



# The role of digital technologies for the LCA empowerment towards circular economy goals: a scenario analysis for the agri-food system

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## Abstract

**Purpose** This paper aims to develop a scenario analysis on the experts' perceptions of benefits and barriers related to adopting digital technologies for the life cycle assessment (LCA) to catalyse a circular economy transition in the agri-food system.

**Methods** A literature review was performed to identify LCA's digital technologies that can be implemented within the agri-food system. Furthermore, an in-depth interview with a panel of senior researchers was conducted to establish a set of items and assess the perceived benefits and barriers associated with an "empowered LCA", i.e. a future-oriented LCA based on digital technologies. To this end, a two-stage exploratory factor analysis relying on the principal component analysis technique was carried out to refine the set of items. Finally, a covariance-based structural equation model was performed, built on a confirmatory factor analysis, to test the measurement model.

**Results and discussion** The study's findings provide five constructs to explore the potential benefits and barriers related to adopting a digital technologies-based LCA (empowered LCA) for a circular economy transition in the agri-food system. More specifically, the benefits can be assessed using the following constructs: "benefits for the data collection and analysis", "benefits for the LCA analysts", "benefits for the management" and "benefits for traceability". In addition, the barriers have been evaluated using a single construct labelled "general barriers".

**Conclusions** The study highlights the relevance of digital technologies for a circular economy transition to develop a more reliable LCA, enhancing legislative compliance and supporting the traceability processes in the agri-food system. The associated implications for LCA experts, agri-food managers and policymakers are presented. Furthermore, limitations and future research directions are also discussed.

**Keywords** Circular economy · Agri-food system · Sustainability · Life cycle assessment · Digital technologies

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## 1 Introduction

Over the last few decades, circular economy (CE) strategies have acquired growing relevance, becoming one of the central points in the international debate on new entrepreneurial approaches. Indeed, implementing such strategies represents an excellent opportunity to adopt sustainable production and consumption models (Niero and Rivera 2018). Organisations face challenges related to the practical implementation of the CE concept and the identification of ways to establish business models that optimise the use of resources and improve productivity and systemic efficiency, enabling such organisations to acquire new competitive spaces (Poponi et al. 2022). In particular, agri-food system (AFS) organisations, which operate in complex supply chains, are called to develop specific circular models according to the

peculiarities of each supply chain, giving greater complexity to the ongoing circular transition process.

The AFS is one of the most relevant systems for the environment, both in positive (e.g. landscape safeguard and protection) and in a negative sense, due to the substantial contribution both to the depletion of natural resources as well as a number of environmental impacts mainly created by a notable increase in food production (Ritchie and Roser 2020).

Agri-food production and consumption can be said to be among the leading causes of environmental burdens, such as habitat change and biodiversity loss, land use and land degradation, climate change, water use and pollution, water scarcity, eutrophication of water bodies and toxic emissions (Brankatschk and Finkbeiner 2014).

According to certain studies, over the next few years, the rise in world population and the changes in eating habits—especially in emerging countries—will lead to increases in the demand for food (about 60% by 2050), energy (50% by 2035) and water (10% by 2050), which represents the so-called energy-food-water nexus (FAO 2014; Alexandratos and Bruinsma 2012). As a result, the destabilisation of the sustainable use of natural resources can arise, leading to environmental, social and geopolitical tensions.

Furthermore, food production has become increasingly globalised, industrialised and standardised. Globalisation, in particular, has led to a growing loss of local markets and a consequent increase in “food miles” (i.e. the transport distances between farmers, industries and consumers), which, in turn, result in social and environmental costs associated with food transport in terms of traffic congestion, air pollution, noise pollution and several accidents (Notarnicola et al. 2012; Reisch et al. 2013; Pieper et al. 2020).

Therefore, the current economic model—based on the “take-make-dispose” paradigm, underpinned by the extraction of raw materials, mass consumption and waste disposal—is progressively becoming more unsustainable (Ghisellini and Ulgiati 2020). In this scenario, a CE, defined as an economy designed to “regenerate itself”—built on the reduce-reuse-recycle approach—plays a pivotal role in more effectively and efficiently advancing towards achieving environmental sustainability in the entire agri-food supply chain (AFSC).

Since the late 1990s, researchers have highlighted that most food chains are not environmentally sustainable due to the impacts at different life cycle stages. Thus, to address these critical issues, various European policies and measures related to sustainable production and consumption have been promoted, and many scholars have started to investigate the CE paradigm and its implementation in the AFS (e.g. Borrello et al. 2016; Toop et al. 2017; Esposito et al. 2020). However, the lack of an unambiguous definition for a CE that is derived from a multi-perspective framework (Korhonen et al. 2018) has led to the development of several assessment tools for the circularity’s

measurement (Elia et al. 2017; De Pascale et al. 2021) and the consequent need to combine existing methods and develop a more holistic approach to assess the sustainability impacts of CE strategies (Walzberg et al. 2021).

In particular, for a CE transition in the AFS, multiple tools have been developed to improve the sustainability performance of products and processes and to assess (both quantitatively and qualitatively) their related impacts on the ecosystem, from a multidimensional perspective. However, the complex methodologies used for the measurement and comparative analysis of environmental performance—promoted within the public and private initiatives—present substantial heterogeneity and discretion regarding the criteria adopted. One of the significant problems of methodological approaches for measuring environmental performances is incompleteness, as they do not use a “cradle to grave” approach and, therefore, do not examine all the products or the organisation’s direct and indirect impacts (Salomone et al. 2011; Notarnicola et al. 2015). For instance, many indicators consider only the use phase, thus excluding the costs of production, disposal or the possibility of reusing and recycling products (De Pascale et al. 2021). Furthermore, some assessments focus on a single environmental indicator, thus excluding certain product life cycle stages and providing a partial view of their impacts.

In this context, life cycle assessment (LCA), which has been applied for over thirty years in agri-food systems, can be considered the most suitable method to identify (with a high degree of detail) environmental hotspots (Dieterle et al. 2018). Moreover, from a CE perspective, scholars have demonstrated that LCA is an ideal methodology for assessing the sustainability impacts of CE strategies and supporting decision-making due to the associated interdisciplinary approach and a holistic view of the interactive elements of a system (Peña et al. 2021a; Mondello et al. 2020; Niero and Schmidt Rivera 2018; Zamagni et al. 2013).

However, different from non-food-based products, the application of LCA in the AFS is very complex and challenging in that the system considered for LCA usually also involves the agricultural zootechnical phases; this implies that the biological processes that represent the biosphere, are considered jointly with those of the technical system of the technosphere (Arzoumanidis et al. 2017). Furthermore, several specific methodological problems arise, due to the nature of food systems, which include aspects such as the definition of the functional unit, the difficulties related to data collection, pesticides and their exposure, fertiliser dispersion patterns, and soil and water use impact categories (Notarnicola et al. 2012; Arzoumanidis et al. 2017; Salomone et al. 2010; Peacock et al. 2011; Schau and Fet 2008; Foster et al. 2006).

One of the critical issues in the AFS is the lack of reliable and up-to-date inventory data on food products and processes for accurate LCA studies and analyses, communication and

labelling of hotspots (Notarnicola et al. 2015). The inventory phase of the agro-industrial sector is still affected by the lack of availability and the uncertainty of data (especially for some types of materials such as herbicides, pesticides and fertilisers) as well as by problems related to the estimation of nitrogen and phosphate compounds, emissions and dispersion pesticides, the use of agricultural machinery and the balance of CO<sub>2</sub> emissions (Notarnicola et al. 2012). This involves using estimates for the evaluation or the complete exclusion of this phase from the study and developing data-driven analyses unrelated to the actual information needs (Salomone et al. 2010). This choice inevitably affects the variability and uncertainty of the results produced.

Moreover, for complex systems such as AFSCs, LCA studies often do not consider all the possible inputs of a production system (Notarnicola et al. 2015). Over time, several life cycle inventory (LCI) databases have been developed. Still, most of them are characterised by a lack of transparency and are often incomplete because they account for only a few input–output flows. This lack of information can lead to ambiguous interpretations and conclusions. Additionally, LCI databases are often outdated and not region or country-specific (Notarnicola et al. 2022). Furthermore, a methodological comparability problem emerged: all databases establish their hypotheses and methodological rules (allocation, cut-off rules, etc.) and substantial differences can be found among data from different databases (Zhang et al. 2020). Therefore, databases are often inconsistent with each other due to the different approaches and assumptions involved. In addition, in the 4.0 era, LCA analysis accuracy and effectiveness are increasingly crucial for strategic decision-making (Bhingé et al. 2015).

During the last decade, researchers have tried to address the need to enhance further the effectiveness of the LCA database by applying several techniques such as: incorporating forecast analyses (i.e. Pehnt 2006); sensitivity and reliability analysis to manage the temporal inconsistencies due to temporally variant datasets (e.g. Guo and Murphy 2012) as well as statistical tools to characterise the data quality (e.g. Reap et al. 2008). However, data collection has emerged as one of the major challenges in enhancing LCA reliability (Bhingé et al. 2015).

In light of these considerations, collecting reliably and systematically data inputs is perceived as a significant issue for LCA practitioners, especially for collecting data related to new products, processes or services (Hospido et al. 2010). Given its relevance, some scholars have begun to investigate the possibility of overcoming these limitations by developing LCA analyses exploiting the potential of digital technologies in data collection processes (e.g. Song et al. 2018; Mieras et al. 2019; Kamble et al. 2020a, b; Kumar et al. 2021). Researchers have demonstrated how combining blockchain technology, IoT, big data analytics and visualisation can support companies in reaching operational excellence in carrying out “empowered

LCA” to enhance sustainability in the supply chains (Zhang et al. 2020). More specifically, the combined application of these technologies to the AFSCs could guarantee data security and validation, providing also traceability, authenticity and legitimacy, which—in turn—impact the effectiveness and reliability of the LCA insights (Aryal et al. 2018; Wang et al. 2019).

Despite its relevance—considering that the topic is still in its infancy—the literature review is scant. Only a few recent contributions have investigated the role of a single DT in LCA studies (e.g. Wang et al. 2019; Ruggieri et al. 2021), providing a general theoretical framework. However, it has been shown that only by combining these technologies may relevant benefits be achieved, in terms of reliability and comparability of LCA analyses (Zhang et al. 2020).

Starting from this background, the present research aims to develop a scenario analysis related to the perceived benefits and barriers of combined DT uses for empowered LCA analyses.

More specifically, this work investigates the state-of-the-art research on the use of DTs in the AFS for conducting LCA analyses, to explore the potential benefits and the main critical elements that hinder their broad adoption. The study highlights how using these technologies can help LCA analysts overcome the limitations associated with a traditional approach to LCA and offer a concrete opportunity for a CE transition in the AFS.

In particular, the present research aims to answer the following research questions:

R1: What are the perceived benefits and barriers related to adopting DTs for conducting LCA analyses in the AFS?

R2: How can we assess the perceived benefits and barriers related to adopting DTs for conducting LCA analyses in the AFS?

The paper is structured as follows: after the introduction, a literature review based on the link between a CE and LCA and the role of DTs in carrying out LCA analyses is presented. Next, Sect. 3 illustrates the research methodology employed, while our results are described in Sect. 4. Section 5 presents the discussion and the implications of our findings. Finally, the main conclusions, limitations and future research directions are discussed.

## 2 Literature review and theoretical framework

### 2.1 The role of LCA in the adoption of CE models

The CE paradigm is becoming increasingly relevant for AFS organisations for orienting development strategies towards innovative solutions that lead to a radical review of production

and consumption paradigm and, thereby, create suitable conditions for the full implementation of Goal 12, “Sustainable production and consumption”, of the 2030 Agenda for sustainable development (Esposito et al. 2020; PACE 2022).

The CE can be considered fundamental for the transformative process that efficiently uses resources and reduces waste production, following a life cycle approach (Zhang et al. 2018; Wang 2018, Sassanelli et al. 2019). Indeed, the LCA methodology represents a key tool for the CE transition, as it assesses all aspects of the use of resources and environmental releases associated with a production system throughout the entire product or service life cycle. It provides a holistic view of the different ecological interactions related to a series of activities (from the extraction of raw materials to the production and distribution of energy through the use, reuse and final disposal) using an interdisciplinary approach (Zamagni et al. 2013; Chau et al. 2015; Gbededo et al. 2018).

Moreover, the objective behind employing this approach is to avoid displacing the impacts from one part of the system to another, and from one type of impact to another (burden shifting) (Roy et al. 2009). This methodology allows the modelling of the technological system-environment interaction and carries out a multi-criteria analysis, thus avoiding the relocation problems among environmental issues. Furthermore, LCA enables the comparison and evaluation of the benefits of specific environmental strategies and helps identify the most useful solutions to implement a company policy firmly based on achieving environmental sustainability (Viola and Marinelli 2016). LCA is also a standardised and harmonised method to avoid manipulability, allowing the enhancement of reuse-reduce-recycle practices (van Stijn et al. 2021; Roy et al. 2009).

An LCA analysis provides quantitative data and information in the form of environmental impact indicators relevant to sustainable disclosures to the market and stakeholders. The LCA guarantees methodological rigour and uniformity when applying the rules for calculating environmental footprints. Moreover, LCA—according to the shared principles and standards on which it is based—can lead to different forms of results validations and independent third-party certifications. LCA furnishes vital inputs to product claims and provides a basis for managing the eco-labelling required by consumers, businesses and NGOs (Notarnicola et al. 2017; Jensen 1998).

Recently, some studies have confirmed the central role of LCA in implementing CE principles in organisations (Niero and Rivera, 2018). Other scholars emphasise that LCA provides a fundamental methodological basis for evaluating the environmental performance of products and services, and defining adequate strategies to make progress in the transition towards a CE (Cordella et al. 2020).

The measurement of circularity is an essential requirement for implementing the transition from a “take-make-dispose”

economic model to one that has a CE as a reference paradigm (Merli et al. 2018). Therefore, LCA can contribute to products’ circularity and environmental impacts, involve suppliers in improving their performance and help decision-makers compare significant environmental impacts when choosing alternative courses of action (Peña et al. 2021a, b).

In this context, it becomes necessary to define precise references for measuring the level of a CE that is standardisable, verifiable and replicable regardless of the specificity of the activities to be monitored (Gusmerotti et al. 2020). In this way, it is possible to stimulate an improvement in CE performance in the AFS, both at the company level and in the territorial socio-economic system.

LCA has many potentialities concerning measuring circularity, especially in its broadest dimension, or when integrated with management accounting tools, such as life cycle costing (LCC), and with analytical systems and tools for evaluating social aspects, such as the social life cycle analysis (SLCA) (Padilla-Rivera et al. 2021; Arzoumanidis et al. 2021). Therefore, it can serve as a sustainability assessment tool to support organisations’ decision-making processes while providing greater awareness of the potential consequences associated with alternative design and production methods and the impacts on the environment and human health and the related costs. Therefore, LCA is a tool suitable for assessing the environmental performance of circular product designs and large-scale changes, such as the shift towards a CE (Schulz et al. 2020).

The ultimate goal of lowering environmental impacts is common to LCA and the CE concept (Haupt and Zschokke 2017). However, to address the technical and operational challenges presented—in particular, those related to reliable and systemic input data collection—it is essential to make progress with implementing the LCA for the evaluation of CE strategies (Dieterle and Viere 2021). The application of LCA across a complete food supply system requires accurate data from many sources, which need to be presented in a usable form. This can create significant limitations and problems for the application of LCA. Key data may be missing, and the filling of the resultant gaps in the databases may require various assumptions to be made. These limitations could be overcome with the support of DT.

Consequently, the implementation of DTs for sustainable growth has drawn growing interest from researchers and professionals. Indeed, the ability to dispose of data and information and connect them in an ever more effective and safe manner can support sustainable development (Bai et al. 2020). In general, the adoption of DTs acquires a pivotal role from a double perspective. On the one hand, DTs can support the efficiency and effectiveness of agri-food processes, from harvesting to commercialisation and food consumption. On the other hand, they support the data creation and helpful collection for developing circular and sustainable strategies and

practices (Serna-Guerrero et al. 2022). Adopting 4.0 technologies boosts transparency and information sharing, improving supply chain performance by integrating processes and activities, automation, digitalisation and improvement into all operational functions (Xu et al. 2018; Nayal et al. 2021).

Each technology can provide its specific contribution to CE (Navin et al. 2020). For instance, blockchain technology can guarantee immutability and support traceability (Carrieres et al. 2021); smart sensors and IoT can collect data during the irrigation, fertilisation, harvest, production and distribution of food (Kamble et al. 2020b); big data analytics and visualisations allow the development of efficient circular strategies through insights visualisations (Zhang et al. 2020). However, the leverage that drives companies to invest in DTs is not environmentally based but is mainly linked to efficiency and cost reduction (Jabbour et al. 2018; Nascimento et al. 2019; Ranieri et al. 2020; de Oliveira Neto et al. 2022; Müller et al. 2018). Consequently, companies that already adopt DTs are called to maximise their potential and converge the use of the data produced and collected towards environmental analysis, in order to develop circular strategies (Dev et al. 2020; Luz et al. 2020).

Despite its relevance, the integration of DTs and CE has not yet been fully explored.

## 2.2 DT adoption in LCA for the AFS

To answer the first research question, a literature review on the use of DTs in the LCA for the AFS has been performed (Voglhuber-Slavinsky et al. 2022). DTs, such as big data analytics, blockchain technology, smart sensors and IoT, refer to all those technological innovations capable of revolutionising a pre-existing business model by redefining the boundaries of the competitive arena. With increasing globalisation and digitisation, AFS organisations have begun to revise their business processes, widely adopting DTs to improve operational efficiency and effectiveness, decision making, transparency and traceability (Leader et al. 2020; Klerkx & Rose, 2020). Currently, organisations in the AFS are increasingly using many emerging technologies, such as barcodes, QR codes, radio-frequency identification (RFID), TraceCore XM, IoT, information and communication technologies (ICT) and blockchain, to make their entire supply chain more productive, sustainable and customer-centric (Kumar et al. 2021).

Some studies have shown that DTs, if fully adopted, can improve competitiveness and enable real-time data acquisition, making AFSCs capable of producing high-quality food with low social and environmental impacts (Hofmann and Rüschi 2017; Režek Jambrak et al. 2021; Francisco and Swanson 2018; Steiner 2015; Rana et al. 2021). Other scientific articles investigate DTs' social and spatial dimensions and their potential applications in the AFS (Kelly et al.

2017). Many scholars agree that DTs can make the whole agri-food chain more sustainable from an economic, environmental and social point of view (Kamble et al. 2020a; Režek Jambrak et al. 2021; Belaud et al. 2019; Li and Wang 2018; Tian 2016; Kamble et al. 2020b).

DTs can be used in applying the LCA methodology for the acquisition, collection and management of the production processes' data inputs and outputs to be analysed (Belaud et al. 2019; Kaluza et al. 2018). Indeed, DTs provide a complete solution for data storage, access, sharing and authenticity (Huang et al. 2020).

In particular, Rolinck et al. (2021) highlight how using a blockchain-based data management system can be a central element in implementing the logical LCA for the extensive collection of data from all life cycle phases. In this way, costs can be optimised and the environmental information of the most reliable products and processes can be obtained for all life cycle phases.

Due to their characteristics, DTs continue to fuel a growing discussion in the literature on how to seize the opportunities they offer to make LCA more efficient and comprehensive. Scholars have started investigating the opportunities related to the implementation of specific DTs in each LCA phase, following the ISO 14040 standard, to empower the results' reliability and—in turn—their strategic power in the decision-making processes. More specifically, some researchers have evaluated the opportunities created by the integration of DTs in the various stages of LCA to make the data acquisition, analysis and interpretation processes more effective and efficient and provide greater strategic power for decision-makers (Zhang et al. 2020).

In particular, in the goal and scope definition phase, the use of DTs in the management of the AFSCs allows greater transparency and traceability of production inputs, reducing the constraints associated with the acquisition of data for LCA analyses. This also makes it easier to define the objective of the LCA and the functional unit (Zhang et al. 2020).

In addition, these technologies minimise the impact of the subjective component linked to the definition of the functional unit that characterises traditional LCA analyses (Christensen et al. 2007; Matos and Hall 2007) and contributes to the widening of the boundaries of the system to be investigated.

Concerning the inventory analysis, scholars have demonstrated that DTs also help overcome the limits related to the complexity of the global nature of product supply chains, as well as the LCA limitations regarding the quality of the data and their completeness enabling the consideration of all the possible inputs of complex AFSCs (Majeau-Bettez et al. 2011; Acquaye et al. 2015; Genovese et al. 2017; Wang et al. 2019). Indeed, in the inventory analysis phase, the data quality, concerning their reliability, traceability, transparency and validity, is crucial (Proto and Supino 2009; Ingraio

et al. 2021). Furthermore, DTs allow analysts to address the limitations associated with the universality and applicability of the data collection methods for the LCI. In fact, they enable the acquirement of reliable, immutable and verifiable inventory data, identifying the relevant inputs and output flows for the LCA. Therefore, the inventory and the entire documentation process become traceable (Rolinck et al. 2021; Zhang et al. 2015; Belaud et al. 2014).

Other studies have investigated the impact assessment phase and highlighted that DTs could also be useful for modelling impact assessment, widely disseminating LCA results, identifying improvement opportunities and reducing production activities' footprints (Mieras et al. 2019). Moreover, it has been demonstrated that integrating big data-driven analyses, with other proven analysis methods, improves the reliability of environmental impact analyses, thanks also to the use of more reliable and real-time data (Song et al. 2018; Mieras et al. 2019; Zhang et al. 2020; Ruggieri et al. 2021; Nayal et al. 2021).

Finally, in the last stage of interpretation, according to Zhang et al. (2020), DTs ensure that all significant, validated and useful results are adequately evaluated for drawing conclusions from the LCA study and making better and faster decisions. Furthermore, a DT-based LCA allows, through the implementation of big data analytics tools, the visualisation of data and results to produce graphical information, that is easily usable by managers in the AFS in order to facilitate the decision-making process (Zhang et al. 2015; Kaluza et al. 2018; Bhinge et al. 2015; Belaud et al. 2019). This allows LCA analyses to provide patterns, connections and relationships from different perspectives and quickly process and interpret large amounts of data.

The scholars' interest in some peculiar DTs for each LCA phase has emerged from the recent literature analysis. In particular, for the goal and scope definition phase, blockchain technology and big data analytics have been mainly investigated (Zhang et al. 2020; Carrières et al. 2021). The inventory analysis phase can be considered the most explored phase since the great opportunities that DTs can provide for data collection and database development. More specifically, the benefits related to the adoption of blockchain, big data, IoT and artificial intelligence have been investigated by several scholars, such as Kamble et al. (2020b), Rolinck et al. (2021) and Mieras et al. (2019). Similarly, other researchers have explored the same DTs for the impact assessment phase and its related benefits (Hellweg and Zah 2016; Kaluza et al. 2018). Lastly, Christensen et al. (2007) have highlighted how decision support systems could support managers in the decision-making process through the interpretation phase.

Despite the concept of integrating DTs with LCA being relatively unexplored, multiple benefits can be obtained from integrating DTs in the various phases of the environmental impact assessment process (Table 1).

However, some barriers also emerge due to, for example, technical problems related to the difficulty of manipulating, transmitting and archiving a large amount of data (Kouhizadeh and Sarkis 2018; Swan 2015; Panarello et al. 2018; Saberi et al. 2019; Rolinck et al. 2021). Some scholars have classified the barriers into four categories, namely inter-organisational, intra-organisational, technical and external. Methods for overcoming these barriers have also been presented (Saberi et al. 2019). Other scholars have highlighted potential obstacles to successfully implementing and adopting DTs within the AFS. These include a lack of willingness to share information, scepticism regarding data security and reliability, unfamiliarity with the technologies, scarce economic resources and capabilities, perceived undesirable cost–benefit ratio, absence of critical mass as well as uncertainty regarding the impact on the current business practices and models (Verdouw et al. 2016; Marshal et al. 2012; Chen et al. 2014; Bewley and Russell 2010).

Table 2 provides the reference lists for each potential barrier retrieved in the literature.

Starting from this background, a theoretical framework can be developed based on integrating the most relevant DTs investigated in the literature within the traditional LCA framework to guide the AFSC toward CE.

As shown in Fig. 1, the “empowered LCA” pushes the AFSCs to identify the weakest links within the activities, both in terms of efficiency losses and environmental impacts. This accurate assessment supports managers to act in order to manage criticalities and make the supply chain's stages more sustainable. Furthermore, the possibility of disseminating among the AFSC's actors, namely data, results and sustainable initiatives, may allow the AFS to drive the circular transition successfully.

Our analysis has highlighted that the potential of these new technologies for LCA is not fully utilised. DTs have been chiefly explored theoretically or from a small-scale perspective (Xing et al. 2016; Mieras et al. 2019). Since there are no well-established tools for assessing the benefits and barriers related to implementing DTs for carrying out an LCA analysis in the AFS, there was a limitation on developing a set of items based only on the literature review. Therefore, the authors have adopted a two-stage methodology to define a reliable measurement model, which is presented in the following section.

### 3 Research methodology

The present research aims to develop and validate a measurement scale of the perceived benefits and barriers associated with adopting DTs to conduct LCA studies in order to support the CE transition in the AFS. The authors have followed a methodology described in Fig. 2.

**Table 1** The main benefits and technologies retrieved in the LCA literature *per* phase

LCA phase	Type of technology	Type of benefit	Source
Goal and scope definition	Blockchain/Big Data	Give an objective insight into the functional unit; consider all possible inputs of complex supply chains	Carrières et al. (2021)
	Blockchain	Minimises the need for subjective judgement of the functional unit as practised in traditional LCAs; makes it easy to define the goal and scope of an LCA study	Zhang et al. (2020)
Inventory analysis	Big Data	Guarantee data privacy; save time and add new sources of data more easily	Belaud et al. (2019)
	Blockchain/Big Data/IoT	Empower the data collection, availability and transparency	Carrières et al. (2021)
	Big Data	Allow the development of open-access databases; allow data sharing; sample big data for smaller geographic areas; guarantee a high level of transparency	Cooper et al. (2013)
	Big Data	Improve data transparency	Hellweg and Zah (2016)
	IoT	Supports collection and sharing of information in real-time	Kamble et al. (2020b)
	Blockchain	Allows the automated documentation of transactions and the gathering and tracing of LCA-relevant data; allows reliability and immutability and traceability after validation	Rolinck et al. (2021)
	Blockchain, Big Data, Internet of Things, Artificial Intelligence	Provide more data for LCI and other parts of LCA studies in a more efficient way; could be used for more robust LCI data on production processes;	Mieras et al. (2019)
	Artificial Intelligence	Supports the data collection and the automated incorporation of Big Data in LCA models	Mieras et al. (2019)
	Blockchain	Enables the analysis of real-time data	Ruggieri et al. (2021)
	Blockchain	Addresses the challenges associated with data integrity, traceability and transparency; allows costs and time reduction due to less planning for organising data collection at multiple locations; allows the development of free and transparent databases due to decentralisation and distributed networks	Teh et al. (2020)
Impact assessment	Blockchain	Allows less time for LCA data collection; improves the data quality and traceability of sources; allows using actual data from suppliers, not from a generic source; stores product environmental information through the end of life to better manage its recycling and disposal; reduces information uncertainty, provides better modelling inputs and outputs	Kouhizadeh and Sarkis (2018)
	Blockchain/Big Data	Automate the environmental impact calculation; save time and resources	Carrières et al. (2021)
	Big Data	Enhance the data utilisation	Hellweg and Zah (2016)
	Big Data Analytics	Reduce data uncertainty and manage heterogeneous data sources	Kaluza et al. (2018)

Table 1 (continued)

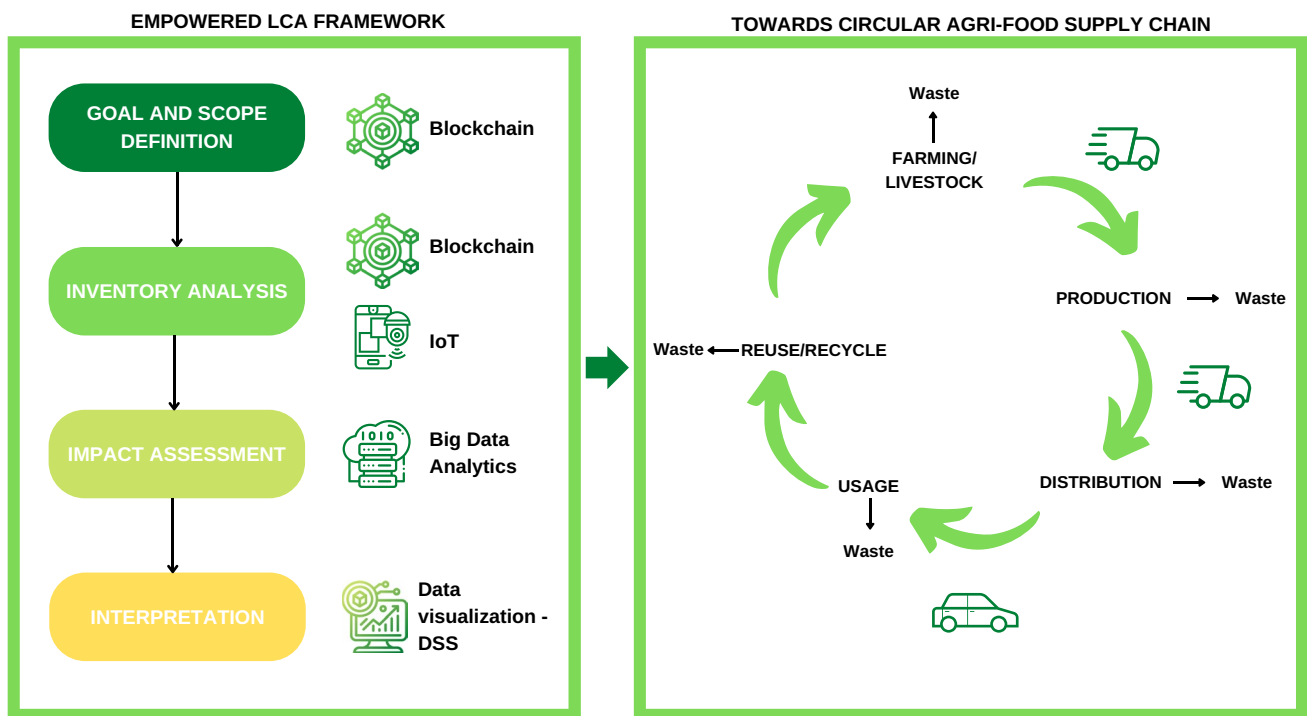
LCA phase	Type of technology	Type of benefit	Source
Interpretation	Blockchain, Big Data, Internet of Things, artificial intelligence	Useful for impact assessment modelling and the LCA results dissemination at a large scale; facilitates automated processing of LCA calculations	Mieras et al. (2019)
	Big Data	Provide more accurate assessments	Zhang et al. (2020)
	Big Data	Generate results through various dynamic and in-depth visualisation techniques	Belaud et al. (2019)
	Big Data/advanced manufacturing	Improve the accuracy of the analysis and the forecast predictions; support the decision-making	Bhingé et al. (2015)
	Blockchain/Big Data	Communicate products' real-time impacts	Carrières et al. (2021)
	Decision support systems	Support managers in the interpretation phase	Christensen et al. (2007)
	Big Data Analytics	Facilitate results interpretation	Kaluza et al. (2018)
	Big Data Analytics	Support the decision-making processes	Kamble et al. (2020b)
	Big Data	Make decision-making processes more efficient for improving environmental management levels	Song et al. (2018)
	Decision support systems	Allow a complete impact assessment	Christensen et al. (2007)
All the phases	Blockchain	Ensures that all data elements are properly assessed and only the validated results are used to draw conclusions from the LCA study	Zhang et al. (2020)
	Blockchain/Big Data	Ensure traceability and transparency and allow conducting dynamic LCA with up-to-date data	Carrières et al. (2021)
	Big Data	Permit a higher comprehensiveness of LCA analyses	Cooper et al. (2013)
	Big Data/Blockchain/IoT	Enhance the reliability of the analysis and the usability of the results	Kamble et al. (2020b)
	Blockchain	Reduces LCA information uncertainty	Kouhizadeh and Sarkis (2018)
	Blockchain, Big data, Internet of Things, artificial intelligence	Facilitate the re-use of data, information and knowledge; enable complete supply-chain transparency, allow data gathering on social issues throughout the supply chain; allow a widespread dissemination of LCA results	Mieras et al. (2019)
	Blockchain	Promotes a more comprehensive LCA	Rolinck et al. (2021)
	Blockchain	Guarantees transparency, security, irrevocability, decentralisation and interoperability with other technologies	Ruggieri et al. (2021)
	Blockchain	Supports sustainability and helps organisations achieve their targeted SDGs; helps address the limitations of LCA by sharing immutable and irreversible information in real-time; allows meeting the information requirements for decision-making processes	Teh et al. (2020)
	Blockchain	Has many direct applications for improving the environmental sustainability of supply chains; reducing the cost of performing LCA operations; improving speed and accuracy significantly; enables instant traceability of data	Zhang et al. (2020)

**Table 2** The main barriers to investigated digital technologies in the LCA domain

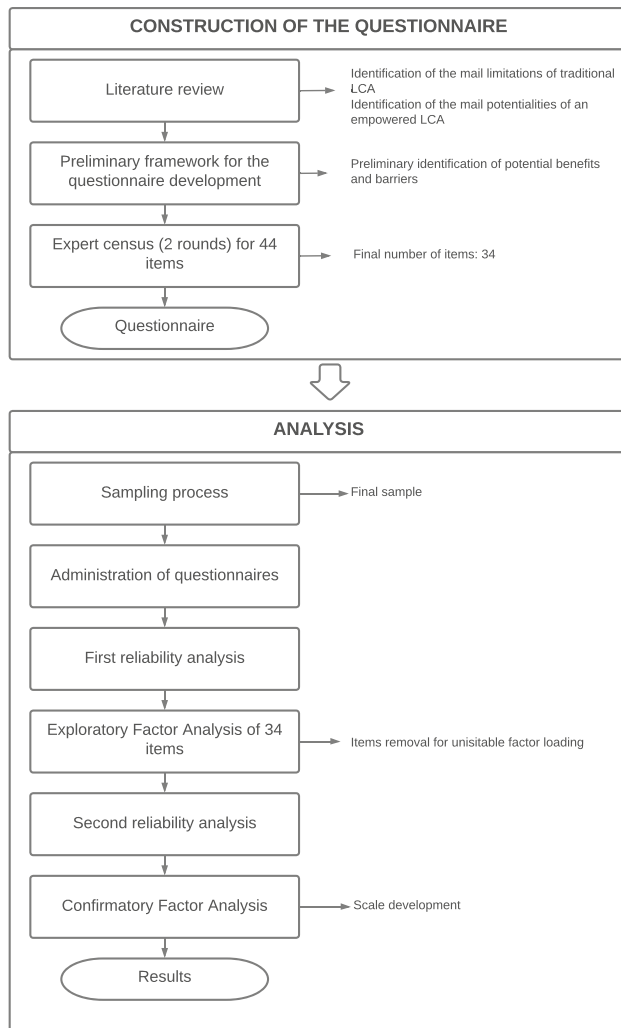
DT	Type of barrier	Source
Blockchain	Inter-organisational, intra-organisational, technical, and external barriers	Saberi et al. (2019), Kelly et al. (2017)
	Absence of privacy; high costs and times for DTs integration in the companies; regulatory problems; cultural issues	Ruggieri et al. (2021)
	Unwillingness to disclose information to some interested parties	Teh et al. (2020)
Blockchain/Big Data	High implementation's costs	Carrières et al. (2021)
IoT	Too expensive; absence of integrated software solutions	Verdouw et al. (2016)
IoT/Blockchain	Numerous vulnerabilities concerning confidentiality, privacy and data integrity; difficulty in managing the unique identity of the devices in a tamper-proof manner	Panarello et al. (2018)
	Barriers at the managerial level (agreement on common standards, nationally different regulations, absence of shared data governance); barriers at the technical level (limitations in transmission rate and data storage, data manipulation previous to uploading data to the blockchain network)	Rolinck et al. (2021)

The first part of the analysis aims to explore and identify critical issues concerning the development of the questionnaire. Accordingly, the researchers performed a comprehensive review of the existing literature to determine, on the one hand, the main limitations of the traditional LCA methodology and, on the other hand, the principal benefits of a DT-based LCA. The literature review results, highlighted in Tables 1 and 2, provide critical insights into developing the preliminary framework described in Fig. 3. Considering that there are no existing tools or conceptual models to describe the potential benefits and barriers

related to adopting DTs for LCAs in the AFS, establishing a set of items based solely on the literature review could be critical for this study. Therefore, the results were used to identify the relevant benefits and barriers and proceed with the development of the items. Hence, a qualitative interview was conducted with a panel of four senior researchers with in-depth knowledge and broad practical experience in conducting LCA in the AFS. More specifically, the researchers involved in the questionnaire development are two full professors in commodity sciences, one LCA researcher and a researcher specialised in circular



**Fig. 1** Empowered LCA framework for agri-food supply chains



**Fig. 2** Methodology adopted in the study

economy applied to the agri-food system. The interview sessions were conducted either over the phone or online. All the conversations were recorded and examined independently for further analysis. At the beginning of the sessions, the research team briefly presented the research objectives to the interviewees and asked them to answer open-ended questions listed in Fig. 3.

### 3.1 Questionnaire development

The rationale behind this choice was that an unstructured questionnaire could allow us to explore the topic without limitations or biases (Nwoire 2011; Pereira and Alvim 2015). The answers were analysed and integrated with previous findings from the literature review. Based on this qualitative outcome, an initial set of forty-four items was developed. A preliminary draft of structured closed-ended questions containing the selected items was then

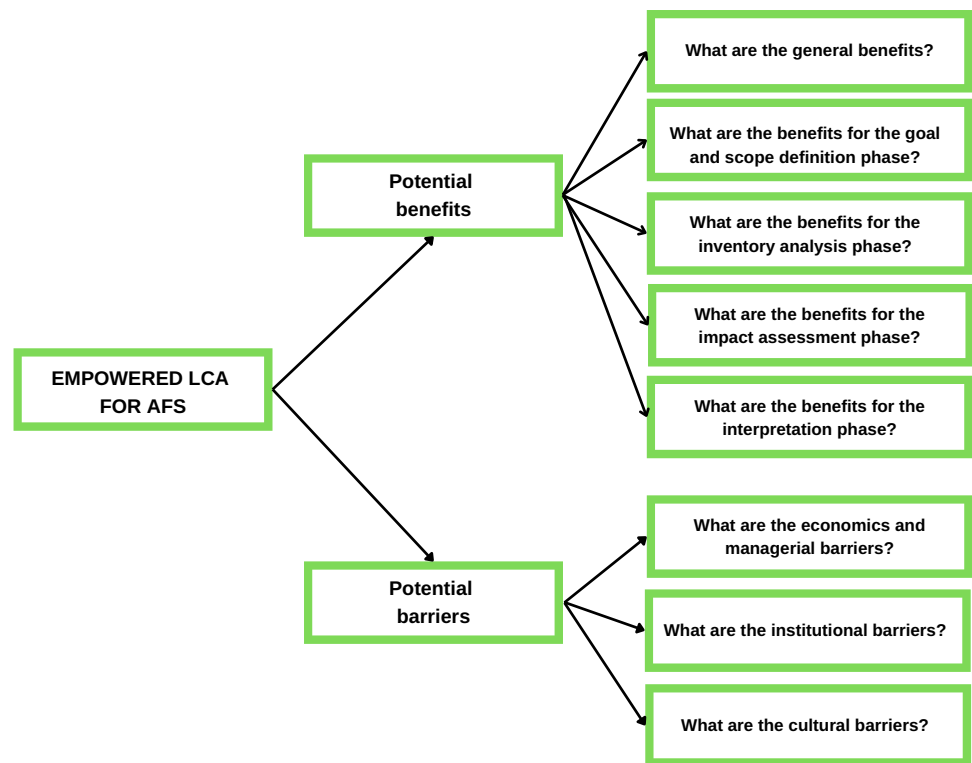
implemented. Next, the four senior researchers were asked to rate each question (using a seven-point Likert scale where “1” means “Not important” and “7” means “Extremely important”) according to its importance in assessing the benefits and barriers associated with adopting DTs for LCA studies in the AFS. Further to this, the researchers were asked to provide suggestions to improve the items’ clarity. Following the work of Garg et al. (2021), the items were chosen based on whether there was a consensus of more than 80% among the researchers; thirty-one items satisfied these criteria, while fifteen did not and received some suggestions for revision from the interviewees. According to this feedback, the fifteen items were modified and sent to the senior researchers again to verify their suitability. The total number of items for more than 80% of consensus among the interviewees after the second round was thirty-four. The opinions of the senior researchers were considered during each step of the questionnaire development to refine the final set of questions. Moreover, the two-stage consensus request allowed the researchers to ensure the content and face validity of the instrument. The definite set of items developed is presented in the results section (Table 3). The questionnaire developed was created using Google Forms. It comprises two parts: (a) personal information and (b) perceived potential benefits and barriers related to the implementation of DTs for LCAs in the AFS, presented in the Appendix.

### 3.2 Data collection

Since this exploratory study aimed to develop a valuable tool for future studies to assess the benefits and barriers related to DT-based LCAs, the researchers considered it essential to engage individuals with deep and specific *expertise* in the topic of the study. Accordingly, data were collected from a sample of Italian LCA experts, technologies experts and agri-food managers. Indeed, Italy was chosen as the country for the study as there has long been a very active community of LCA scholars in the food system (Notarnicola 2011).

A structured double-stage sampling process has been developed. A random sampling process for the mailing list of two relevant Italian scientific networks in the field of LCA studies (the “Rete Italiana LCA” association and the “Accademia Italiana di Scienze Merceologiche [AISME]” association) was performed in the first stage. The link to the questionnaire and a cover letter summarising the study’s purpose were sent to the 547 companies through the online contact forms available on their official websites and the mailing lists of AISME and Rete Italiana LCA associations from April to May 2022. All responses from the LCA and DTs experts and the agri-food companies were collected and analysed (Table 3).

**Fig. 3** Preliminary framework for the questionnaire development



The response rate for the experts was 59.72%. Thus, the final sample size ( $n$ ), calculated using the formula for a finite population ( $N$ ), was considered sufficiently representative of the expert panel. In particular, for the expert population size ( $N$ : 283), 164 answers were required to obtain a sample size with a confidence level of 95% and an error of about 5%. The authors received 171 responses. Therefore, our sample was considered sufficiently representative to continue the analysis.

### 3.3 Data analysis

The data analysis involved the following four aspects: (1) demographic profile, (2) instrument’s reliability, (3) exploratory factor analysis (EFA), and (4) confirmatory factor analysis (CFA).

After the analysis of the demographic characteristics of the respondents, an assessment of the instrument’s reliability was performed. More specifically, the internal consistency and reliability of the examined constructs were verified to ensure the measurement model’s quality and the scale’s validity (Broadbent et al. 2006). A measurement

scale is considered reliable if it systematically represents the same phenomenon consistently in repeated measurements (Fleishman and Benson 1987). At the same time, the internal consistency ensures that the indicators are significantly and substantially related, thus expressing “the latent construct” to be measured (Rust and Cooil, 1994). To test the internal consistency, Cronbach’s alpha coefficient was chosen among several techniques employed in past research (Sun and Hong 2002). Furthermore, the validity of the constructs was assessed. A measurement scale is considered valid if it represents the phenomenon of interest intended to measure the validity of the content, construct and criterion. The authors performed an EFA and then a covariance-based structural equation model (SEM) to answer the research questions by carrying out a CFA. An SEM consists of a measurement and structural models (De Vellis 1991; Bagozzi et al. 1984). The measurement model aims to ensure the validity of the measurement scale. In contrast, the structural model aims to investigate each latent construct’s potential relationships and impacts on each other (Bagozzi et al. 2010). To answer the research questions, the present study is based only on the measurement model,

**Table 3** Sampling process

Category	Sent questionnaires	Response rate	Non-response rate
Experts (i.e. Rete Italiana LCA:150; AISME: 133)	283	60.43% (171)	39.57% (112)

which is the pillar of a covariance-based SEM of its ability to provide more testable characteristics and—therefore—less bias in the estimated model (Garg et al. 2021).

A two-stage EFA using the SPSS 20 software was performed. The primary objective of an EFA is to identify the latent structure underlying a set of given variables and refine the item group (Kaiser 1974; Iacobucci 2010). In developing a measurement scale, EFA allows a preliminary estimation of factor loadings (i.e. the saturations of the indicators for latent factors) and verifies the suitability of the supplementary scale purification (Stewart 1981). This analysis represents the first step required to develop a measurement scale (Garg et al. 2021). The authors used PCA for the factor loading estimation. The EFA was implemented, followed by an orthogonal rotation method (i.e. Varimax). In addition, Bartlett's and Kaiser–Meyer–Olkin (KMO) tests were conducted to assess the sampling adequacy. After performing the two-stage EFA, ten items were excluded from the measurement due to the presence of cross-loadings (Kim 1978). The final set was composed of twenty-three items, presented in Table 6. Furthermore, a second step was performed to assess the reliability of the extracted items.

Last, a CFA was carried out using LISREL 8.80. The CFA aimed to prove the constructs' reliability and validity to allow future research to examine the inter-relationships among the extracted constructs, using structural equation models (SEM) (Fornell and Larcker 1981; MacCallum and Austin 2000). A covariance-based SEM was constructed “due to its ability to offer more verifiable characteristics and, hence, less bias in the estimated model” (Garg et al. 2021, p. 11). Composite reliability (CR) was tested to assess the constructs' reliability (Smaldone et al. 2020). At the same time, the constructs' validity can be measured by evaluating the convergent and discriminant validities.

The convergent validity expresses how two measures capture a shared construct (Carlson & Herdman, 2012). The higher the values of standardised construct loadings are, the higher the degree of the convergent validity expressed (Hair et al. 2010). Further to this, the discriminant validity ensures that the latent constructs do not measure the same phenomenon and, in turn, do not create multicollinearity problems (Hamid et al. 2017). Following Fornell and Larcker (1981), the average variance extracted (AVE) was calculated to test the convergent and discriminant validities. This index measures the amount of variance observed in the construct with regard to the amount of variance generated by the error (Ingoglia 2013). There is evidence of convergent validity if the AVE index is higher than 0.50. In fact, in this case, the indicators share more than 50% of their variance with the constructs. With regard to evaluating the discriminant validity of the constructs, Fornell and Larcker (1981) suggest comparing the AVE of two constructs (which yields the shared average variance) with the shared variance

between the two constructs. There is evidence of discriminating validity when the correlation square is less than the AVE of each construct.

Finally, following Faraci et al. (2013), the overall validity of the model was assessed using the following model fit indices: the Normed Fit Index (NFI), the Goodness of Fit Index (GFI), the Root Mean Square of Error Approximation (RMSEA), the Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI).

The final measurement model presented in Fig. 3 represents the factors that affect the expected benefits and barriers associated with a DT-based LCA in the AFS for a CE transition.

## 4 Results

The collected data have been analysed using several statistical tools and techniques to develop a measurement scale. In particular, after the descriptive statistics of the respondents, the constructs' internal consistency and reliability were verified. Moreover, a CFA was performed to ensure the validity of the measurement scale.

### 4.1 Descriptive statistics

Table 4 provides the descriptive statistics for the demographic characteristics of respondents. In line with the sample composition (i.e. scholars and LCA experts), no CEO/agri-food manager answered the questionnaire. The highest percentage of respondents comprised LCA experts (i.e. 42.69%), while only 7.60% were CE experts.

**Table 4** Demographic characteristics of respondents

Demographic variable	Categories	Response rate
Gender	Female	60.24% (103)
	Male	38.01% (65)
	I prefer not to specify	1.75% (3)
Age range	≤ 35 years	43.86% (75)
	> 35 years	56.14% (96)
Education	Master/PhD	92.40% (158)
	Graduation	7.60% (13)
Designation	Disruptive technology expert	10.53% (18)
	CE expert	7.60% (13)
	LCA expert	42.69% (73)
	Others	39.18% (67)

Table 5 provides the descriptive statistics for each construct. To investigate whether the items involve biases (e.g. social desirability, acquiescence, lack of clarity of the item), a

variance analysis between the mean and median of each item was carried out (Smaldone et al. 2020). The greater the deviation between the mean and median, the weaker the item in

**Table 5** Descriptive statistics for each construct

Construct	Item	Mean ( $\bar{x}$ )	Median (Me)	St. dev. ( $\sigma$ )
Potential benefits for AFS and companies	1. Improve transparency	5.590	6	1.109
	2. Improve traceability	6.158	6	0.746
	3. Improve retraceability	5.818	6	0.905
	4. Enhance food safety and security	5.766	6	0.978
	5. Improve full legislative compliance	5.473	6	1.224
	6. Support the environmental and quality management systems and other sustainability tools	5.748	6	0.976
Potential benefits in performing LCA phases: goal and scope definition	7. Enhance the overall goal and scope definition process	5.228	5	1.251
	8. Reduce subjectivity for functional unit	5.245	5	1.296
	9. Reduce subjectivity to system boundaries	5.362	6	1.230
	10. Enhance the LCA comprehensiveness	5.397	5	1.258
Potential benefits in performing LCA phases: the inventory analysis	11. Help real-time tracking	5.859	6	1.042
	12. Enhance efficiency and effectiveness	5.836	6	1.016
	13. Improve the reliability of the input's data collection	5.947	6	0.828
	14. Improve the reliability of the output's data collection	5.772	6	1.127
	15. Reduce the use of secondary and tertiary data	5.491	6	1.276
	16. Include upstream and downstream data of the SC	5.772	6	1.029
	17. Allow the development of regional or country-specific LCI databases	5.707	6	1.099
	18. Improve the data pooling and sharing on LCI databases	5.696	6	1.112
	19. Optimise transparency of the data acquisition time	5.690	6	1.214
	20. Simplify the materials and energy flows analysis	5.520	6	1.271
Potential benefits in performing LCA phases: the impact assessment	21. Improvement of results reliability	5.795	6	1.034
	22. Improvement of results comparability	5.783	6	1.043
Potential benefits in performing LCA phases: the interpretation	23. Efficiently support the decision-making processes	5.772	6	0.819
	24. Improve the data visualisation and avoid ambiguous interpretations	5.801	6	0.924
	25. Facilitate an immediate understanding of the LCA results	5.263	5	1.290
Economic and managerial barriers	26. Imply high costs for DT implementation	5.631	6	1.142
	27. Imply high costs for human resource training	5.386	6	1.149
	28. Imply difficulties in calculating the return on investment	4.888	5	1.229
	29. Impose major organisational challenges	5.842	6	0.996
Institutional barriers	30. Increase the technology dependence	5.626	6	1.111
	31. Changes in legislative policies and measures	5.433	5	1.062
Cultural barriers	32. Lack of governments incentives	5.444	6	1.122
	33. Difficulties in the use of DT for LCA	5.011	5	1.549
	34. Lack of knowledge and competences	5.620	6	1.112

**Table 6** Results for the preliminary reliability analysis of the developed constructs

Construct	Cronbach $\alpha$
1. Potential benefits for AFS and companies	0.795
2. Potential benefits in performing LCA phases: goal and scope definition	0.890
3. Potential benefits in performing LCA phases: the inventory analysis	0.917
4. Potential benefits in performing LCA phases: the impact assessment	0.888
5. Potential benefits in performing LCA phases: the interpretation	0.703
6. Economic and managerial barriers	0.815
7. Institutional barriers	0.785
8. Cultural barriers	0.754

the scale measurement. Table 4 shows adequately satisfactory results, suggesting a low probability of having bias problems.

## 4.2 Reliability of the instrument

The instrument's reliability allows researchers to measure its quality, and it is considered an essential step in ensuring the scale's validity (Broadbent et al. 2006). Scholars have developed several approaches to test the reliability of an instrument, i.e. to test the measures' stability, equivalence and internal consistency (Salmond 2008). However, the instruments' internal consistency and reliability are considered the most effective aspects in this field of study (Rust and Cool 1994). Accordingly, the authors assessed the internal consistency and reliability of the constructs by computing Cronbach's alpha values (Sun and Hong 2002).

Before starting the analysis, a first Cronbach's alpha was calculated for each construct to pre-test the reliability of the developed constructs. Table 6 shows the values retrieved from this process. In the social sciences, the threshold value for Cronbach's alpha is higher than 0.60 during the scale development processes and higher than 0.70 when the scale is already validated (Cronbach 1951). Our results show that Cronbach's alpha value is always higher than 0.70, indicating excellent internal consistency. For all the constructs, the item-to-total correlation values are higher than the threshold (i.e. 0.50) (Cudeck and O'Dell 1994). Furthermore, Cronbach's alpha-if-deleted values do not exceed the constructs' Cronbach's alpha values, suggesting that no construct needs to be omitted from the analysis.

## 4.3 Exploratory factor analysis

The EFA is a statistical technique used to synthesise the information obtained from the observed variables into a reduced set of factors to identify latent variables (Straub et al. 2004). A double-stage EFA was performed to refine the set of items. The thirty-four items were analysed using the PCA to understand the data structure, followed by a Varimax rotation. The software used to perform this analysis (SPSS 20) retrieved eight factors according to the Kaiser

rule (Brown 2009). Moreover, the resulting scree plot interpretation in the output suggests the same factor numbers (Yong and Pearce 2013).

The PCA started with extracting the maximum variances and allocating them to the first factor. Next, the Varimax rotation decreased the number of variables with high factor loadings for each factor and, in the meantime, further reduced the small loadings (Garg et al. 2021). The KMO measure of sampling adequacy and Bartlett's test of sphericity were used to assess the data's suitability (Dziuban and Shirkey 1974). The KMO was between 0 and 1 and higher than the threshold of 0.70 (i.e. 0.754). Moreover, the *p*-value of Bartlett's test of sphericity was significant (i.e. 0.000).

Next, the commonalities for each item were examined. All the extraction values were higher than the threshold of 0.50. The higher the value is, the better the item performs. The highest value retrieved was 0.888 for the item "improvement of results comparability", while the lowest one was 0.646 for "improve the data visualisation and avoid ambiguous interpretations". The shared percentage of variance, explained by the eight factors extracted after the Varimax rotation, was 75.884. The analysis of the factor loading retrieved for each item led to the removal of items with high cross-loadings. Seven items were deleted (i.e. 1, 4, 12, 15, 16, 22, 25, 26 and 34). While item 14, "reliability of output data collection", was encompassed in item 13 "reliability of the input data collection", which resulted in a unique construct named "reliability of input and output data collection". The second stage of the PCA was carried out to extract the final number of constructs to perform the CFA and test the measurement model. This second step retrieved

**Table 7** Results for reliability analysis of the extracted constructs

Construct	Cronbach $\alpha$
Factor 1: Benefits for data collection and analysis	0.893
Factor 2: Benefits for LCA analysts	0.875
Factor 3: General barriers	0.833
Factor 4: Benefits for the management	0.700
Factor 5: Benefits for traceability	0.706

a KMO of 0.721 and a significant Bartlett's test of sphericity value (i.e.  $p$ -value = 0.000). Furthermore, in this case, the commonalities were all higher than 0.50. Using the Kaiser rule technique, the software retrieved five factors, explaining 72.402% of the shared variance. The final set of the extracted items is presented as follows.

Factor 1 was labelled "benefits for data collection and analysis" due to high factor loadings for items such as "help real-time tracking", "improve the reliability of the inputs and outputs data collection", and "allow the development of region- or country-specific LCI databases". The first factor has an eigenvalue of 3.863 and explains the 16.04% variance.

Factor 2 was labelled "benefits for LCA analysts" due to high factor loadings for items such as "reduce subjectivity for functional unit", "reduce subjectivity for system boundaries" and "enhance the LCA comprehensiveness".

The second factor has an eigenvalue of 15.848 and explains the 3.803% variance.

Factor 3 was labelled "general barriers" due to high factor loadings for items, such as "imply high costs for human resource training", "impose major organisational challenges" and "increase the technology dependence". The third factor has an eigenvalue of 13.773 and explains the 3.306% variance.

Factor 4 was labelled "benefits for the management" due to high factor loadings for items, such as "improve full legislative compliance" and "support the environmental and quality management systems and other sustainability tools". The fourth factor has an eigenvalue of 10.624 and explains the 2.550% variance.

Finally, Factor 5, labelled "benefits for traceability", comprises two items: "improve traceability" and "improve retraceability". This factor has an eigenvalue of 8.506 and explains the 2.041% variance.

**Table 8** Reliability and items loading

Construct	Items	Description	Factor loading	Cronbach ( $\alpha$ )	CR ( $\rho$ )	AVE
Benefits for data collection and analysis	X1	Help real-time tracking	0.826	0.893	0.894	0.587
	X2	Improve the reliability of the inputs and outputs data collection	0.713			
	X3	Allow the development of regional or country-specific LCI databases	0.658			
	X4	Improve the data pooling and sharing on LCI databases	0.725			
	X5	Optimise transparency of the data acquisition time	0.857			
	X6	Simplify the materials and energy flows analysis	0.801			
Benefits for LCA analysts	X7	Reduce subjectivity for functional unit	0.788	0.875	0.883	0.562
	X8	Reduce subjectivity to system boundaries	0.929			
	X9	Enhance the LCA comprehensiveness	0.783			
	X10	Improvement of results reliability	0.776			
	X11	Improve the data visualisation and avoid ambiguous interpretations	0.822			
	X12	Enhance the overall goal and scope definition process	0.765			
General barriers	X13	Imply high costs for human resource training	0.684	0.833	0.835	0.505
	X14	Impose major organisational challenges	0.747			
	X15	Increase the technology dependence	0.830			
	X16	Changes in legislative policies and measures	0.696			
	X17	Lack of governments incentives	0.804			
	X18	Difficulties in the use of DT for LCA	0.829			
Benefits for the management	X18	Improve full legislative compliance	0.724	0.700	0.735	0.504
	X19	Support the environmental and quality management systems and other sustainability tools	0.732			
	X20	Efficiently support the decision-making processes	0.725			
Benefits for traceability	X21	Improve traceability	0.898	0.706	0.748	0.608
	X22	Improve retraceability	0.925			

#### 4.4 Confirmatory factor analysis

The CFA started with the second-stage reliability analysis to test the constructs' internal consistency (Streiner 2003). As a result, Cronbach's alpha for each factor has been computed. Table 7 displays the reliability analysis results, showing that the coefficients are higher than the threshold of 0.70. As a result, these measures could be considered reliable and used for subsequent SEM analyses.

The CFA was performed using LISREL 8.80 software. The measurement model's analysis aims to confirm the presence of the necessary level of construct validity and reliability, for further examining the inter-relationship among the constructs through a structural model (Fornell and Larcker 1981). The final measurement model describes the distinct factors affecting DTs' expected benefits and barriers in the AFS concerning LCA analyses. To test the convergent validity—which represents the extent of the convergence of items for each construct (Hair et al. 2010)—the CR indices and the AVE values were analysed and have been reported in Table 8 (Fornell and Larcker 1981; Hair et al. 2010). Both the indices for each factor are higher than the related thresholds (i.e.  $CR > 0.70$  and  $AVE > 0.50$ ) (Nunnally and Bernstein 1994; Fornell and Larcker 1981). Therefore, all the constructs representing the perceived benefits and barriers associated with DTs for LCA analyses present considerable reliability.

Moreover, the convergent validity has been measured through the standardised construct loadings. The standardised factor loadings should be higher than 0.50. Furthermore, the higher the value is, the greater its ability to demonstrate the construct (Hair et al. 2010). The results, reported in Table 7, are in the range of 0.658–0.929, indicating that the observed variables are suitable and significantly represent their latent variable.

Two analyses were conducted to test the discriminant validity, which represents the extent to which each latent variable differs from the others. The first one was based on the correlation matrix analysis of the constructs (Table 9). Since each set of items measures different constructs, the correlation among the latent variables was not expected to be high. Accordingly, the highest correlations were checked, as they could violate the discriminant validity

**Table 9** Correlation matrix among latent variables

	F1	F2	F3	F4	F5
F1	1.00				
F2	0.476	1.00			
F3	0.284	0.227	1.00		
F4	0.624	0.327	0.121	1.00	
F5	0.608	0.278	0.352	0.37	1.00

criterion. The second analysis, conducted to ensure the discriminant validity, was based on comparing the AVE of each construct and the highest correlations retrieved in the PHI matrix. In fact, the AVE indicates whether the individual constructs in the measurement model are higher than the shared variance of each construct. They should be higher than the correlations between the latent variables. In particular, the square correlation between Factor 4 and Factor 1 of 0.624 was compared with the AVE values of each factor (i.e. 0.389). Since the AVE values of the constructs F4 and F1 were higher than their squared correlation, the discriminant validity criterion was respected. The same process was performed for the correlation between Factor 5 and Factor 1. In addition, in this case, the square correlation between Factor 5 and Factor 1 of 0.608 was compared with the AVE values of each factor (i.e. 0.369). Since the AVE values of the constructs, F5 and F1 were higher than their squared correlation, the discriminant validity criterion was maintained. Moreover, the low correlations among the other constructs highlight each construct's independence in the model.

The model's overall validity was tested using the fit indices of the model provided in Table 10. All the values presented are within a range that can be considered adequate, except for the TLI, which is slightly lower than 1 (chi-squared/df between 1 and 3; RMSEA  $< 0.06$ ; CFI close to 0.95; RMR  $< 0.09$ ; GFI  $> 0.90$ ; NFI  $\geq 0.90$ ).

## 5 Discussions and implications

This study aimed to develop a tool to assess and validate the perception of the benefits and barriers associated with implementing DTs in the AFS for LCA analyses identified in the literature.

The use of DTs broadens the management of business processes by going beyond the mere development of an LCA analysis, as DTs can be beneficial for improving the transparency, safety and traceability of the entire AFSCs. In fact,

**Table 10** Summary of goodness-of-fit indices for measurement model

Model fit index	Value
Chi-squared	613.07
df	221
Chi-squared/df	2.774
RMSEA	0.058
CFI	0.959
RMR	0.089
<i>p</i> -value test of close fit	0.0298
NFI	0.961
GFI	0.993
TLI	0.989

they enable greater control over the data, robustness and resilience of the system. The opportunity to track the level of CO<sub>2</sub> emissions, energy and water consumption of food during its entire life cycle in real-time and to guarantee the data immutability provides objectivity in performing impact assessment analysis and—in turn—pick out strategies and policies to address to the emergency to react to the unsustainability of the AFS. For instance, blockchain technology can be considered a bridge between data collection and big data analytics, allowing the automated assessment of the environmental impacts, saving time, and resources and establishing consumer trust through the real-time disclosure of products' impacts.

Additionally, agri-food organisations can use “empowered LCA” to support quality and environmental management systems and other sustainability tools.

The results from the descriptive analysis provided in Table 3 and the statistical analysis described in Table 7 could be discussed from two perspectives. The preliminary descriptive results provide different insights compared to the results retrieved from the covariance-based SEM performed. The following discussions have been articulated accordingly.

The experts who answered the questionnaire exhibited a considerable interest in DTs supporting the various stages of LCA analysis.

In particular, in the goal and scope definition phase, DTs are considered essential to enhance the overall process, reducing subjectivity for the functional unit, for system boundaries as well as enhancing the LCA's comprehensiveness.

The phase in which the perceived benefits are most relevant relates to the inventory analysis, as DTs make it more reliable, transparent, effective and efficient. Indeed, for instance, DTs help real-time tracking, improve the reliability of the input and output data collection, reduce the use of secondary and tertiary data, allow the development of the region- or country-specific LCI databases, as well as improve data pooling and sharing on LCI databases, simplifying the materials and energy flow analysis.

Therefore, the experts point out that DTs' adoption offers the opportunity to overcome the limitations associated with a traditional LCA approach, drastically improving its efficiency. When an LCA is based on DTs, it reduces the cost of performing LCA operations and improves their speed and accuracy.

In the impact assessment and in interpretation phases, DTs improve the results' reliability and comparability, enabling an immediate understanding. By increasing the capabilities of data analysis and interpretation, LCA becomes even more essential and effective support for decision-making processes. In this way, organisations will be able to improve the monitoring and management of the environmental sustainability performance of their supply chain activities. Investing in DTs for LCA implementation allows companies to track important environmental data, highlighting

if the relevant commitments have been met. In this way, they will be able to continuously improve their sustainability performance and enhance their reputation and competitiveness. DTs enable data traceability and transparency, helping companies build greater customer trust and loyalty, leading to increased sales and better market performance. Greater control over processes also results in better legislative compliance management (Zhang et al. 2020).

However, from the data analysis, some potential barriers emerged that could hinder the adoption of an LCA system based on DTs. These barriers can be economical, managerial, institutional or cultural. They mainly affect small and medium-sized companies, which comprise a large part of the world's production segment, and do not have sufficient resources to implement the available solutions. Furthermore, such companies experience unfamiliarity with technologies, perceived undesirable cost–benefit ratios or even a significant amount of information they do not understand what to do with (Bewley and Russell 2010).

After applying the scale development techniques, the items previously analysed from a descriptive perspective were grouped into five constructs, as summarised in Table 7. Therefore, our results show that the benefits could be clustered according to how the use of DTs could support the agri-food system for a CE transition. More specifically, how DTs could be beneficial for LCA analysts and agri-food managers (i.e. F2 and F4), for data collection and analysis (F1) and for traceability (F5).

In particular, our results highlight that the benefits for data collection and analysis could be related to real-time tracking and reliability in data collection (both for inputs and outputs), the development of region- or country-specific LCI databases, the optimisation of transparency and data acquisition time and, last, the simplification of the materials and energy-flows analyses.

In line with Zhang et al. (2020), it was found that the LCA analysts could be supported by DTs, allowing practitioners to reduce subjectivity when defining the goal and scope, the functional unit and the system boundaries. Moreover, in the interpretation phase, DTs could enhance the effectiveness and comprehensiveness of the results, preventing ambiguous interpretations and, thus, improving their reliability. AFS managers could also be supported in adopting environmental and quality management systems and other sustainability tools. Furthermore, DTs could improve full legislative compliance and support the decision-making process.

In the end, agri-food companies can widely embrace DTs to improve traceability and re-traceability, as food security and safety protocols require.

Our results suggest that all the barriers identified in the qualitative analysis could be grouped into a single construct that encompasses institutional, managerial and cultural barriers.

The scenario analysis performed has shown the vast opportunities that the implementation of DTs could provide to the AFS in the CE transition. However, since the present research aims to present a general framework of the experts' perceptions of DTs for LCA analysis within the AFS, our results do not focus on the role each DT could provide to the agri-food circular transition. The literature review has allowed the researchers to identify the investigated technologies within the LCA field. However, the ratio that has guided us in the methodological choice to explore only the scenario opportunities in which these technologies could be implemented has a twofold nature. In particular, considering the need to involve all the supply chains to assess the environmental impacts of products successfully and, as a consequence, reach the CE transition, the crucial point of our choice is represented by the differences existing within the agri-food chains and between the different agri-food chains. The "inter" and "intra" AFSC differences have suggested first investigating the general context and then going in-depth into each technology.

On the one hand, the "inter" agri-food supply chain differences are related to each AFSC's peculiarity according to the nature of each product, making it difficult to generalise the investigation and the consequent results. On the other hand, the "intra" agri-food supply chain stage differences impact the modalities to implement each DT.

Accordingly, the existing differences among DTs requires an in-depth investigation both within a single type of AFSC for each stage and in comparing its benefits and barriers among various kinds of supply chains.

## 5.1 Implications

The present research provides implications for academics, practitioners and policymakers, who can rely on our results to delve deeper into the use of DTs in the transition of the AFS toward CE models.

This research's main contribution is providing a foundation for future studies in the "enlarged LCA" field to facilitate the implementation of CE models within the AFS. Furthermore, this study aimed to enrich the literature on DTs for the CE transition. In particular, the main contribution of our research is developing a tool to assess the perceived benefits and barriers associated with adopting DTs for carrying out LCA analyses to assess CE practices and performances. The observed variables were determined with the help of professionals and secondary sources. At the beginning of the research, the authors classified the potential benefits and barriers identified from the literature according to the LCA phases defined by the UNI EN ISO 14040 standard. After a structured process, the resulting observed variables were reclassified according to who or what benefits from implementing an "enlarged LCA" for a CE transition. The

validation of the instrument provides relevant insights from academics, LCA practitioners and managers from the AFS to obtain an in-depth understanding of the benefits and barriers related to DT adoption.

Our results demonstrate that the AFS could benefit from adopting DTs from a dual perspective despite the identified barriers and limitations.

On the one hand, LCA practitioners could enhance their analyses from the beginning of the process, increasing the veracity of the data and results from the collection to the interpretation phase. On the other hand, managers could facilitate the CE transition, more easily comply with the law and regulations and easily implement quality and sustainability management systems. Moreover, the potential development of region- and country-specific LCI databases could significantly contribute to the formulating analyses that are as truthful as possible.

However, the limitations retrieved from our results reveal that the biggest challenge for the AFS is related to the need for more expertise and capital. A collaborative work environment is needed to share information for safe and reliable decision-making (Lehmann et al. 2012). This finding is in line with Esposito et al. (2020), according to which the CE transition is required at the supply chain level rather than the individual company level. Accordingly, implementing DTs could enhance the AFS by facilitating sharing information and data and co-creating value for sustainable development.

Policymakers will certainly play an essential role in promoting the sharing of all industry data as well as providing an agile regulatory framework that invites organisations to shift from a linear to a circular economy using DTs.

## 6 Conclusion

This study offers the first in-depth version of a conceptual framework to analyse the role of DTs in shifting toward CE. Despite the importance of sustainability-oriented digitisation at the corporate level, previous literature has paid little attention to the interconnection between digital transformation and sustainability.

This research discusses the advantages and barriers identified by experts and researchers associated with implementing an "empowered LCA" system. Experts argued that DTs could help managers and analysts overcome traditional LCA limitations, particularly regarding the quality of the data and their completeness in complex AFSCs. The ability of DTs to interact with other managerial and operational skills within an organisation is beneficial in a complex and dynamic environment such as the AFS. Thanks to the results of LCA analyses based on DTs, experts and managers point out that the results enhanced the effectiveness of collecting, analysing and

disseminating information that affects the supply chain's design activities and the development and improvement of products to reduce environmental impacts. It also affects strategic planning, allowing companies to identify more sustainable solutions and corporate accounting processes easily.

In conclusion, to create value from a sustainability perspective, organisations must have lean business processes and consider DTs to enable business process innovation to respond and adapt to a rapidly changing environment. In this way, new business models can be developed that can revolutionise the competitive arena of the AFS, good for the environment and the organisation's reputation. Moreover, they allow companies to gain market share to the detriment of backward and late competitors. In this way, new business models that could redefine the competitive landscape of the AFS could be developed to facilitate systemic change towards CE-related goals.

The challenge for the AFS will be associated with the large-scale adoption of DTs in the various phases of an LCA study, making organisations aware of the many and varied benefits that can be derived from them.

This study is not without limitations, which provide directions for future research.

First, the study analyses the relevance of a group of DTs for a transition to the CE in order to develop a more reliable LCA. The scenario analysis confirms the strategic link between DTs and sustainability strategies. It will therefore be necessary to continue to explore this topic, currently poorly understood in the literature, by analysing specific technologies to understand how the advantages and barriers in their concrete application to LCA differ and whether the impacts are also different considering the different phases of the LCA analysis.

Second, the analysis was conducted on sample-based LCA experts. Accordingly, future research could focus on the perceptions of agri-food managers and boards of directors.

Third, the research is based in Italy. Hence, future studies could extend this analysis by providing comparisons between different geographical areas.

Finally, this study only analyses the measurement model and does not consider the potential causal links between variables. Further investigations could focus on the impacts of the observed variables on the latent variables developed in this study.

## Appendix

This questionnaire was developed by a research team of the University of Salerno and the San Raffaele Roma University. It aims to determine the percep-

tion of the potential benefits and barriers linked to the adoption of DT (e.g. blockchain technology, IoT, smart sensors, big data analytics) in the LCA analysis for the AFS.

The questionnaire is divided into two parts:

Part A: General information, and

Part B: Perceived potential benefits and barriers linked to implementing DT for the LCA in the AFS.

The questionnaire is developed using a 7-point Likert scale where "1" means "strongly disagree", and "7" means "strongly agree". Please, express your opinion by clicking the number you consider the most appropriate for each questionnaire item.

### Part A

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Gender  
Age  
Education  
Designation

---

### Part B

- 
- |    |                                                                                                                                 |
|----|---------------------------------------------------------------------------------------------------------------------------------|
| 1  | DTs could improve transparency                                                                                                  |
| 2  | DTs could improve traceability                                                                                                  |
| 3  | DTs could improve retraceability                                                                                                |
| 4  | DTs could improve food safety and security                                                                                      |
| 5  | DTs could improve full legislative compliance                                                                                   |
| 6  | DTs could support the adoption of environmental and quality management systems as well as other sustainability management tools |
| 7  | DTs could enhance the overall goal and scope definition process                                                                 |
| 8  | DTs could reduce subjectivity for functional unit                                                                               |
| 9  | DTs could reduce subjectivity to system boundaries                                                                              |
| 10 | DTs could enhance the LCA comprehensiveness                                                                                     |
| 11 | DTs could help with real-time tracking                                                                                          |
| 12 | DTs could enhance efficiency and effectiveness                                                                                  |
| 13 | DTs could improve the reliability of the input's data collection                                                                |
| 14 | DTs could improve the reliability of the output's data collection                                                               |
| 15 | DTs could reduce the use of secondary and tertiary data                                                                         |
| 16 | DTs could allow the data acquisition also for upstream and downstream data of the supply chains                                 |
| 17 | DTs could allow the development of regional or country-specific life cycle inventory databases                                  |
-

18	DTs could improve the data pooling and share on life cycle inventory databases
19	DTs could optimise transparency and the data acquisition time
20	DTs help to streamline the materials and energy flow analysis
21	DTs could improve the results' reliability
22	DTs could enhance the results' comparability
23	DTs could efficiently support the decision-making processes
24	DTs could improve the data visualisation and avoid ambiguous interpretations
25	DTs could facilitate an immediate understanding of the LCA results
26	DTs imply high costs for their adoption and implementation
27	DTs entail high costs for human resource training
28	DTs imply difficulties in the return-on-investment assessment
29	DTs impose major organisational changes and challenges
30	DTs increase the technology dependence
31	DTs entail substantial updates in legislative policies and measures
32	Lack of governments' incentives for the adoption of DT
33	LCA experts may experience more complexity in performing LCA analyses
34	DTs require the enhancement of a diversified set of knowledge and skills

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**Data availability** The datasets generated during and/or analysed during the current study are not publicly available because all data have been collected by a questionnaire. They are available from the corresponding authors upon reasonable request.

## Declarations

**Conflict of interest** The authors declare no competing interests.

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