additionally, the understanding of the mechanism of using DTs to enable CE strategies remains unclear. We aim to fill the gap by investigating the digital functions and the underlying mechanisms that can support firms to implement CE strategies. We intend to address the following research questions:

- RQ1: What are the main functions of DTs for the circular economy?
- RQ2: How can these digital functions be used to implement circular economy strategies?

The study adopts a systematic literature review method to answer the two questions and proposes a framework to address the integration of DT for CE and reveal the underlining mechanisms. We examined 174 papers and created 782 original codes, from which we identify 13 digital functions of DT that can be used to improve CE, under three categories (RQ1). We also propose a DF4CE framework to explain how these digital functions could be used to enhance different CE strategies (RQ2). The framework reveals the "maturity level" of the DT-CE mechanisms, based on the frequency with which they are covered in the relevant literature. In this way, the study advances the theoretical understanding of synergies between DTs and CE, building a comprehensive theoretical framework that covers overall CE strategies. The proposed framework provides a structured way for managers to explore the appropriate digital functions for their CE strategies, so as to identify required digital technologies and new value creation through digital functions. The results, in addition, identify future research needs and highlight the directions available for investigating specific digital functions for a particular CE strategy.

The remainder of this paper is structured as follows. The next section describes the methodology of our systematic literature review and the coding process. Section 3 summarises the results of the bibliometric analysis. The coding results are interpreted and clustered into digital functions to answer RQ1 in Section 4, while Section 5 explains the mechanisms and maturity level for RQ 2. Section 6 discusses the implications and possible future research agendas. Finally, Section 7 draws some conclusions arising from the research.

2 | METHODOLOGY

A systematic literature review approach (Denyer & Tranfield, 2009; Tranfield et al., 2003) is employed in this paper to analyse current research on using DTs for the CE paradigm. The approach locates the existing studies and selects and analyses them following a rigorous and well-defined research protocol. It generates an unbiased overview of current studies, with an audit trail for all the research steps (Denyer & Tranfield, 2009; Thomé et al., 2016). On this basis, the systematic literature review is more likely to increase research validity and reliability than a traditional literature review. As shown in

Figure 1, the study begins with a descriptive analysis of the selected papers. Then we analyse the papers within the guidelines provided by qualitative coding method so as to answer our research question and address future research agendas. Each step was recorded in detail to ensure the process was replicable and transparent.

2.1 | Identifying and refining the review scope

In this phase, we define the review scope so that it aligns with the proposed research questions (Denyer & Tranfield, 2009). The need for focusing the RQs closely lies in the vast number of different topics associated with DTs, ranging from specific technologies, such as IoT and BDA (Cai et al., 2016), to generalised concepts such as digitalisation and I4.0 (Daú et al., 2019; Lukac, 2015). The need also arises from the wide application of CE in a variety of different areas.

We chose to mainly study three DTs: IoT, BDA, and AI. The choice of IoT and BDA was made because these are considered the most promising technologies for CE (Cwiklicki & Wojnarowska, 2020). IoT refers to the inter-networking of physical items that enable objects to collect and exchange data (Oztemel & Gursev, 2020), while BDA is the application of a collection of advanced techniques and technologies to the analysis of massive data sets, aimed at obtaining meaningful insights (Ghasemaghaei et al., 2015; Mikalef et al., 2018; Russom, 2011). BDA coupled with IoT can track and share product lifecycle data to reduce waste, enhance waste recovery and connect waste management practices (Esmaeilian et al., 2018). As for AI, this has been attracting growing attention in CE research recently. It can provide a fast and agile learning process for data analysis (Kaplan & Haenlein, 2019; Kristoffersen et al., 2020), which allows faster and more flexible actions based on larger data sets, hence creating new possibilities for CE (Ellen MacArthur Foundation, 2019). In order to

uncover detailed insights on the digital functions of the DTs, our study focuses on the digital aspect of Industry 4.0, rather than the ones with a general and perhaps superficial coverage of Industry 4.0 concepts.

2.1.1 | Selecting studies

The literature examined in this paper was searched and selected by following the rules from Briner and Denyer (2012) and Denyer and Tranfield (2009). The search for studies was conducted in EBSCOhost, Scopus, ProQuest, ScienceDirect, and Web of Science. The search string was constituted by ("digit*" OR "Internet of Things" OR "IoT" OR "Big data" OR "artificial intelligence" OR "AI" OR "industry 4.0") AND ("circular economy" OR "circularity"). Both journal papers and published conference papers were included to mitigate the publication bias (Briner & Denyer, 2012). Only publications written in English were included. The material searches were conducted in September 2021, extracting 1626 papers after eliminating duplicates. We defined a series of inclusion and exclusion criteria to select the final papers listed below.

Inclusion criteria:

- Focuses on both DTs and CE
- Addresses one or more technologies within scopes (IoT, big data, and AI)
- Addresses either the biological or technical sides of CE

Exclusion criteria:

- Technical papers focusing on modelling, optimisation, algorithms or developing a specific DT
- Non-English papers. These were automatically excluded from the search in five of the databases described above.
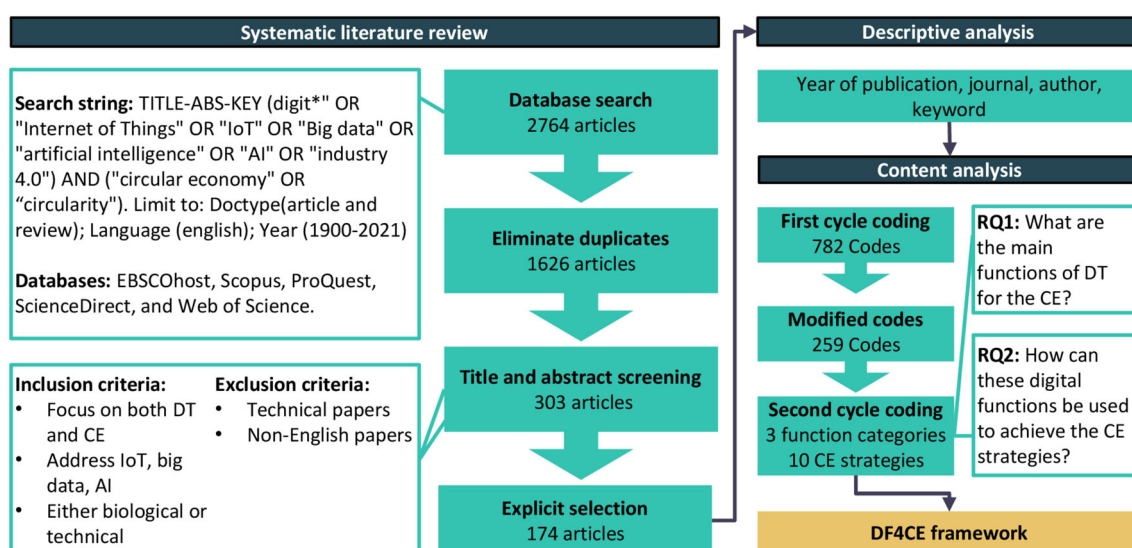

FIGURE 1   Systematic literature review process [Colour figure can be viewed at wileyonlinelibrary.com]

Two researchers then screened the title and the abstracts of 1626 papers based on the criteria. After this, the remaining 303 papers' main text was closely examined. One hundred seventy-four papers were finally chosen for our review process.

2.2 | Literature analysis and synthesis

The study reviewed the papers in two steps: descriptive analysis and content analysis. The first one aimed to reveal research trends among the 174 papers. The journals publishing most papers, the papers published each year, and the most frequent keywords were analysed as suggested by Yang and Tate (2012). The results are presented in Section 4.

The second part of this literature review is constituted by in-depth qualitative content analysis, in which we have coded the reviewed papers to extract relevant information for pattern detection (Miles et al., 2014). We have applied the two cycle coding method suggested by Saldaña (2015). We established a conceptual structure to cluster the refined codes to reveal the patterns and mechanisms that can answer research questions.

2.3 | Building the structure of conceptual framework

To answer the first research question, we need to identify the key digital functions that have been or can be used to improve CE in the literature. Here, the digital function is regarded as one which enables digital technologies to deliver smart services (Allmendinger & Lombreglia, 2005). To answer the second research question, the identified digital function should be associated with different CE strategies. Inspired by the IoT-CE cross-section heat map (Ingemarsdotter et al., 2019), we built a structure for analysis, with digital functions as the y-axis and CE strategies as the x-axis (see Figure 4).

A number of previous studies have proposed CE or DT related frameworks of one kind or another. Okorie et al. (2018), for instance,

proposed a framework that utilizes the technology life cycle concept. Kamble et al. (2018) developed a framework comprising Industry 4.0 technologies and their activities, business process integration, and sustainable outcomes. Ingemarsdotter et al. (2019) categorized circular strategies according to five IoT capabilities (i.e., tracking, monitoring, control, optimization, and design evolution). Kristoffersen et al. (2020) proposed a smart CE framework for exploiting IoT- and BDA-based business analysis for CE implementation and innovation. It focuses on business analytics. Among the existing frameworks, only a few of them have directly addressed digital functions (Ingemarsdotter et al., 2019) or similar lenses. They constitute, for this reason, an inadequate foundation on which to analyse the digital function as it relates to CE.

2.3.1 | y-axis: Digital function category

Our y-axis includes three categories: data collection and integration, data analysis, and automation. This is based on the smart CE framework and the analytics and knowledge hierarchy (Kristoffersen et al., 2020; Siow et al., 2018) because data lie at the centre of the chosen technologies, as indicated in Figure 2. Data collection and integration is defined as the first process that provides data and information. Data serve, then, as the base of the knowledge hierarchy. It is mostly collected from physical and virtual sources. Information is constituted by the interpreted data within specific contexts (Siow et al., 2018). It is mostly generated by descriptive analytics in the data integration process.

The second category is data analysis, and the third is automation. Data analysis builds on the first process to generate knowledge and wisdom. "Knowledge" here refers to diagnostic analytics with understanding and meaning, while "wisdom" refers to discovered, predictive, or prescriptive insights. We added "automation" as a third category of digital function to represent the physical processes. This category captures the self-organized robotics control and decision-making process that occur without human interference (Liebrecht et al., 2021).
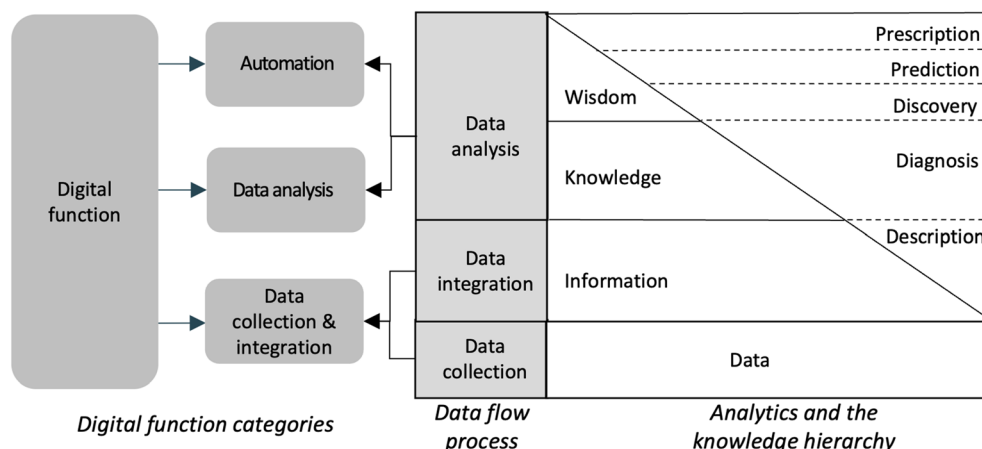

FIGURE 2 Digital function categories (adapted from Kristoffersen et al., 2020, and Siow et al., 2018) [Colour figure can be viewed at wileyonlinelibrary.com]

2.3.2 | x-axis: Circular economy strategy

For the x-axis, the existing research of CE-DT do not currently provide a commonly agreed categories of CE strategy. Cagno et al. (2021) and Jabbour et al. (2018) mapped digital and physical technologies based on the ReSOLVE model proposed by the Ellen MacArthur Foundation (2015). Cwiklicki and Wojnarowska (2020), on the other hand, combined the ReSOLVE model, 3R strategy, and three other concepts to compare five technologies. Similarly, Ingemarsdotter et al. (2019) combined 3R strategy with three in-use strategies to identify IoT capabilities. Kristoffersen et al. (2020) categorized IoT, big data, and data analytics cases according to the Circular Strategies Scanner from Blomsma et al. (2019), which involves a detailed multi-layered strategy mapping based on 9R strategies from Potting et al. (2017).

For this research, the important thing was to build a holistic view of digital functions for CE. We decided that the most appropriate basis for this was to use the 9R CE framework devised by Potting et al. (2017) Three factors underpinned this decision. First, previous IoT- and BDA-focused research favoured the use of 3R or 9R strategy over other possible strategies, indicating that Rs strategies are indeed suitable for DT-focused analysis. Second, 9R strategy is an extension of the 3R strategy (reduce, reuse, recycle), representing comprehensive CE strategies in an easily accessible manner (Blomsma et al., 2019). Lastly, Bag, Gupta, and Kumar (2021) found that a higher degree of I4.0 implementation can create higher 9R strategy-based manufacturing capabilities. This finding statistically validated the applicability of the 9R framework for DT-CE research in the manufacturing industry. The definition of the elements comprising the 9R framework is laid out in Figure 3.

We then established the digital function for the circular economy (DT4CE) framework (Figure 4) with three digital function categories on the y-axis and nine CE strategies on the x-axis. Our review aimed to identify the relevant digital functions from codes and sort them according to the three categories. Then we referred to the evidence and cases from literature and mapped the codes to the x-axis and y-axis accordingly. The intersections of the x-axis and y-axis form various combinations of using a specific digital function to enhance a specific CE strategy. We use the size of dots to represent the frequency of related codes. The higher frequency indicates a higher maturity level of using a specific digital function for a specific CE strategy.

2.4 | Coding process

All selected papers were coded in the first cycle coding following a predefined coding protocol to minimize the bias in the literature analysis and synthesis phase. The first cycle coding resulted in 782 codes, including 441 with theoretical evidence and 341 with empirical evidence. Before the second cycle coding, the codes were modified and merged to improve data quality (Saldaña, 2015), from which 102 codes with conceptual evidence and 157 codes with empirical evidence emerged.

In the second cycle of coding, we clustered the refined codes to reveal patterns and meanings. As exemplified in Table 1, we examined the original text of all the codes before clustering them in a manner which was consistent with what was in the literature. The first step in this involved choosing a word from the code that can describe the digital function referred to, based on our understanding of the literature. This step resulted in the identification of 13 digital functions, as

Smart product use and manufacturing	R0	Refuse	Make product redundant by abandoning its function or by offering the same function with a radically different product
	R1	Rethink	Make product use more intensive (e.g. through sharing products or by putting multi-functional products on market)
	R2	Reduce	Increase efficiency in product manufacture or use by consuming fewer natural resources
Extend lifespan of product and its parts	R3	Reuse	Re-use by another consumer of discarded product which is still in good condition and fulfils its original function
	R4	Repair	Repair and maintenance of defective product so it can be used with its original function
	R5	Refurbish	Restore an old product and bring it up to date
	R6	Remanufacture	Use parts of discarded product in a new product with the same function
	R7	Repurpose	Use discarded products or its part in a new product with a different function
Useful application of material	R8	Recycle	Process materials to obtain the same (high grade) lower (low grade) quality
	R9	Recover	Incineration of material with energy recovery

FIGURE 3 Category of circular economy strategies: 9R circularity strategies (: adapted from Potting et al., 2017) [Colour figure can be viewed at wileyonlinelibrary.com]
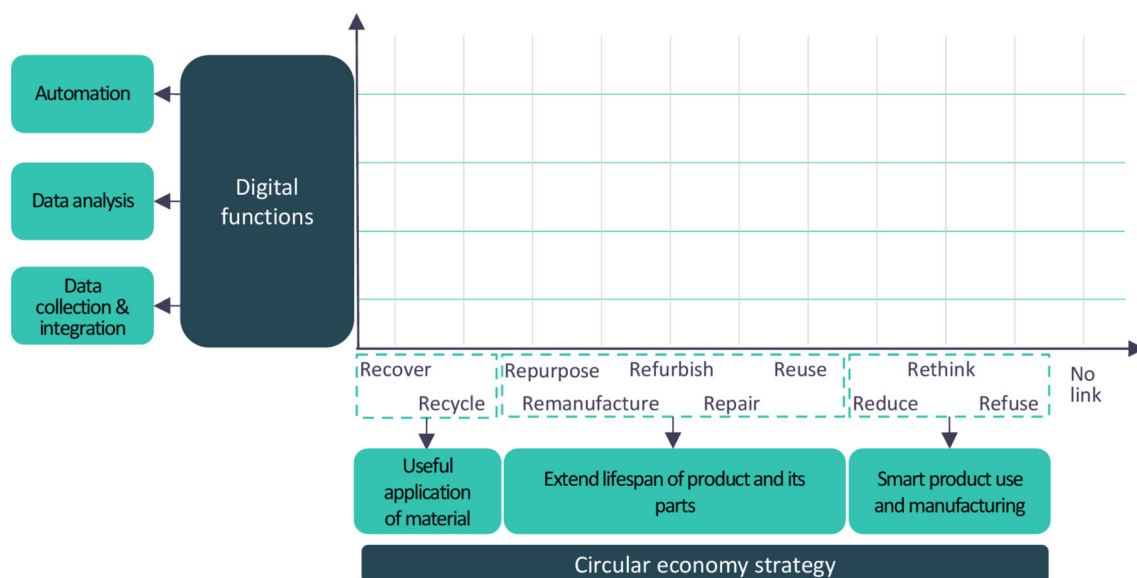
FIGURE 4 The structure of the conceptual framework [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Coding process examples

First cycle coding	Modification after first cycle	Second cycle coding	
		Digital functions	**CE strategies**
Adapt offerings to the actual usage	Learn the users' habits regarding appliances usage - adapt the offering - attract more users - increase efficiency and sharing (with empirical evidence)	Innovate	Rethink
Monitoring status - predicting replacement -enhancing collection activities	Monitoring status - predicting replacement - enhancing collection activities (with empirical evidence)	Monitor	Repair
Assessing end-of-life recovery of products	Assessing end-of-life recovery of products to increase efficiency (without empirical evidence)	Assess	Reduce

TABLE 2 Journal and conference publication each year

Journal/Conference	Year of publication									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Sustainability	-	-	-	-	-	1	8	6	11	26
Journal of Cleaner Production	-	-	-	-	1	-	5	4	8	18
Procedia CIRP	-	-	-	-	4	2	1	2	4	13
Resources Conservation and Recycling	-	-	-	-	-	-	2	6	2	10
Technological Forecasting and Social Change	-	-	-	-	-	-	2	-	5	7
Applied Sciences	-	-	-	-	-	1	-	1	1	3
Procedia Manufacturing	-	-	-	-	-	-	2	1	-	3
Business Strategy and The Environment	-	-	-	-	-	-	-	-	3	3
International Journal of Production Research	-	-	-	-	-	-	-	2	1	3
Johnson Matthey Technology Review	-	-	-	-	-	-	-	3	-	3
Waste Management	-	-	-	-	-	1	1	1	-	3
Others	1	-	-	1	4	8	14	26	28	82
Total	1	0	0	1	9	13	35	52	63	174

will be explained in Section 4. The second step was to allocate the functions to the theoretical DF4CE framework and map the frequency of the code. This revealed seven mechanisms indicating how the implementation of DTs can support CE, together with the maturity level of each. This provides an answer to our second research question, as will be explained in Section 5.

TABLE 3 Journal and conference publication from different authors

Authors	No. of publications	Year of publication
Gupta, S.	6	1 (2019), 1 (2020), 4 (2021)
Bag, S.	5	3 (2020), 2 (2021)
Charnley, F.	5	1 (2017), 1 (2018), 3 (2019)
Lawrenz, S.	5	2 (2020), 3 (2021)
Moreno, M.	5	1 (2017), 1 (2018), 3 (2019)
Tiwari, A.	5	1 (2017), 1 (2018), 2 (2019), 1 (2021)
Tseng, M.L.	5	2 (2019), 2 (2021)
Sassanelli, C.	4	3 (2020), 1 (2021)
Terzi, S.	4	3 (2020), 1 (2021)
Turner, C.	4	1 (2017), 1 (2018), 1 (2019), 1 (2020)
Others	3 or less	-

3 | DESCRIPTIVE ANALYSIS

As shown in Table 2, the research topic covered in this article is one which has been attracting increasing interest since 2017. The first relevant paper was published in 2013. The amount of research increased rapidly from 2017 onwards, with 35 papers published in 2019, 52 in 2020, and 63 in 2021 (until September). Due to the interdisciplinary nature of the topic, most of the selected papers are scattered across different journals. It is clear from this pattern that the topic constitutes a growing and pioneering research field.

Among the journals, *Sustainability* published 15% of the selected papers. Eleven out of the 26 of these were published in 2021. The *Journal of Cleaner Production* also published a significant number, 18 papers in total. Thirteen papers were published in association with the CIRP conferences, making that a vital knowledge provider. Since 2019 *Resources Conservation and Recycling* has also contributed to the field by publishing 10 papers, and *Technological Forecasting and Social Change* provided seven papers. All of these journals have added significantly to the body of knowledge in this field.

Regarding the number of documents published by author (Table 3), S. Gupta and S. Bag are have clearly been significant contributors to the field, especially as they have worked together to publish
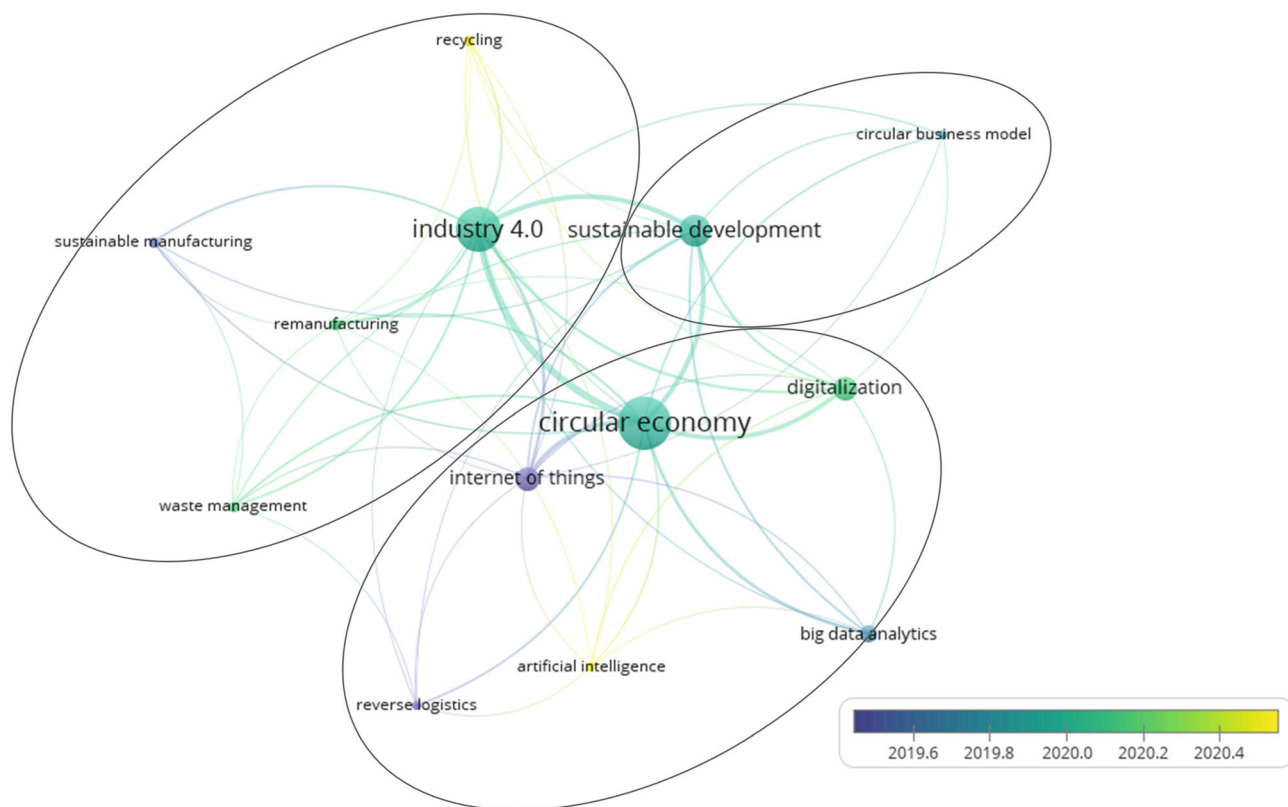

FIGURE 5 Co-occurrence network of author keywords [Colour figure can be viewed at wileyonlinelibrary.com]

some joint papers—one paper in 2018 and two others in 2021 (Bag et al., 2018; Bag, Gupta, & Kumar, 2021; Bag, Pretorius, et al., 2021). Some other authors have also established effective research collaboration and have published together. The latter applies to F. Charnley, M. Moreno, A. Tiwari, and C. Turner who were all co-authors in papers published in 2017, 2018, and 2019 (Charnley et al., 2019; Moreno et al., 2017, 2019; Okorie et al., 2018; Turner et al., 2019).

We examined the co-occurrence of author keywords to understand how the research topics associated with circular economy and digital technologies are related to each other. The commonality of author keywords was built on the basis of keywords appearing at least five times in a paper. Figure 3 shows the 13 keywords identified and the connections between them. The six most frequently used keywords were: *circular economy*, *Industry 4.0*, *sustainable development/ sustainability*, *digitalization/digital technologies*, *IoT (or Internet of Things)*, and *big data analytics*. One hundred four papers, about 60% of the total, used "circular economy" as keywords, making it clear that this was central to the research of the authors. The second most frequent keyword was industry 4.0 with 76, followed by sustainable development/sustainability with 41 occurrences.

In Figure 5, three main clusters are identified. The first one focuses on the combination of circular economy with digital technologies like the internet of things, big data, and artificial intelligence. The second cluster is related to industry 4.0 and remanufacturing, sustainable manufacturing, recycling, and waste management. The third one covers discussion of circular business models with sustainable development and digitalization. In this cluster, the papers highlighted digitalized servitization, also known as the product-service system (Alcayaga et al., 2019; Bressanelli et al., 2018a,b; Ingemarsdotter et al., 2019; Zheng et al., 2019). In Figure 5, the dark blue colour represents the average publication year that the keyword occurs. The

yellow circle shows keywords used more recently by the papers. While the internet of things and big data are topics widely explored by the literature, the new studies focus more on AI and recycling.

4 | THE MAIN FUNCTIONS OF DIGITAL TECHNOLOGIES FOR THE CIRCULAR ECONOMY

After two rounds of coding, our study identified 13 digital functions from the existing literature where DTs can be used to improve CE performance in Table 4. This heatmap highlights the most frequently discussed codes with darker shades so as to visualize the trends in the reviewed papers. We then classified the 13 digital functions according to the predefined categories.

From the technology perspective, IoT was often discussed together with collecting and monitoring, because it connects wireless sensing devices to each other and to the internet. Whereas BDA and AI were mostly applied for digital functions in the data analysis category, due to their advanced data processing ability. BDA can handle and analyse enormous and multifarious volumes of data, coming from both the physical world and human society at an ever-accelerating pace (Gupta et al., 2019). AI can provide a faster and more agile learning process for data analysis based on larger data set (Kaplan & Haenlein, 2019; Kristoffersen et al., 2020). Lastly, general DTs were linked with all digital functions as it integrates different technologies' abilities. It showed a slightly stronger link with two functions: sharing and auto-control, which especially require a combined support from multiple DTs.

The differences between empirical and conceptual codes varies in accordance with the technology concerned. IoT has an almost

TABLE 4 Identified digital functions and their supporting technologies in a heatmap

Category	Digital function	IoT E	IoT C	BDA E	BDA C	AI E	AI C	General E	General C	Total
Automation	Auto-plan		2			1		5		8
	Auto-control		2	2		4		10	1	19
	Sort and classify	2	2			3	3	2	1	13
Data analysis	Optimize	5	1	6	5	7	1	1	3	29
	Innovate	1		2	2	8	5	3	3	24
	Forecast		3	2	1	6	7	5		24
	Connect		3	1		1		3	3	11
	Assess	3	1		5			3	1	13
	Detect	1	2	1			1	3	2	10
	Track and Trace	8	3	1	1	1		3	2	19
	Monitor	11	10	4	2	4	3	6	1	41
Data collection and integration	Share	1	1	2				7	3	14
	Collect	8	11	3	1	3		4	4	34
Total		40	41	24	17	38	20	55	24	259

Abbreviations: AI, artificial intelligence; BDA, big data analytics; C, conceptual code; E, empirical code; IoT, Internet of Things.

equivalent amount of both codes, while all the others are weighted to the empirical codes. The implementation dimension of AI and general DTs, especially, carry almost twice as many empirical codes as conceptual codes. The AI codes are mainly drawn from papers published after 2020, and most are related to generating wisdom through data analysis.

The most frequently discussed digital functions for CE were collection, monitoring, tracking and tracing, and optimisation. Auto-plan, auto-control, and assess clearly based largely on empirical evidence. Auto-control has the most concentration of empirical codes, with 16 of these against three conceptual codes. Collect, monitor, and forecast, however, have a similar number of empirical and conceptual codes.

The detail of each digital function is discussed below in the corresponding categories.

4.1 | Data collection and integration

Data collection, together with data integration, forms the basis for data analysis. Data collection provides a massive amount of data as the basis of analytical functions (Siow et al., 2018). Data integration extracts information from raw data through aggregation, interpretation, selection, and sorting of various data (Dalamagas et al., 2020; Kristoffersen et al., 2020). Although data integration is vital for demonstrating information (Chen et al., 2020), it is rarely discussed as a single function of IoT, BDA, or AI in the reviewed literature. Collect and share are the functions in this category, as exemplified below.

4.1.1 | Collect

Data collection generates and gathers data from various heterogeneous sources (Kristoffersen et al., 2020). It is the fundamental support for other functions in the framework (Ranta et al., 2021; Siow et al., 2018). IoT provides the internet connection for infrastructure to transmit generated data into a central system (McEwen & Cassimally, 2013; Rossi et al., 2020). This system enables data collection with embedded sensors to measure real-time data and report information with minimum human interaction (Zacharaki et al., 2020). Data sources range from companies' internal processes to external supply chain partners and customers (Ranta et al., 2021). The collected data makes possible the analytical and automatic functions, such as monitoring, optimization, and innovation.

4.1.2 | Share

Data sharing can increase information availability and support data analysis for optimization and real-time control. Shared data can be unprocessed raw data or integrated information. Raw data can be shared by granting access to databases or allowing external data collection, such as collecting data from customers via personal devices.

The information shared between companies is often inferred or transformed from data (Kristoffersen et al., 2020).

Additionally, sharing data can strengthen the existing interconnection and create new communication and collaboration. The use of DT can greatly improve the information exchange between different production processes, including production machines, automatic warehouses, and other devices facilitating value creation (Garcia-Muiña et al., 2018). Digital data platforms can combine data collection and data sharing functions for analysis or autonomous use. It can gather information from various sources either within or across business boundaries (Blömeke, Mennenga, et al., 2020).

4.2 | Data analysis

Data analysis is the process of deriving knowledge and wisdom from integrated information. It provides insights and knowledge to support decision making by answering how and why questions (Kristoffersen et al., 2020). It helps companies manage their operations, makes data-driven decisions, creates an efficient supply chain network, and co-ordinates production elements (Gupta et al., 2019; Kerin & Pham, 2019; Romero & Noran, 2017).

IoT, BDA, and analytical AI are all discussed in the literature as supports to the data analysis functions. Many calculations can be undertaken quickly with these technologies. Human experts then use the resulting data to solve problems which requires the level of creatively that computers cannot achieve. Such applications can be found in logistic route planning, container designing, and performing tasks in remanufacturing (Ellen MacArthur Foundation, 2019; Wilson et al., 2021). These technologies can make CE businesses more dynamic and unlock their full potential (Romero & Noran, 2017).

4.2.1 | Monitor

Monitoring gives real-time updates on processes and environments in a specific location. IoT collects continuous data about the changes in the state of processes, conditions or materials, such as temperature and moisture, production and machine conditions, product usage performance by the customer, and waste bin conditions (Kintscher et al., 2021; Nižetić et al., 2019; Rossi et al., 2020; Yang, Raghavendra M. R., et al., 2018). The constant status update allows fast decision-making in response to changes, increasing the operational flexibility and stabilizing the process.

4.2.2 | Track and trace

Track and trace collects information on the status of items through their lifecycle, specifying their previous paths and the changes which they undergo such as the real-time movements and location, usage information, and remanufacturing stages (Abideen et al., 2021; Garrido-Hidalgo et al., 2020; Modgil et al., 2020; Zhang et al., 2019).

Compared with monitoring, this function emphasises the changes relating to a specific item, enabling its traceability in the value chain. For example, tracking the locational change of spare parts makes them easier to retrieve for remanufacturing (Ranta et al., 2021). One typical technology is the RFID tags that store and carry the information of items. They travel with items throughout the value chain, so that people can retrieve items' information by scanning the tags (Garrido-Hidalgo et al., 2020).

4.2.3 | Detect

This is the function that identifies deviation in performance or abnormal characteristics in items or processes (Enyoghasi & Badurdeen, 2021; Pagoropoulos et al., 2017). Possible application of detecting involves identifying differences in object's appearances for end-of-life solutions. For example, computer algorithms can decide whether to repair, recycle, or discard items based on the results from examining the returned product for scratches and defects, or detecting different materials in wastes (Turner et al., 2020; Zhang et al., 2019). Another application of detection is to identify abnormal process behaviours through monitoring, making it possible to stabilize performances (Ingemarsdotter et al., 2021; Tiwari et al., 2021).

4.2.4 | Assess

Assessment can be targeted on physical objects such as materials, end-of-life recovery of products, machine efficiency, and conceptual entities such as environmental impact (Rosa et al., 2020; Zhang et al., 2020). Its results can support a variety of different objectives such as revealing hidden patterns, reducing cost, and facilitating predictive maintenance.

4.2.5 | Connect

DTs offer the opportunity of establishing multi-actor connection networks. Customer and reverse logistic service providers, and recycling centres, can be connected through smart devices and digital platforms. Connection through digital platforms can foster industrial symbiosis by connecting factories in different industries (Birat et al., 2021). Such connection can also accelerate the collection of used devices, so that they can be delivered to recycling centres (Lawrenz & Leiding, 2021). The connection also gives customers more access to the production, design, and recycling processes, laying the basis for customer-centred production and service (Huynh, 2021).

4.2.6 | Forecast

This is the function that enables future events to be predicted, based on past and present data. It is often applied to predict the demand

trends for products, materials and critical service parts (Boone et al., 2017). Another popular application is the predictive maintenance that forecasts need for maintenance by calculating the product failure tendency (Jabbour et al., 2018; Kerin & Pham, 2020; Morella et al., 2020). Furthermore, AI-based digital twin technology can simulate different predictive maintenance options to find out the best solution (Zacharaki et al., 2020).

The predictive function can also applied in estimating the by-product potential of production which can be used as materials in other industries, as also in determining whether or not a product can be recycled (Ghoreishi & Happonen, 2020a). Additionally, predicting the resource and energy needed for agriculture, such as greenhouse lighting, can guide the design of new production lines or farming arrangements (Ranta et al., 2021).

4.2.7 | Innovate

The innovate function relates to the discoveries and creations stemming from analytic results. AI technologies can contribute to identifying new patterns, revealing industrial symbiotic links, testing designs, and validating business model innovations (Birat et al., 2021; Dalamagas et al., 2020; Fraga-Lamas et al., 2021; Getor et al., 2020; Kristoffersen et al., 2020; Rossi et al., 2020). Apart from accelerating the innovation processes, DTs and intelligent products allow creativity in improving and developing product and service designs. Examples include information platforms for industrial symbiosis, smart recycling and waste factories, and intelligent device retrieval services (Blömeke, Mennenga, et al., 2020; Lawrenz & Leiding, 2021; Sarc, 2021).

4.2.8 | Optimize

Optimization can be achieved at all lifecycle stages, such as in the design of products and services, production procedures, logistic operations, customers' usage behaviour, and the reuse or recycling of products. The goal of optimization is often to improve performances and reduce negative impact, such as increasing efficiency and reliability in the production system while reducing emissions and energy consumption. It rests on the results of data analysis, such as that related to gaining knowledge about customers' behaviour and product usage or identifying bottlenecks in production (Jabbour et al., 2018; Yang, Raghavendra M. R., et al., 2018).

4.3 | Automation

The third category applies DTs to enable automation and support robotics (Goering et al., 2018). It refers to the independent process of operating, acting, or self-regulating without human intervention (Liebrecht et al., 2021; Nof, 2009). Automation can enable decentralized decision-making, self-configuration, and self-optimize so as to enhance flexibility, strengthen resilience, and reduce disturbance

(Kamble et al., 2018; Lee et al., 2015). Unsupervised machine operation can reduce human labour, especially for simple and repetitive tasks, and increase energy efficiency (Alcayaga et al., 2019; Yang, Raghavendra M. R., et al., 2018). Its application for CE includes automated waste separation, smart agriculture, and smart energy control (Laskurain-Iturbe et al., 2021; Reis et al., 2021; World Economic Forum, 2016).

Automation functions is one way to apply the results of wisdom-level data analysis when machines can independently transform knowledge into actionable instructions for making decisions or taking actions (Kristoffersen et al., 2020). We have identified three functions under the automation category: sort and classify, self-control, and auto-plan.

4.3.1 | Sort and classify

This function is commonly applied in separating waste, determining the reusability of waste products and recycling materials. At the disassembly line, for instance, AI algorithms can classify the level of disassembly required based on component information collected from IoT-based devices (Blömeke, Mennenga, et al., 2020). AI can also advise customers on suitable disposal options based on the visual data of wastes (Kurniawan et al., 2021). Combined with IoT, AI-empowered robotics can conduct complicated sorting tasks using different items to maximize resource recovery (Alcayaga et al., 2019; Ellen MacArthur Foundation, 2019; Ghoreishi & Happonen, 2020a; Kintscher et al., 2021).

4.3.2 | Auto-control

Auto-control is related to autonomous systems and intelligent robotics. Both can complete operational tasks without human intervention. On the one hand, autonomous systems can monitor processes and systems with minimum human interaction (Zacharaki et al., 2020). IoT collects real-time data for automated decision making and operations (Basso et al., 2021). Auto-control function can adjust the air and light conditioning, turn on and off machines, and even operate intelligent machinery (Laskurain-Iturbe et al., 2021; Reis et al., 2021). On the other hand, intelligent robotics can increase process efficiency and accuracy. It can minimize energy consumption, reduce defects, and make better use of the materials (Laskurain-Iturbe et al., 2021).

4.3.3 | Auto-plan

Auto-plan uses AI for decentralized decision-making without human interference on both the predictive and prescriptive levels. Such intelligent systems can generate personalized disassembly plans for each part based on cognition information and shared databases (Blömeke, Mennenga, et al., 2020). Condition-based monitoring can automatically schedule maintenance interventions and generate information on necessary material requirements before an actual breakdown (Kristoffersen et al., 2020; Rossi et al., 2020). Other possibilities include the automatically generation of procurement plans, end-of-life strategy decisions, and feasible logistics routes (Bag, Wood, et al., 2020; Mboli et al., 2020; Rossi et al., 2020).

5 | THE FRAMEWORK OF DIGITAL FUNCTIONS FOR CIRCULAR ECONOMY

We categorised the codes in relation to the DT functions discussed in reviewed papers into corresponding circular strategies. The results are mapped onto the DF4CE framework (Figure 6). The size of the circles represents the number of second-round codes. It shows that in literature, these digital functions are most frequently used for *reduce*, followed by *rethink*, and *recycle*. We further analysed the codes and their contexts in literature and proposed seven underlying mechanisms as follows.

5.1 | Digital functions for useful application of material

5.1.1 | Mechanism 1—Recycling: Digital functions empower the reverse supply chain

We identified this mechanism as using digital functions to empower the reverse supply chain through building a faster, more precise, and automated recycling system. The recycling strategy benefits from most of the digital functions covered in this article. *Sort and classify* seems to be the most useful function for recycling, followed by *innovate* and *detect*. *Sort and classify* is almost exclusively related to *recycling*, while *forecast* has not yet been linked with this mechanism.

We found that the digital functions used to improve the efficiency of linear manufacturing processes can be largely applied in the reverse supply chain in a similar way. In the forward supply chain, DTs are often applied for improving production efficiency and optimising logistics planning to increase companies' profits. Similarly, companies can use IoT to collect data from the reverse supply chain, such as the locations and conditions of used products and wastes. These data can be analysed to improve the reverse supply chain efficiency, especially through accelerating the recycling process and increasing material recovery (Dev et al., 2020; Rajput & Singh, 2019; Vetrova & Ivanova, 2021).

This similarity can be observed when applying *monitor* and *track and trace* functions on the reverse supply chain. Companies have increasingly used DT to *monitor* the recycling processes for minimising wastes (Kerdlap et al., 2019), to *track and trace* items for planning route, scheduling waste collection and transport (Rajput & Singh, 2019), as well as reducing emission and energy consumption. For example, in an electric vehicle battery remanufacturing case, IoT systems are used to collect and share real-time data of batteries and their carriages so as to *monitor* their status, and *track and trace* the batteries' lifetime data (Ren et al., 2020; Zhang et al., 2020).
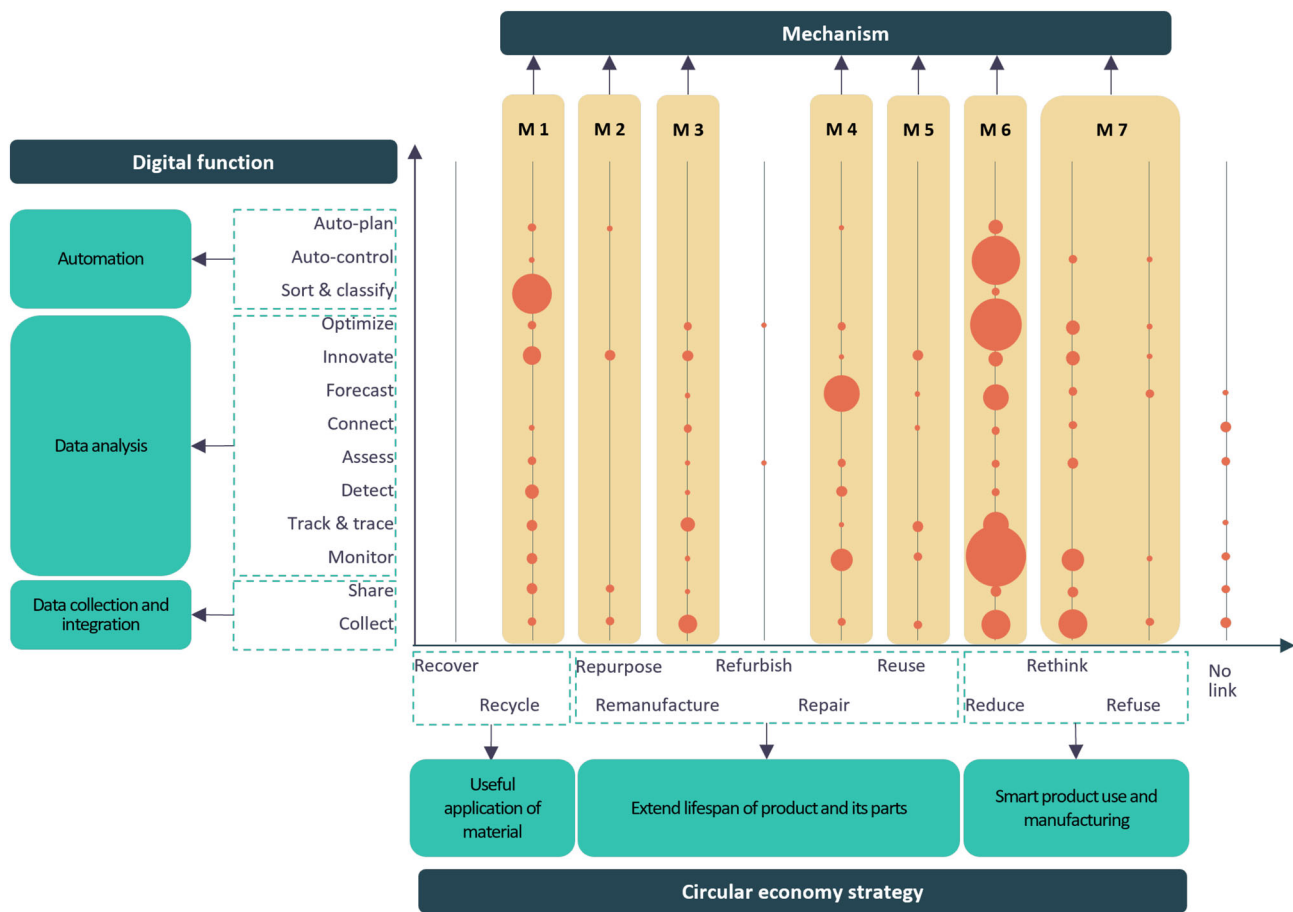
FIGURE 6 A framework of digital function for circular economy (DF4CE) and the seven mechanisms: M1 – Empowering the reverse supply chain, M2 – Fostering industrial symbiosis, M3 – Supporting remanufacturing activities, M4 – Enabling predictive and prescriptive maintenance, M5 – Supporting reselling and sharing used products, M6 – Improving energy and resource efficiency, and M7 – Supporting circular product design, manufacturing and use [Colour figure can be viewed at wileyonlinelibrary.com]

In addition, we identified the digital functions applied in reverse supply chain that do not often exist in linear supply chain. In reverse supply chain, for instance, sensors are often used to measure wastes and waste bins to facilitate recycling (Fatimah et al., 2020). DT empowers the recycling system to *detect* damages on used products, such as rust and scratches, and therefore support disassembly for end-of-life products (Blömeke, Mennenga, et al., 2020). The optimization algorithm evaluates the end-of-life decisions, such as whether to refurbish, remanufacture, or recycle (Mboli et al., 2020; Zacharaki et al., 2020).

Our study discovered that *sort and classify* might be designated for increasing the recycling efficiency. In this occasion, technologies are used for separating wastes, deciding whether an item should be reused, repaired, refurbished, remanufactured, recycled, or disposed. Such *sorting and classifying* process involves not only using digital calculation to decide on the end-of-life options, but also applying automatic robotics to physically separate wastes. These decisions can derive from other digital functions, for instance, *detecting* damage

levels or material compositions (Ellen MacArthur Foundation, 2019; Laskurain-Iturbe et al., 2021; Sarc, 2021; Wilts et al., 2021).

5.2 | Digital functions for extending lifespan of product and its parts

Extending lifespan of product and its parts is mainly achieved through repurpose, remanufacture, refurbish, reuse and repair. Digital functions in the data analysis category are the most frequently used, while the one in automation category are rarely mentioned.

Analysing data for matching the products' supplies and demands is especially important for extending lifespans. IoT can support this purpose by collecting and sharing data between users, technicians, service providers, and potential second-hand buyers. DT-based tools, procedures, and platforms can accelerate the exchange of information between offers and demands. BDA then supports in generating personalised after-sale services (Rosa et al., 2020).

Among these CE strategies, repairing and remanufacturing are the most frequent ones in terms of adopting DT for lifespan extension. Altogether, we identified four mechanisms for using digital functions to extend product lifespan as follows.

5.2.1 | Mechanism 2—Repurpose: Digital functions foster industrial symbioses

The repurpose mechanism focuses on using DTs to foster industrial symbiosis, in which wastes or by-products generated in one industry can be converted into production resources for other industries. Since companies often lack the knowledge for such a cross-sectoral exchange of waste, material and service, exchanging information among multiple industries can help them discover new opportunities.

One proposed digital solution for industrial symbiosis was the information exchange platform for regional industries (Dalamagas et al., 2020). It can *collect* data on the location, type, and quantity of input materials and waste (Song et al., 2017) and *share* them between traditionally separated industries in the same region (Acerbi et al., 2020; Kristoffersen et al., 2020; Zeiss et al., 2020). The data shared on information platforms can support real-time waste-to-resource matching, so as to reduce the uncertainty of by-product availability and ensure the appropriate quality for further exploitation (Birat et al., 2021; Dalamagas et al., 2020; Kristoffersen et al., 2020). These actions result in *innovating* industrial symbiosis links among companies in the same region (Zeiss et al., 2020).

5.2.2 | Mechanism 3—Remanufacture: Digital functions support remanufacturing activities

The remanufacturing mechanism applies DTs to retrieve parts that is still functioning from the non-functional products, so as to repair and rebuild the parts into new products that are similar to the original ones. Ten out of 13 digital functions discussed in this article were related to this mechanism, which covered all the functions under *data analysis* category and *data collection and integration* category. However, none of the functions under the *automation* category were yet to be linked with remanufacturing.

Digital functions can support the whole remanufacturing process, involving identifying useful parts, disassembling and repairing them, reselling and rebuilding them in a new product. For instance, DTs can *detect* a product's wear by means of embedded sensors in the products or through data *shared* by customers (Kerin & Pham, 2019). *Track and trace* provide insights into the availability and condition of used products and spare parts (Ingemarsdotter et al., 2020; Subramoniam et al., 2021). The information can enable companies to make personalized remanufacturing processes that minimizes wastes and material consumption (Moreno et al., 2019), to *optimize* process efficiency as referred elsewhere (Kerin &

Pham, 2020; Zacharaki et al., 2020), or to secure the spare parts sourcing, which can often be a significant challenge for industry (Dev et al., 2020; Garrido-Hidalgo et al., 2020; Rosa et al., 2020). Other possibilities include predicting the remaining lifetime of products, checking the functionality during remanufacturing, and supporting design for remanufacturing (Aziz et al., 2021; Blömeke, Rickert, et al., 2020; Garrido-Hidalgo et al., 2020).

5.2.3 | Mechanism 4—Repair: Digital functions enable predictive and prescriptive maintenance

The repair mechanism uses DTs to extend machines and products lifespan through predictive and prescriptive maintenance, which means carrying out customized maintenance tasks on devices before the actual breakdown happens. It was frequently discussed in the reviewed papers, in which *monitoring* and *forecasting* were often mentioned. However, *sharing* and *connecting* does not receive enough attention, nor does the functions in the automation category.

Digital systems can support failure detection, condition-based maintenance, and automatic task scheduling for products and machines (Akkad & Bányai, 2021; Bressanelli et al., 2018a; Kristoffersen et al., 2020; Nobre & Tavares, 2020b). If the maintenance is accurately predicted with a prescription of required actions, the maintenance worker can improve the repair efficiency, in addition to reducing unnecessary services and the on-site visits (Ghoreishi & Happonen, 2020a; Ingemarsdotter et al., 2020). Another suggestion was to connect customers with companies for product maintenance. For companies, learning each product's wear and tear from customers can help them arrange more personalised remanufacturing and parts' replacement (Moreno et al., 2019), while customers can start maintaining their tools with companies' technical support (Ranta et al., 2021).

5.2.4 | Mechanism 5—Reuse: Digital functions support reselling and sharing used products

This mechanism uses DTs to support reusing products through reselling and sharing used products, such as second-hand market. Used products which are in good condition can extend their lifespan with second-hand users. Digital functions mainly support relocating used products through finding the reusable products, then selling them to the second-hand customers. *Track and trace*, *monitor*, and *collect* were considered useful for the finding and provide information about products that are ready for reuse, such as the products in-use data, the real-time condition, and their location (Vetrova & Ivanova, 2021). *Innovate*, unlike the former, mainly supports the trading process. Developing new DT-based tools, platforms, systems, and services can efficiently connect potential second-hand buyers to the products because these technologies

accelerate the information exchange process (Cagno et al., 2021; Rocca et al., 2020).

5.3 | Digital functions for smart product use and manufacturing

5.3.1 | Mechanism 6—Reduce: Digital functions improve energy and resource efficiency

Our study suggests that the reduce mechanism is often related to improving energy and resource efficiency at all product lifecycle stages. It is the most frequently discussed topic in our reviewed literature, in which sense it is clearly seen as the most feasible way to adopt DT for CE. Improving production efficiency and energy efficiency are proven benefits of Industry 4.0 (Mohamed, 2018; Oztemel & Gursev, 2020) and a sustainable value driver. One direct impact of improved process efficiency is less waste in materials and energy. *Monitoring*, *optimization*, and *auto-controlling* are the most applied digital functions. *Forecast*, *track and trace*, and *collect* also contribute strongly to this mechanism.

Logistics *optimization* is one of the central topics (Cagno et al., 2021) covered in the reduce strategy. It leads to reduced fossil fuel consumption for transportation. *Collecting* and *sharing* data like trucks' location and movement, loads, shipment, and product condition supports *optimizing* routes and loading. In addition, technologies help optimizing the real-time waste collection route leads to an increasing rate of recycling (Akkad & Bányai, 2021; Garrido-Hidalgo et al., 2020; Rossi et al., 2020).

Increasing production efficiency is another well-discussed topic. In the short term, real-time *monitoring* can support quick and interactive equipment management with greater energy efficiency (Reis et al., 2021). *Self-control* robotics and systems are deployed to increase efficiency and reduce human conduct failings (Laskurain-Iturbe et al., 2021). In the middle to long term, *tracking and tracing* makes analysis and planning more precise, reducing waste from faulty conduct (Wegner-Kozlova & Guman, 2020). *Optimization, forecast, and innovative* functions further improve the efficiency.

End-of-life efficiency is also discussed. Apart from the valuable insights generated from data analysis, as it does in other stages, disassembly efficiency benefits from AI and control technologies. For example, *detecting* defects helps AI to decide disassembly levels, choosing end-of-life solutions, and sorting wastes (Sassanelli et al., 2021). Furthermore, AI can *connect* waste generators and collectors so as to increase waste recovery efficiency (Kurniawan et al., 2021). Automatic *sorting and classifying* wastes not only improves recycling efficiency but also reduces human labour.

5.3.2 | Mechanism 7—Rethink and refuse: Digital functions support product design, manufacturing, and use

This mechanism uses DTs to focus on fundamental changes in product and service design, production processes, and user behaviour, so as to abandon the wasteful behaviour and replaces non-renewable materials with recycled or renewable ones. It benefits more from digital functions in the data analysis, collection and integration category rather than the automation category. *Collet*, *monitor*, *innovate*, and *optimize* seem to contribute the most for rethinking and refusing the unsustainable practices, while *detect* and *track and track* were not directly relevant to this mechanism in the reviewed papers.

In the design phases, DT provides information and accelerates the development of prototypes. On one hand, building a product biography can support CE design, which is "a composite of trajectories rather than following a linear path from design to manufacture and disposal" (Spring & Araujo, 2017; Spring & Araujo, 2017, p. 27). Data *collected* and *shared* at all product lifecycle stages can elaborate a systematic and comprehensive product biography, which can be used to support the circular design of product (Kerin & Pham, 2020) or product-service systems (Ingemarsdotter et al., 2020; Kerin & Pham, 2020; Yang & Evans, 2019; Yang, Smart, et al., 2018). On the other hand, AI can test different design models' stability and quality, accelerating the design process with the use of fewer prototypes (Getor et al., 2020; Ghoreishi & Happonen, 2020b). It can be used to find suitable renewable raw materials or recycled materials, replacing the non-renewable ones (Morella et al., 2020; Ranta et al., 2021).

DT can also be used to reshape the production process. The strategic analysis can integrate environmental impact factors into identifying novel value creation opportunities, such as production with renewable resources (Ranta et al., 2021). Embedded lifecycle assessment indicators can also reduce the environmental impact of the production process (Birat et al., 2021).

As for changing the usage behaviour, DTs provide the *connectivity* that brings customers closer to companies. For customers, it can encourage them to change their non-circular habitual usages and adopt sustainable behaviour. For instance, they can have more information about recyclable products and their environmental impact (Huynh, 2021). At the disposal stage, customers can receive advice on where to discard the waste for end-of-life solutions (Kurniawan et al., 2021). As for companies, they can increase recycling rates by developing *innovative* services and offerings to customers (Kristoffersen et al., 2020). They can also help customers reduce careless behaviour in product use by *monitoring* of product conditions and customer activities (Kintscher et al., 2021; Rossi et al., 2020).

5.4 | Maturity level of the digital functions mechanisms for circular economy

The maturity level of each specific digital function for each specific CE strategy can be interpreted from the size of their circles in the DF4CE framework (Figure 6). The size represents the number of second-round codes, hence the amount of related discussions in prior studies. More discussion provides a more comprehensive understanding of how to realize the digital functions for CE strategies. In other words, a larger circle means a higher maturity level of relevant discussion.

Among seven mechanisms, *reduce (M6)—digital functions improve energy and resource efficiency* seems to have a significantly higher level of maturity than the rest. Overall, this study found 36% of the second-round codes relating to this mechanism, among which *monitoring*, *optimizing*, and *auto-control* were the most related digital functions. *Recycling (M1)* and *rethink and refuse (M7)* have the second level of maturity, with 15% and 16% second-round code respectively related to them. The least discussed mechanism is the *repurpose (M2)—digital functions foster industrial symbioses*, which appears to be an emerging topic in recent years. The *recycling mechanism (M1)* and *repairing mechanism (M4)* appears to rely heavily on specific digital functions, as 28% of the codes that are grouped under *recycling* represent the digital function of *sort and classify*. Similarly, 35% of the codes under *repairing* belongs to the *forecast* function.

There are still missing links in prior researches. From the CE aspect, our study found no digital functions that are linked to the *recovering* strategy (e.g., recovering energy by incineration of material). Only two codes suggest the application for *refurbishing* old products. As for digital functions, it is still unclear how the digital functions under the *automation* category can support extending products and parts lifespan. Additionally, we found 14 second-round codes that did not relate to any of the CE strategies.

6 | DISCUSSION

6.1 | Theoretical implication

This study has sought to advance theoretical understanding of how DTs can support different CE strategies. More specifically, it constitutes a novel attempt to identify the ways in which DT-enabled digital functions can improve CE performances. The study provides a holistic theoretical DF4CE framework by including IoT, BDA, AI, and general DTs in the review process. After examining 174 papers, creating 782 original codes and 259 second-round codes, the study identified 13 critical digital functions of DTs which are of relevance. These were divided into three categories: Data Collection and Integration (collect and share), Data Analysis (monitor, track and trace, detect, assess, connect, forecast, innovate, and optimize) and Automation (sort and classify, auto-control, and auto-plan).

The study reveals clearly the intensity of the impact which DTs can have on transitions towards CE, as evident in the role they can play in specific CE strategies. The research demonstrates how and to what extent the adoption of currently operative DTs can improve CE transformations in a structured and comprehensive way. Our analysis uses and builds upon the 9R CE framework so as to ensure that CE strategies are covered in an overall manner. The DF4CE framework reveal the existence of seven mechanisms that DTs can currently improve CE performances: M1 (empowering the reverse supply chain), M2 (fostering industrial symbiosis), M3 (supporting remanufacturing activities), M4 (enabling predictive and prescriptive maintenance), M5 (supporting the relocation of products, M6 (improving energy and resource efficiency), and M7 (supporting circular transformation in

design, production, and usage). Our study also indicates which functions are more mature in terms of possible implementation as well as what missing links there are in the empirical and theoretical research.

The DF4CE framework extends the "capability mapping" on CE strategies (Nobre & Tavares, 2020b), establishes an operative layer for the "smart CE framework" (Kristoffersen et al., 2020), and improves the IoT-CE "cross-section occurrence map" (Ingemarsdotter et al., 2019) by adding functions from a wider range of DT and CE perspectives. Our results also refine Bressanelli et al. (2018a)'s framework by generalizing the functions and adding more CE strategies to them.

Finally, our results indicate the critical role of data from both inside and outside of companies. Three DF categories are directly linked to the data dimension. The automation category, furthermore, operates on a basis of instant data feedback. The focus on data in our DF4CE framework can be explained by theories related to value creation from large scale data. Previous studies have shown that DT can improve companies' value creation by generating new avenues based on analysing supply chain data (Bordeleau et al., 2018; Rehman et al., 2016). Our research complements this perspective.

6.2 | Practical implication

Managers should be able to use the DF4CE framework developed in this study to explore new forms of value creation through digital functions. Based on the identified mechanisms, manufacturers can take account of product lifecycle management and zero-waste manufacturing. Distributors and service providers can investigate the digitalised circular product-service system. Companies for disassembly and reuse, remanufacturing, and waste management can also use our framework for their DT implementation process (Alcayaga et al., 2019; Kerdlap et al., 2019; Kerin & Pham, 2019; Rosa et al., 2020; Sarc et al., 2019).

6.2.1 | The importance of multi-dimensional and multi-actor data requires collaboration enhancement

Our results show that collecting multi-dimensional and multi-actor real-time data plays a fundamental role in supporting CE transformation. Data collected inside the organization is often used to increase energy and resource efficiencies, which follows the green-lean manufacturing and logistics management concepts (Chen et al., 2020; Mariani & Borghi, 2019). In comparison, external information from outside the organisation shows an even more vital link to the CE paradigm. Such information exchange requires high-level trust and close collaboration among the stakeholders, based on a shared understanding of the whole system and all related practices (Abideen et al., 2021; Gupta et al., 2019; Mishra et al., 2019; Yang et al., 2021). For instance, sharing information among the supply chain stakeholders can support their end-of-life activities, collaborative cradle-to-cradle design approach, and industrial symbiosis (Birat et al., 2021; Getor et al., 2020; Huynh, 2021; Massaro et al., 2021).

Additionally, the research shows that the customer has become a vital actor in CE transformation because DTs bring customer data into business decision-making, such as the design phase (Vetrova & Ivanova, 2021). It also provides customers with feedback on environmental impacts to raise customers' sustainable awareness (Akkad & Bányai, 2021). The role of DTs is clearly of vital importance in that regard.

6.2.2 | The importance of creating a safe and secure information sharing environment

The importance of sharing information calls for building a safe and secure data-sharing environment. Data scientists need to provide new solutions to encrypt and share data, prevent information leaks and espionage, perhaps through the use of blockchain technology (Daneshgar et al., 2019). Business studies should explore inter-organizational collaboration forms, such as the reverse supply chain information marketplace (Blömeke, Mennenga, et al., 2020). Policymakers and practitioners could increase information security and lead knowledge-sharing actions by setting up regulations and standards for data integration within industrial networks. Meanwhile, the government should also protect customers' privacy from misuse by corporations.

6.3 | Future research agenda

Five significant areas for future research and theorising have become clear through the current study. These are covered below.

6.3.1 | Advancing the understanding of perspectives coming from management theory

Our study has revealed a lack of research that based on management theory. This could be due to the interdisciplinary character of the DF-CE subject area. Most of the studies undertaken focus on empirical research or on developing exploratory conceptual frameworks. Only a limited number of studies seek to advance the understanding of DT-CE implementation through the lenses of management theories, such as from the resource-based view or the stakeholder theory (Awan et al., 2021; Bag, Dhamija, et al., 2020).

6.3.2 | Advancing the understanding of digital technologies in the cross-sectional study

Future research could usefully seek to provide a deeper understanding in clarifying the boundaries and synergies between different technologies and their functions. This is crucial and could lead to the development of a detailed theoretical framework for DT integration practices.

Some of the limitations in existing studies, as far as this factor is concerned, are worth making explicit. First, the DT terms need to be made consistent across the field. For example, some reviewed literature sees IoT as a means of supporting the collection, storing and processing of data, and even enabling fully autonomous systems to be created (Basso et al., 2021; Rossi et al., 2020). Others see the role of IoT as a connector between different technologies (Rocca et al., 2020; Turner et al., 2020). Second, the digital function terms also have different characteristics. For example, "detect" can refer to finding undiscovered symbiotic links (Dalamagas et al., 2020), or to identifying differences in objects such as scratches and materials. Third, some digital function terms can have overlapping meanings. Our review, having synthesized 782 original codes, defined "monitoring" as a function that covers real-time updates on processes in a fixed position, while "tracking & tracing" covers a specific moving item's past and current changes. However, some literature uses these terms differently, such as tracking the environment (Tseng et al., 2021), monitoring used product parts (Ada et al., 2021), and monitoring and tracking products (Vetrova & Ivanova, 2021; Wegner-Kozlova & Guman, 2020).

6.3.3 | Innovating technology applications for the circular economy

Our study has revealed the need of innovative DT applications for closing the loop, especially for extending products and parts lifespan. Our findings suggest that current DT implementations for CE are often a readaptation of existing practices that aim to increase productivity and efficiency (Frank et al., 2019), which have limited contribution in closing the material loop. Among the end-of-life solutions, recycling attracts more attention than the others. However, the emphasis remains on improving efficiency in the reverse supply chain (Furstenau et al., 2020). Because CE requires a radical change of our current production and production patterns (Merli et al., 2018; Reim et al., 2021), we argue that the existing DT applications are insufficient to support the CE paradigm. Further research should create new ways to fill in the missing links in the DF4CE framework discussed in this study.

6.3.4 | Advancing empirical research

Future research needs also to focus on finding solutions for the barriers and challenges of DTs to CE. Previous papers have elaborated on the barriers in various industries, such as those by Lobo et al. (2022), Abdul-Hamid et al. (2020), and Liu et al. (2021). They provide the basis for seeking practical solutions. Additionally, future research needs to help in developing practical tools that help companies overcome barriers and assist companies in the CE transition.

6.3.5 | Advancing management research

Our research reveals that the DT-CE have positive links to industrial symbiosis and value creation, which raise the need to examine their relationship with other management practices, such as business model innovation (Evans et al., 2017; Tunn et al., 2021) and business ecosystem (Kanda et al., 2021). For example, since DTs enhance communication and establish a collaboration network, future research could explore the structure and dynamics of change in circular business models and business ecosystem caused by DT implementation (Hofmann et al., 2022). Future research can also investigate the rebound effects of the smart circular economy, such as its social impact or the increased energy consumption of DT implementation (Lange et al., 2020).

7 | CONCLUSION AND LIMITATIONS

As an emerging interdisciplinary research topic, the current understanding of DT application for CE requires a comprehensive understanding from the operative perspective. Our study has sought to investigate the digital functions of DTs and how they can support different CE strategies based on a systematic literature review. We applied the coding method to examine 174 papers, resulting in 782 original codes and 259 second-round codes, in order to inductively identify the digital functions and reveal their underlying mechanisms. We proposed a Digital Function for Circular Economy (DF4CE) framework to summarize the results of this study. This framework identified 13 critical digital functions of DTs in three categories for improving CE. It also reveals seven mechanisms of digital functions and their maturity level to achieve different CE strategies.

This study contributes to the theoretical understanding by advancing the synergies between the DT and CE paradigms. The identified digital functions and mechanisms provide a theoretical foundation for future theoretical and empirical research. Additionally, by revealing the well-studied digital functions for CE and the less studied field, this study provides the research directions for academics to further investigate the specific digital functions for enhancing a particular CE strategy. For practitioners, our results suggest that collaboration and data security are vital for exchanging information for CE. For business managers, we provide new insight into DT implementation at different products' life cycle stages. The DF4CE framework can be used as an innovation tool to support companies' decision making. Additionally, we discussed five areas for future research and theorising.

One limitation in our study the DTs studied focus mainly on IoT, BDA, and AI. Other DTs, such as 3D printing and virtual reality, were not included in our study. Hence studying the implementation of other technologies for CE could provide more insights. Another limitation is that the reviewed literature did not consider the energy-increasing effect of digitalization. Further research should investigate how to mitigate this effect when reducing energy consumption in other aspects. Lastly, the digital functions are concluded from academic papers that have not yet reached a mature state. Hence, the definitions require further validation in academic and practical studies.

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REFERENCES

Abdul-Hamid, A.-Q., Ali, M. H., Tseng, M.-L., Lan, S., & Kumar, M. (2020). Impeding challenges on industry 4.0 in circular economy: Palm oil industry in Malaysia. *Computers & Operations Research*, *123*, 105052. https://doi.org/10.1016/j.cor.2020.105052

Abideen, A. Z., Pyeman, J., Sundram, V. P. K., Tseng, M.-L., & Sorooshian, S. (2021). Leveraging capabilities of technology into a circular supply chain to build circular business models: A state-of-the-art systematic review. *Sustainability*, *13*(16), 8997. https://doi.org/10.3390/su13168997

Acerbi, F., Sassanelli, C., Terzi, S., & Taisch, M. (2020). In M. Rossi, M. Rossini, & S. Terzi (Eds.), *Towards a data-based circular economy: Exploring opportunities from digital knowledge management*. Springer. https://doi.org/10.1007/978-3-030-41429-0_33

Ada, N., Kazancoglu, Y., Sezer, M. D., Ede-Senturk, C., Ozer, I., & Ram, M. (2021). Analyzing barriers of circular food supply chains and proposing industry 4.0 solutions. *Sustainability*, *13*(12), 6812.

Akkad, M. Z., & Bányai, T. (2021). In K. Jarmai & K. Voith (Eds.), *Applying sustainable logistics in industry 4.0 era*. Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-981-15-9529-5_19

Alcayaga, A., Wiener, M., & Hansen, E. G. (2019). Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production*, *221*, 622–634. https://doi.org/10.1016/j.jclepro.2019.02.085

Allmendinger, G., & Lombreglia, R. (2005). Four strategies for the age of smart services. *Harvard Business Review*, *83*(10), 131.

Awan, U., Sroufe, R., & Shahbaz, M. (2021). Industry 4.0 and the circular economy: A literature review and recommendations for future research. *Business Strategy and the Environment*, *30*, 2038–2060. https://doi.org/10.1002/bse.2731

Aziz, N. A., Adnan, N. A. A., Wahab, D. A., & Azman, A. H. (2021). Component design optimisation based on artificial intelligence in support of additive manufacturing repair and restoration: Current status and future outlook for remanufacturing. *Journal of Cleaner Production*, *296*, 126401.

Bag, S., Dhamija, P., Gupta, S., & Sivarajah, U. (2020). Examining the role of procurement 4.0 towards remanufacturing operations and circular economy. *Production Planning & Control*, *32*(16), 1368–1383.

Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of Production Economics*, 231, 107844.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, 120420.

Bag, S., Telukdarie, A., Pretorius, J., & Gupta, S. (2018). Industry 4.0 and supply chain sustainability: Framework and future research directions. *Benchmarking: An International Journal*, 28(5), 1410–1450. https://doi.org/10.1108/BIJ-03-2018-0056

Bag, S., Wood, L. C., Mangla, S. K., & Luthra, S. (2020). Procurement 4.0 and its implications on business process performance in a circular economy. *Resources Conservation and Recycling*, 152, 104502.

Basso, B., Jones, J. W., Antle, J., Martinez-Feria, R. A., & Verma, B. (2021). Enabling circularity in grain production systems with novel technologies and policy. *Agricultural Systems*, 193, 103244.

Birat, J.-P., Colla, V., Pietrosanti, C., Malfa, E., Peters, K., Fick, G., Chiappini, M., Millet, D., & Alix, T. (2021). Environment 4.0: How digitalization and machine learning can improve the environmental footprint of the steel production processes. *Matériaux & Techniques*, 108(5–6), 507.

Blömeke, S., Mennenga, M., Herrmann, C., Kintscher, L., Bikker, G., Lawrenz, S., Sharma, P., Rausch, A., Nippraschk, M., Goldmann, D., Poschmann, H., Brüggemann, H., Scheller, C., & Spengler, T. (2020). Recycling 4.0: An integrated approach towards an advanced circular economy. *ICT4S2020: Proceedings of the 7th International Conference on ICT for Sustainability*, 66–76. https://doi.org/10.1145/3401335.3401666

Blömeke, S., Rickert, J., Mennenga, M., Thiede, S., Spengler, T. S., & Herrmann, C. (2020). Recycling 4.0—Mapping smart manufacturing solutions to remanufacturing and recycling operations. *Procedia CIRP*, 90, 600–605. https://doi.org/10.1016/j.procir.2020.02.045

Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D. C. A., Hildenbrand, J., Kristinsdottir, A. R., Kristoffersen, E., Shahbazi, S., Nielsen, K. D., Jönbrink, A.-K., Li, J., Wiik, C., & Mcaloone, T. C. (2019). Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation. *Journal of Cleaner Production*, 241, 118271. https://doi.org/10.1016/j.jclepro.2019.118271

Boone, C. A., Skipper, J. B., & Hazen, B. T. (2017). A framework for investigating the role of big data in service parts management. *Journal of Cleaner Production*, 153, 687–691. https://doi.org/10.1016/j.jclepro.2016.09.201

Bordeleau, F.-E., Mosconi, E., & Santa-Eulalia, L. A. (2018). Business Intelligence in Industry 4.0: State of the art and research opportunities. *Proceedings of the 51st Hawaii International Conference on System Sciences*, 3944–3953. http://hdl.handle.net/10125/50383

Bressanelli, G., Adrodegari, F., Perona, M., & Saccani, N. (2018a). Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability*, 10(3), 639.

Bressanelli, G., Adrodegari, F., Perona, M., & Saccani, N. (2018b). The role of digital technologies to overcome circular economy challenges in PSS business models: An exploratory case study. *Procedia CIRP*, 73, 216–221. https://doi.org/10.1016/j.procir.2018.03.322

Briner, R. B., & Denyer, D. (2012). Systematic review and evidence synthesis as a practice and scholarship tool. In D. M. Rousseau, *The Oxford Handbook of Evidence-Based Management* (pp. 112–129). New York: Oxford University Press.

Cagno, E., Neri, A., Negri, M., Bassani, C. A., & Lampertico, T. (2021). The role of digital technologies in operationalizing the circular economy transition: A systematic literature review. *Applied Sciences*, 11(8), 3328.

Cai, H., Xu, B., Jiang, L., & Vasilakos, A. V. (2016). IoT-based big data storage systems in cloud computing: Perspectives and challenges. *IEEE Internet of Things Journal*, 4(1), 75–87.

Charnley, F., Tiwari, D., Hutabarat, W., Moreno, M., Okorie, O., & Tiwari, A. (2019). Simulation to enable a data-driven circular economy. *Sustainability*, 11(12), 3379. https://doi.org/10.3390/su11123379

Chen, X., Despeisse, M., & Johansson, B. (2020). Environmental sustainability of digitalization in manufacturing: A review. *Sustainability*, 12(24), 10298.

Ciliberto, C., Szopik-Depczyńska, K., Tarczyńska-Łuniewska, M., Ruggieri, A., & Ioppolo, G. (2021). Enabling the Circular Economy transition: A sustainable lean manufacturing recipe for Industry 4.0. *Business Strategy and the Environment*, 30(7), 3255–3272.

Cwiklicki, M., & Wojnarowska, M. (2020). Circular economy and industry 4.0: One-way or two-way relationships? *Engineering Economics*, 31, 387–397. https://doi.org/10.5755/j01.ee.31.4.24565

Dalamagas, T., Kokossis, A., & Gentimis, T. (2020). Circular intelligence: Digital services to facilitate industrial symbiosis. *Ercim News, The Climate Action*, 20–21.

Daneshgar, F., Sianaki, O. A., & Guruwacharya, P. (2019). Blockchain: A research framework for data security and privacy. In *Workshops of the International Conference on Advanced Information Networking and Applications* (pp. 966–974). Springer.

Daú, G., Scavarda, A., Scavarda, L. F., & Portugal, V. J. T. (2019). The healthcare sustainable supply chain 4.0: The circular economy transition conceptual framework with the corporate social responsibility mirror. *Sustainability*, 11(12), 3259. https://doi.org/10.3390/su11123259

Denyer, D., & Tranfield, D. (2009). *Producing a systematic review. The Sage handbook of organizational research methods*. Sage Publications Ltd.

Dev, N. K., Shankar, R., & Qaiser, F. H. (2020). Industry 4.0 and circular economy: Operational excellence for sustainable reverse supply chain performance. *Resources Conservation and Recycling*, 153, 104583.

Ellen Macarthur Foundation. 2019. Artificial intelligence and the circular economy—AI as a tool to accelerate the transition. Ellen MacArthur Foundation,.

Ellen Macarthur Foundation, S. F. U. U. N. S., Deutsche Post Foundation, Mckinsey Center For Business And Environment, 2015. Growth within: A circular economy vision for a competitive Europe.

Enyoghasi, C., & Badurdeen, F. (2021). Industry 4.0 for sustainable manufacturing: Opportunities at the product, process, and system levels. *Resources Conservation and Recycling*, 166, 105362.

Esmaeilian, B., Wang, B., Lewis, K., Duarte, F., Ratti, C., & Behdad, S. (2018). The future of waste management in smart and sustainable cities: A review and concept paper. *Waste Management*, 81, 177–195. https://doi.org/10.1016/j.wasman.2018.09.047

European Commission. 2020. Leading the way to a global circular economy: State of play and outlook.

Evans, S., Vladimirova, D., Holgado, M., Van Fossen, K., Yang, M., Silva, E., & Barlow, C. (2017). Business model innovation for sustainability: Towards a unified perspective for creation of sustainable business models. *Business Strategy and the Environment*, 26(5), 597–608. https://doi.org/10.1002/bse.1939

Fatimah, Y. A., Govindan, K., Murniningsih, R., & Setiawan, A. (2020). Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia. *Journal of Cleaner Production*, 269, 122263. https://doi.org/10.1016/j.jclepro.2020.122263

Fraga-Lamas, P., Lopes, S. I., & Fernández-Caramés, T. M. (2021). Green IoT and edge AI as key technological enablers for a sustainable digital transition towards a Smart circular economy: An industry 5.0 use case. *Sensors*, 21(17), 5745. https://doi.org/10.3390/s21175745

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies.

International Journal of Production Economics, *210*, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Franzo, S., Urbinati, A., Chiaroni, D., & Chiesa, V. (2021). Unravelling the design process of business models from linear to circular: An empirical investigation. *Business Strategy and the Environment*, *30*(6), 2758–2772. https://doi.org/10.1002/bse.2892

Furstenau, L. B., Sott, M. K., Kipper, L. M., Machado, E. L., Lopez-Robles, J. R., Dohan, M. S., Cobo, M. J., Zahid, A., Abbasi, Q. H., & Imran, M. A. (2020). Link between sustainability and industry 4.0: Trends, challenges and new perspectives. *IEEE Access*, *8*, 140079–140096.

Garcia-Muiña, F., González-Sánchez, R., Ferrari, A., & Settembre-Blundo, D. (2018). The paradigms of industry 4.0 and circular economy as enabling drivers for the competitiveness of businesses and territories: The case of an Italian ceramic tiles manufacturing company. *Social Sciences*, *7*(12), 255. https://doi.org/10.3390/socsci7120255

Garrido-Hidalgo, C., Ramirez, F. J., Olivares, T., & Roda-Sanchez, L. (2020). The adoption of internet of things in a circular supply chain framework for the recovery of WEEE: The case of lithium-ion electric vehicle battery packs. *Waste Management*, *103*, 32–44. https://doi.org/10.1016/j.wasman.2019.09.045

Getor, R. Y., Mishra, N., & Ramudhin, A. (2020). The role of technological innovation in plastic production within a circular economy framework. *Resources Conservation and Recycling*, *163*, 105094.

Ghasemaghaei, M., Hassanein, K., & Turel, O. (2015). Impacts of big data analytics on organizations: A resource fit perspective.

Ghoreishi, M., & Happonen, A. (2020a). Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies. 13th International Engineering Research Conference (EURECA), Nov 27 2019a Taylors Univ Lakeside Campus, Subang Jaya, MALAYSIA. Amer Inst Physics. https://doi.org/10.1063/5.0001339

Ghoreishi, M., & Happonen, A. (2020b). New promises AI brings into circular economy accelerated product design: A review on supporting literature. 7th International Conference on Environment Pollution and Prevention (ICEPP), Dec 18–20 2019b Melbourne, Australia. E D P Sciences. https://doi.org/10.1051/e3sconf/202015806002

Goering, K., Kelly, R., & Mellors, N. (2018). The next horizon for industrial manufacturing: Adopting disruptive digital technologies in making and delivering. *Digital McKinsey*, 1–10.

Gupta, S., Chen, H. Z., Hazen, B. T., Kaur, S., & Gonzalez, E. D. R. S. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change*, *144*, 466–474. https://doi.org/10.1016/j.techfore.2018.06.030

Huynh, P. H. (2021). Enabling circular business models in the fashion industry: The role of digital innovation. *International Journal of Productivity and Performance Management*. ahead-of-print, 26.

Ingemarsdotter, E., Jamsin, E., & Balkenende, R. (2020). Opportunities and challenges in IoT-enabled circular business model implementation—A case study. *Resources Conservation and Recycling*, *162*, 105047.

Ingemarsdotter, E., Jamsin, E., Kortuem, G., & Balkenende, R. (2019). Circular strategies enabled by the internet of things—A framework and analysis of current practice. *Sustainability*, *11*(20), 5689.

Ingemarsdotter, E., Kambanou, M. L., Jamsin, E., Sakao, T., & Balkenende, R. (2021). Challenges and solutions in condition-based maintenance implementation—A multiple case study. *Journal of Cleaner Production*, *296*, 126420.

Jabbour, A. B. L. D., Jabbour, C. J. C., Godinho, M., & Roubaud, D. (2018). Industry 4.0 and the circular economy: A proposed research agenda and original roadmap for sustainable operations. *Annals of Operations Research*, *270*, 273–286.

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*, 408–425. https://doi.org/10.1016/j.psep.2018.05.009

Kanda, W., Geissdoerfer, M., & Hjelm, O. (2021). From circular business models to circular business ecosystems. *Business Strategy and the Environment*, *30*(6), 2814–2829. https://doi.org/10.1002/bse.2895

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*, 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kerdlap, P., Low, J. S. C., & Ramakrishna, S. (2019). Zero waste manufacturing: A framework and review of technology, research, and implementation barriers for enabling a circular economy transition in Singapore. *Resources, Conservation and Recycling*, *151*, 104438. https://doi.org/10.1016/j.resconrec.2019.104438

Kerin, M., & Pham, D. T. (2019). A review of emerging industry 4.0 technologies in remanufacturing. *Journal of Cleaner Production*, *237*, 117805. https://doi.org/10.1016/j.jclepro.2019.117805

Kerin, M., & Pham, D. T. (2020). Smart remanufacturing: A review and research framework. *Journal of Manufacturing Technology Management*, *31*, 1205–1235. https://doi.org/10.1108/JMTM-06-2019-0205

Kintscher, L., Lawrenz, S., & Poschmann, H. (2021). A life cycle oriented data-driven architecture for an advanced circular economy. *Procedia CIRP*, *98*, 318–323. https://doi.org/10.1016/j.procir.2021.01.110

Korhonen, J., Honkasalo, A., & Seppala, J. (2018). Circular economy: The concept and its limitations. *Ecological Economics*, *143*, 37–46. https://doi.org/10.1016/j.ecolecon.2017.06.041

Kristoffersen, E., Blomsma, F., Mikalef, P., & Li, J. Y. (2020). The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies. *Journal of Business Research*, *120*, 241–261. https://doi.org/10.1016/j.jbusres.2020.07.044

Kurniawan, T. A., Lo, W., Singh, D., Othman, M. H. D., Avtar, R., Hwang, G. H., Albadarin, A. B., Kern, A. O., & Shirazian, S. (2021). A societal transition of MSW management in Xiamen (China) toward a circular economy through integrated waste recycling and technological digitization. *Environmental Pollution*, *277*, 116741. https://doi.org/10.1016/j.envpol.2021.116741

Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecological Economics*, *176*, 106760. https://doi.org/10.1016/j.ecolecon.2020.106760

Lasi, H., Kemper, H. G., Fettke, P., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *6*, 239–242. https://doi.org/10.1007/s12599-014-0334-4

Laskurain-Iturbe, I., Arana-Landín, G., Landeta-Manzano, B., & Uriarte-Gallastegi, N. (2021). Exploring the influence of industry 4.0 technologies on the circular economy. *Journal of Cleaner Production*, *321*, 128944. https://doi.org/10.1016/j.jclepro.2021.128944

Lawrenz, S., & Leiding, B. (2021). *The Hitchhiker's guide to the end-of-life for smart devices* (pp. 196–202). Institute of Electrical and Electronics Engineers Inc.

Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

Liebrecht, C., Kandler, M., Lang, M., Schaumann, S., Stricker, N., Wuest, T., & Lanza, G. (2021). Decision support for the implementation of industry 4.0 methods: Toolbox, assessment and implementation sequences for industry 4.0. *Journal of Manufacturing Systems*, *58*, 412–430. https://doi.org/10.1016/j.jmsy.2020.12.008

Liu, Q., Yang, L., & Yang, M. (2021). Digitalisation for water sustainability: Barriers to implementing circular economy in smart water management. *Sustainability*, *13*, 11868. https://doi.org/10.3390/su132111868

Liu, Y., Zhang, Y., Ren, S., Yang, M., Wang, Y., & Huisingh, D. (2020). How can smart technologies contribute to sustainable product lifecycle

management? *Journal of Cleaner Production*, 249, 119423. https://doi. org/10.1016/j.jclepro.2019.119423

Lobo, A., Trevisan, A. H., Liu, Q., Yang, M., & Mascarenhas, J. (2022). Barriers to transitioning towards smart circular economy: A systematic literature review. In S. G. Scholz, R. J. Howlett, & R. Setchi (Eds.), *Sustainable design and manufacturing, 2022 Singapore* (pp. 245–256). Springer Singapore.

Lukac, D. (2015). The fourth ICT-based industrial revolution "Industry 4.0" — HMI and the case of CAE/CAD innovation with EPLAN P8. 23rd Telecommunications Forum Telfor (TELFOR), 835–835. https://doi. org/10.1109/TELFOR.2015.7377595.

Lutje, A., Willenbacher, M., Engelmann, M., Kunisch, C., & Wohlgemuth, V. (2020). Exploring the system dynamics of industrial Symbiosis (IS) with machine learning (ML) techniques—A framework for a hybrid-approach. In R. Schaldach, K. H. Simon, J. Weismuller, & V. Wohlgemuth (Eds.), *Advances and new trends in environmental informatics: ICT for sustainable solutions*. Springer International Publishing Ag. https://doi.org/10.1007/978-3-030-30862-9_9

Mariani, M., & Borghi, M. (2019). Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. *Technological Forecasting and Social Change*, 149, 119752. https://doi.org/10.1016/j.techfore.2019.119752

Massaro, M., Secinaro, S., Dal Mas, F., Brescia, V., & Calandra, D. (2021). Industry 4.0 and circular economy: An exploratory analysis of academic and practitioners' perspectives. *Business Strategy and the Environment*, 30, 1213–1231. https://doi.org/10.1002/bse. 2680

Mboli, J. S., Thakker, D., & Mishra, J. L. (2020). An internet of things-enabled decision support system for circular economy business model. *Software: Practice and Experience*, 52(3), 772–787.

McDowall, W., Geng, Y., Huang, B., Barteková, E., Bleischwitz, R., Türkeli, S., Kemp, R., & Doménech, T. (2017). Circular economy policies in China and Europe. *Journal of Industrial Ecology*, 21, 651–661. https://doi.org/10.1111/jiec.12597

McEwen, A., & Cassimally, H. (2013). *Designing the internet of things*. John Wiley & Sons.

Merli, R., Preziosi, M., & Acampora, A. (2018). How do scholars approach the circular economy? A systematic literature review. *Journal of Cleaner Production*, 178, 703–722. https://doi.org/10.1016/j.jclepro. 2017.12.112

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management*, 16, 547–578. https://doi.org/10.1007/s10257-017-0362-y

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). Sage.

Mishra, J. L., Chiwenga, K. D., & Ali, K. (2019). Collaboration as an enabler for circular economy: A case study of a developing country. *Management Decision.*, 59, 1784–1800. https://doi.org/10.1108/MD-10-2018-1111

Modgil, S., Gupta, S., & Bhushan, B. (2020). Building a living economy through modern information decision support systems and UN sustainable development goals. *Production Planning & Control*, 31(11–12), 967–987.

Mohamed, M. (2018). Challenges and benefits of industry 4.0: An overview. *International Journal of Supply and Operations Management*, 5(3), 256–265.

Morella, P., Lambán, M. P., Royo, J., Sánchez, J. C., & Ng Corrales, L. D. C. (2020). Development of a new green indicator and its implementation in a cyber–physical system for a green supply chain. *Sustainability*, 12(20), 8629.

Moreno, M., Court, R., Wright, M., & Charnley, F. (2019). Opportunities for redistributed manufacturing and digital intelligence as enablers of a circular economy. *International Journal of Sustainable Engineering*, 12, 77–94. https://doi.org/10.1080/19397038.2018.1508316

Moreno, M., Turner, C., Tiwari, A., Hutabarat, W., Charnley, F., Widjaja, D., & Mondini, L. (2017). Re-distributed manufacturing to achieve a circular economy: A case study utilizing IDEF0 modeling. *Manufacturing Systems 4.0*, 63, 686–691.

Nižetić, S., Djilali, N., Papadopoulos, A., & Rodrigues, J. J. P. C. (2019). Smart technologies for promotion of energy efficiency, utilization of sustainable resources and waste management. *Journal of Cleaner Production*, 231, 565–591. https://doi.org/10.1016/j.jclepro.2019. 04.397

Nobre, G. C., & Tavares, E. (2020a). Assessing the Role of Big Data and the Internet of Things on the Transition to Circular Economy: Part II: An extension of the ReSOLVE framework proposal through a literature review. *Johnson Matthey Technology Review*, 64(1), 32–41. https://doi. org/10.1595/205651319X15650189172931

Nobre, G. C., & Tavares, E. (2020b). Assessing the Role of Big Data and the Internet of Things on the Transition to Circular Economy: Part I: An extension of the ReSOLVE framework proposal through a literature review. *Johnson Matthey Technology Review*, 64(1), 19–31.

Nof, S. Y. (2009). *Springer handbook of automation*. Springer Science & Business Media. https://doi.org/10.1007/978-3-540-78831-7

Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C., & Tiwari, A. (2018). Digitisation and the circular economy: A review of current research and future trends. *Energies*, 11(11), 3009. https://doi.org/10. 3390/en11113009

Oztemel, E., & Gursev, S. (2020). Literature review of industry 4.0 and related technologies. *Journal of Intelligent Manufacturing*, 31, 127–182. https://doi.org/10.1007/s10845-018-1433-8

Pagoropoulos, A., Pigosso, D. C. A., & McAloone, T. C. (2017). The emergent role of digital technologies in the circular economy: A review. *9th Cirp Industrial Product/Service-Systems (Ipss) Conference: Circular Perspectives on Product/Service-Systems*, 64, 19–24.

Pieroni, M. P. P., McAloone, T. C., & Pigosso, D. C. A. (2019). Business model innovation for circular economy and sustainability: A review of approaches. *Journal of Cleaner Production*, 215, 198–216. https://doi. org/10.1016/j.jclepro.2019.01.036

Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2017). *Circular economy: Measuring innovation in the product chain*. PBL Publishers.

Rajput, S., & Singh, S. P. (2019). Connecting circular economy and industry 4.0. *International Journal of Information Management*, 49, 98–113. https://doi.org/10.1016/j.ijinfomgt.2019.03.002

Ranta, V., Aarikka-Stenroos, L., & Vaisanen, J. M. (2021). Digital technologies catalyzing business model innovation for circular economy—Multiple case study. *Resources Conservation and Recycling*, 164, 105155.

Rehman, M. H. U., Chang, V., Batool, A., & Wah, T. Y. (2016). Big data reduction framework for value creation in sustainable enterprises. *International Journal of Information Management*, 36, 917–928. https:// doi.org/10.1016/j.ijinfomgt.2016.05.013

Reim, W., Sjodin, D., & Parida, V. (2021). Circular business model implementation: A capability development case study from the manufacturing industry. *Business Strategy and the Environment*, 30(6), 2745–2757. https://doi.org/10.1002/bse.2891

Reis, J. S. D. M., Espuny, M., Nunhes, T. V., Sampaio, N. A. D. S., Isaksson, R., Campos, F. C. D., & Oliveira, O. J. D. (2021). Striding towards sustainability: A framework to overcome challenges and explore opportunities through industry 4.0. *Sustainability*, 13(9), 5232. https://doi.org/10.3390/su13095232

Ren, Y. P., Meng, L. L., Zhang, C. Y., Zhao, F., Saif, U., Huang, A. H., Mendis, G. P., & Sutherland, J. W. (2020). An efficient metaheuristics for a sequence-dependent disassembly planning. *Journal of Cleaner Production*, 245, 118644.

Reuter, M. A. (2016). Digitalizing the circular economy. *Metallurgical and Materials Transactions B*, 47, 3194–3220. https://doi.org/10.1007/ s11663-016-0735-5

Rocca, R., Rosa, P., Sassanelli, C., Fumagalli, L., & Terzi, S. (2020). *Industry 4.0 solutions supporting circular economy*. Institute of Electrical and Electronics Engineers Inc.

Romero, D., & Noran, O. (2017). Towards green sensing virtual enterprises: Interconnected sensing enterprises, intelligent assets and smart products in the cyber-physical circular economy. *Ifac Papersonline*, *50*, 11719–11724. https://doi.org/10.1016/j.ifacol.2017.08.1944

Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between circular economy and industry 4.0: A systematic literature review. *International Journal of Production Research*, *58*, 1662–1687. https://doi.org/10.1080/00207543.2019.1680896

Rossi, J., Bianchini, A., & Guarnieri, P. (2020). Circular economy model enhanced by intelligent assets from industry 4.0: The proposition of an innovative tool to analyze case studies. *Sustainability*, *12*, 22. https://doi.org/10.3390/su12177147

Russom, P. (2011). Big data analytics. *TDWI Best Practices Report, Fourth Quarter*, *19*, 1–34.

Saldaña, J. (2015). *The coding manual for qualitative researchers*. Sage.

Sarc, R. (2021). The "ReWaste4.0" Project—A review. *Processes*, *9*(5), 764.

Sarc, R., Curtis, A., Kandlbauer, L., Khodier, K., Lorber, K. E., & Pomberger, R. (2019). Digitalisation and intelligent robotics in value chain of circular economy oriented waste management—A review. *Waste Management*, *95*, 476–492. https://doi.org/10.1016/j.wasman.2019.06.035

Sassanelli, C., Rosa, P., & Terzi, S. (2021). Supporting disassembly processes through simulation tools: A systematic literature review with a focus on printed circuit boards. *Journal of Manufacturing Systems*, *60*, 429–448. https://doi.org/10.1016/j.jmsy.2021.07.009

Siow, E., Tiropanis, T., & Hall, W. (2018). Analytics for the internet of things. *ACM Computing Surveys*, *51*, 1–36.

Song, B., Yeo, Z., Kohls, P., & Herrmann, C. (2017). Industrial Symbiosis: Exploring big-data approach for waste stream discovery. *24th Cirp Conference on Life Cycle Engineering*, *61*, 353–358.

Spring, M., & Araujo, L. (2017). Product biographies in servitization and the circular economy. *Industrial Marketing Management*, *60*, 126–137. https://doi.org/10.1016/j.indmarman.2016.07.001

Stock, T., & Seliger, G. (2016). Opportunities of Sustainable Manufacturing in Industry 4.0. *13th Global Conference on Sustainable Manufacturing - Decoupling Growth from Resource Use*, *40*, 536–541.

Subramoniam, R., Sundin, E., Subramoniam, S., & Huisingh, D. (2021). Riding the digital product life cycle waves towards a circular economy. *Sustainability*, *13*(16), 8960.

Sun, X., Yu, H., & Solvang, W. D. (2021). In Y. Wang, K. Martinsen, T. Yu, & K. Wang (Eds.), *Industry 4.0 and sustainable supply chain management*. Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-981-33-6318-2_74

Thomé, A. M. T., Scavarda, L. F., & Scavarda, A. J. (2016). Conducting systematic literature review in operations management. *Production Planning & Control*, *27*, 408–420. https://doi.org/10.1080/09537287.2015.1129464

Tiwari, D., Miscandlon, J., Tiwari, A., & Jewell, G. W. (2021). A review of circular economy research for electric motors and the role of industry 4.0 technologies. *Sustainability*, *13*(17), 9668. https://doi.org/10.3390/su13179668

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, *14*, 207–222. https://doi.org/10.1111/1467-8551.00375

Trevisan, A. H., Castro, C. G., de Gomes, L. A. V., & Mascarenhas, J. (2022). Unlocking the circular ecosystem concept: Evolution, current research, and future directions. *Sustainable Production and Consumption*, *29*, 286–298. https://doi.org/10.1016/j.spc.2021.10.020

Tseng, M.-L., Tran, T. P. T., Ha, H. M., Bui, T.-D., & Lim, M. K. (2021). Sustainable industrial and operation engineering trends and challenges toward industry 4.0: A data driven analysis. *Journal of Industrial and Production Engineering*, *38*(8), 581–598.

Tunn, V. S., Van Den Hende, E. A., Bocken, N. M., & Schoormans, J. P. (2021). Consumer adoption of access-based product-service systems: The influence of duration of use and type of product. *Business Strategy and the Environment*, *30*(6), 2796–2813. https://doi.org/10.1002/bse.2894

Turner, C., Moreno, M., Mondini, L., Salonitis, K., Charnley, F., Tiwari, A., & Hutabarat, W. (2019). Sustainable production in a circular economy: A business model for re-distributed manufacturing. *Sustainability*, *11*(16), 4291. https://doi.org/10.3390/su11164291

Turner, C., Okorie, O., Emmanouilidis, C., & Oyekan, J. (2020). A digital maintenance practice framework for circular production of automotive parts. *IFAC-PapersOnLine*, *53*(3), 19–24. https://doi.org/10.1016/j.ifacol.2020.11.004

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0—A glimpse. *Procedia Manufacturing*, *20*, 233–238. https://doi.org/10.1016/j.promfg.2018.02.034

Vetrova, M., & Ivanova, D. (2021). Closed product life cycle as a basis of the circular economy. *GATR Journal of Business and Economics Review*, *5*, 36–50. https://doi.org/10.35609/jber.2021.5.4(4)

Wegner-Kozlova, E. O., & Guman, O. M. (2020). Digitalization of Environmental Monitoring as an Enabler of Circular Economy Transition. 2nd International Scientific and Practical Conference on Modern Management Trends and the Digital Economy - from Regional Development to Global Economic Growth (MTDE), Apr 16–17 2020 Yekaterinburg, Indonesia. Atlantis Press, 1282–1286.

Whitmore, A., Agarwal, A., & Da Xu, L. (2015). The internet of things—A survey of topics and trends. *Information Systems Frontiers*, *17*, 261–274. https://doi.org/10.1007/s10796-014-9489-2

Wilson, M., Paschen, J., & Pitt, L. (2021). The circular economy meets artificial intelligence (AI): Understanding the opportunities of AI for reverse logistics. *Management of Environmental Quality*, *1733*(1), 9–25.

Wilts, H., Garcia, B. R., Garlito, R. G., Gómez, L. S., & Prieto, E. G. (2021). Artificial intelligence in the sorting of municipal waste as an enabler of the circular economy. *Resources*, *10*(4), 28.

World Economic Forum, E. M. F. (2016). In R. Sheppard (Ed.), *Intelligent assets: Unlocking the circular economy potential*. Ellen MacArthur Foundation.

Yadav, G., Luthra, S., Jakhar, S. K., Mangla, S. K., & Rai, D. P. (2020). A framework to overcome sustainable supply chain challenges through solution measures of industry 4.0 and circular economy: An automotive case. *Journal of Cleaner Production*, *254*, 120112. https://doi.org/10.1016/j.jclepro.2020.120112

Yang, H., & Tate, M. (2012). A descriptive literature review and classification of cloud computing research. *Communications of the Association for Information Systems*, *31*(1), 2.

Yang, M., & Evans, S. (2019). Product-service system business model archetypes and sustainability. *Journal of Cleaner Production*, *220*, 1156–1166. https://doi.org/10.1016/j.jclepro.2019.02.067

Yang, M., Fu, M., & Zhang, Z. (2021). The adoption of digital technologies in supply chains: Drivers, process and impact. *Technological Forecasting and Social Change*, *169*, 120795. https://doi.org/10.1016/j.techfore.2021.120795

Yang, M., Smart, P., Kumar, M., Jolly, M., & Evans, S. (2018). Product-service systems business models for circular supply chains. *Production Planning & Control*, *29*, 498–508. https://doi.org/10.1080/09537287.2018.1449247

Yang, S., Raghavendra M. R., A., Kaminski, J., & Pepin, H. (2018). Opportunities for industry 4.0 to support remanufacturing. *Applied Sciences*, *8*(7), 1177.

Zacharaki, A., Vafeiadis, T., Kolokas, N., Vaxevani, A., Xu, Y., Peschl, M., Ioannidis, D., & Tzovaras, D. (2020). RECLAIM: Toward a new era of refurbishment and remanufacturing of industrial equipment. *Front Artif Intell*, *3*, 570562.

Zeiss, R., Ixmeier, A., Recker, J., & Kranz, J. (2020). Mobilising information systems scholarship for a circular economy: Review, synthesis, and directions for future research. *Information Systems Journal*, *31*, 148–183.

Zhang, A., Venkatesh, V. G., Liu, Y., Wan, M., Qu, T., & Huisingh, D. (2019). Barriers to smart waste management for a circular economy in China. *Journal of Cleaner Production*, *240*, 118198.

Zhang, X. M., Li, Z. Z., & Wang, Y. (2020). A review of the criteria and methods of reverse logistics supplier selection. *Processes*, *8*(6), 705.

Zheng, P., Wang, Z. X., Chen, C. H., & Khoo, L. P. (2019). A survey of smart product-service systems: Key aspects, challenges and future perspectives. *Advanced Engineering Informatics*, *42*, 100973. https://doi.org/10.1016/j.aei.2019.100973

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