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Industry 4.0 and life cycle assessment: Evaluation of the technology applications as an asset for the life cycle inventory

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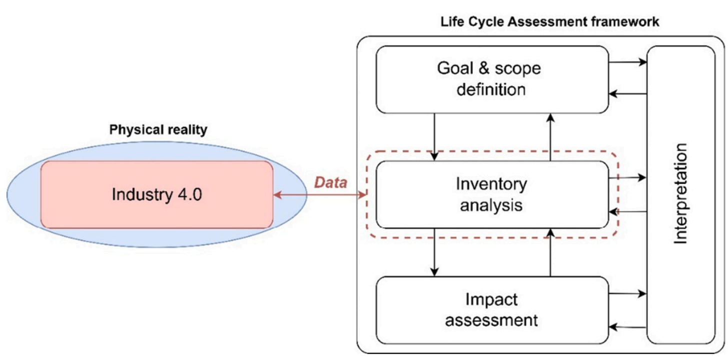
HIGHLIGHTS

- Selection of Industry 4.0 technologies and their application in manufacturing business processes
- Evaluation scheme of Industry 4.0 technologies for Life Cycle Inventory constitution
- Classification of I4.0 technologies to support the development of a Life Cycle Assessment

GRAPHICAL ABSTRACT



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ABSTRACT

Industry 4.0 technologies present transformative potential in data acquisition for production activities, promising to revolutionize the Life Cycle Inventory process. Despite acknowledging their utility in environmental impact analysis, a gap exists in understanding the specific applicability of these technologies to fulfill ISO 14044 criteria. This study addresses the gap by introducing innovative approaches to Life Cycle Assessment through Industry 4.0 technologies. Beyond existing research, technologies directly impacting LCA development are identified, along with a classification for optimal usage in the LCA process. The crucial role of these technologies in enhanced data collection across life cycle phases is highlighted, introducing a scoring mechanism to identify the technology excelling in enabling Life Cycle Inventory development. Employing a developed framework and systematic literature review, the study aims to identify Industry 4.0 technologies in manufacturing that facilitate LCA. Findings illuminate potential contributions across different product life cycle stages, with cyber-physical systems, the Internet of Things, and Simulation and Modelling identified as the most effective technologies for constructing Life Cycle Inventories. The outcomes provide guidance for practitioners in integrating Industry 4.0 technologies into manufacturing activities, offering valuable insights for environmental sustainability assessment.

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Nomenclature

AI	artificial intelligence
AM	additive manufacturing
BD	big data
CPPS	cyber physical production systems
CPS	cyber-physical systems
CT	cloud technology
IoT	Internet of things
I4.0	Industry 4.0
LCA	life cycle assessment
LCI	life cycle inventory
S&M	simulation and modelling
SLR	systematic literature review
SME	small and medium-sized enterprises
VT	visualization technology
WOS	Web of Science

1. Introduction

By identifying and quantifying energy and material usage and waste discharges, evaluating potential environmental impact, and assessing opportunities for environmental improvements over the course of the product's life cycle, life cycle assessment (LCA) is a method for defining and reducing the environmental burdens associated with a process, product, or activity (Azapagic and Clift, 1999). The second and most time- and energy-intensive aspect of the Life Cycle Assessment method, the Life Cycle Inventory (LCI) (Klöpffer, 2012; Islam et al., 2016), is governed by the ISO 14040 (Management, n.d.) and ISO 14044 (British Standards Institution, n.d.) sets of international technical standards.

The LCI entails identifying and quantifying the input and output flows from the system under consideration throughout its lifetime to create an environmental load database (Ciroth et al., 2020). This is accomplished by identifying and quantifying the use of resources (raw materials, water, and recycled goods), energy (thermal and electrical), air, water, and soil pollutants (Cuenca-Moyano et al., 2017). LCI is the most sensitive and difficult stage of an LCA study because it results in the creation of an analogous model of reality that precisely reflects all interactions between the various manufacturing process stages (Patouillard et al., 2019). An inventory of environmental loads is created by gathering the input and output information for every stage of the process inside the system limits and identifying the beginning and ending points of each phase (Righi et al., 2018). The complexity of LCI is one of the factors that makes LCA studies difficult to conduct because the collection of primary data within the business is time-consuming and therefore cost-intensive. Moreover, the quality of the available primary data usually requires manipulations to be reported to the functional unit, which introduces an approximation and, consequently, an uncertainty (Schlegl et al., 2019). Typically, primary production data related to the study's reference year, particularly actual reality, must be employed for LCA analysis of a product manufacturing process. It is feasible to use the average production data or literature data in the absence of primary production data. Therefore, it is evident that gathering basic data in complex manufacturing processes that include several phases and even non-sequential exchanges of semi-finished goods may be a time-consuming and complicated procedure that increases the risk of mistakes and/or force simplifications (Bailey et al., 2020; Baruffaldi et al., 2019).

The advent of the Fourth Industrial Revolution, commonly denoted as Industry 4.0 (I4.0), represents a transformative paradigm that has significantly impacted manufacturing landscapes (Frank et al., 2019). Originating from a 2011 project within the high-tech strategy of the German government, Industry 4.0 has evolved into a multifaceted approach aimed at bolstering industry competitiveness through the seamless integration of physical systems into Cyber Physical Production Systems (CPPS) (Frank et al., 2019; Xu et al., 2021).

This revolutionary shift has notably democratized access to advanced tools, especially benefiting Small and Medium-Sized Enterprises (SMEs) (Dassisti et al., 2019). These tools serve as indispensable assets, empowering SMEs to monitor and optimize various manufacturing phases (Perini et al., 2017). Beyond mere monitoring, Industry 4.0 tools facilitate the meticulous collection of data, encompassing material flows, energy consumption, and water usage (Jena et al., 2020). This not only fosters real-time insights but also enables SMEs to make informed decisions, thereby enhancing operational efficiency and competitiveness.

At its core, Industry 4.0 is characterized by the intricate integration of intelligent devices, machines, and information technologies to create a digital manufacturing system (Javaid and Haleem, 2020). This paradigm seeks to establish a controlled and smart network, leveraging innovative digital technologies to meet consumer demands for high-quality and customized products (Bonilla et al., 2018). However, it is essential to note that while I4.0 primarily focuses on digitalization and production flexibility, it has somewhat shifted away from the original principles of social fairness and sustainability (European Commission, 2023).

In essence, Industry 4.0 stands as a technology-driven revolution, driven by the relentless pursuit of higher efficiency and productivity. As an umbrella term, it encapsulates a group of interconnected technological advances, laying the foundation for an increasingly digitized business environment (Xu et al., 2021). This comprehensive integration of technologies not only transforms manufacturing processes but also holds profound implications for the broader industry landscape.

Industry 4.0 operates as a sophisticated digital system designed to gather and interpret data from every stage of the manufacturing process, thereby generating valuable knowledge for decision-making (Chofreh et al., 2020). This digital prowess enables real-time factory monitoring and fosters improved data and process integration. Notably, it facilitates the seamless interchange of live information between various organizational levels within a corporation and the production environment (Morgan and O'Donnell, 2018).

At the heart of Industry 4.0 lies the integration of diverse emerging technologies, culminating in the creation and deployment of Cyber-Physical Systems (CPS) (Frank et al., 2019). These systems, often manifested as innovative "I4.0 solutions" (Benitez et al., 2020), play a pivotal role in reshaping manufacturing landscapes. For instance, manufacturing lines embracing reconfigurable production and mass customization exemplify integrated solutions. These lines integrate sensors, flexible machines, real-time production scheduling systems, and collaborative robots, offering a glimpse into the future of manufacturing systems that allow seamless vertical integration between manufacturing and corporate information systems.

While these integrated solutions hold immense potential, their implementation is intricate and demands mastery of a diverse set of technologies and skills. This includes proficiency in hardware, software, and digital technologies such as big data and artificial intelligence (Kahle et al., 2020). The inherent complexity stems from the multifaceted nature of Industry 4.0, necessitating a comprehensive understanding of the interplay between various technological components.

The lines and citations above highlight how different perspectives on I4.0 have been discussed in the literature, including both technical and managerial perspectives, as well as a comprehensive analysis of the various manufacturing processes. However, the issue of which technologies are most appropriate for LCA implementation has not yet been addressed. Several scientific studies have recently praised the use of this technology or its potential to help analyze the environmental impact of processes, goods, or activities. For instance, Ferrari et al. (Ferrari et al., 2021) adopted Internet of Things (IoT) technologies to obtain real-time manufacturing data. Shou et al. (Shou and Domenech, 2022) combined blockchain technology with LCA and Xing et al. (Xing et al., 2016) employed cloud technology (CT) to promote collaborative LCA and sharing of lifecycle information throughout supplier chains, Muñoz et al. (Muñoz et al., 2021) determined whether additive manufacturing leads to an overall environmental benefit compared with traditional methods, but none of these or other works in the literature attempted to analyze which I4.0 technology fulfills LCI development according to what explicated in §4.3.2.3 of ISO 14044 (Islam et al., 2016). This criterion includes energy inputs, raw material inputs, ancillary inputs, other physical inputs, products, co-products, and waste, which are released to air, water, soil, and other environmental factors.

The present paper bridges this gap by introducing innovative approaches to LCA through Industry 4.0 technologies. Going beyond existing research, I4.0 technologies that directly impact LCA development were identified. The research provides a classification detailing how and which Industry 4.0 technologies can optimally be employed in the LCA process. Delving into each life cycle phase, the crucial role these technologies play in facilitating enhanced data collection was highlighted. Additionally, the study introduces a scoring mechanism to distinctly identify the technology that excels in enabling Life Cycle Inventory (LCI) development.

This comprehensive approach not only addresses a critical void in the literature but also contributes to advancing the understanding of synergies between Industry 4.0 technologies and LCA, offering a valuable roadmap for future research in environmental sustainability assessment.

2. Material and methods

2.1. Conceptual framework

Seuring et al.'s (Seuring and Gold, 2012) inductive–deductive methodology was used in this study. A conceptual framework was created as the foundation (Fig. 1). The two fundamental components of this framework are the life cycle phases and the I4.0-enabling technology. The intersection row-column of the framework indicates the effects of implementing each technology examined at each stage of the lifecycle. Key concepts, variables, and other aspects as well as any potential links between them are key topics that need to be explored (Matthew and Miles, 1994). Therefore, the setting of the authors' research is represented by this framework, where a qualification based on the exploitation of the technology is provided, giving a value of 1 or 0 depending on whether the technology meets the following criteria: the score is given if the technology, according to §4.3.2.3 of ISO 14044 (British Standards Institution, n.d.), provides any information regarding the following:

- energy inputs, raw material inputs, ancillary inputs, other physical inputs,
- products, co-products and waste,
- releases to air, water and soil, and
- other environmental aspects.

In Section 3, tables for each technology, defining the features provided by different manufacturing processes, and offering the scheme used as the baseline to perform the assessment are presented. To pursue the research scope of the identification of I4.0 technologies that could have an impact on LCI development, an analysis of compliance with the criteria defined above was performed. Second, the sum of the scores for the different life-cycle stages of each technology was considered. In this way, it was possible to present the results and emphasize the phase of the life cycle in which the technologies aid in data collection, and to give a score that clearly identifies which technology can better enable LCI. (See Fig. 2, Tables 4, and 6–14.)

2.2. Literature selection strategy

In this section, the authors describe the methodology they used to choose I4.0 technologies that were tied to industrial applications. To address this research topic, academic articles were examined using Systematic Literature Review (SLR) methodology. In fact, SLR synthesizes existing knowledge and evaluates the research works currently

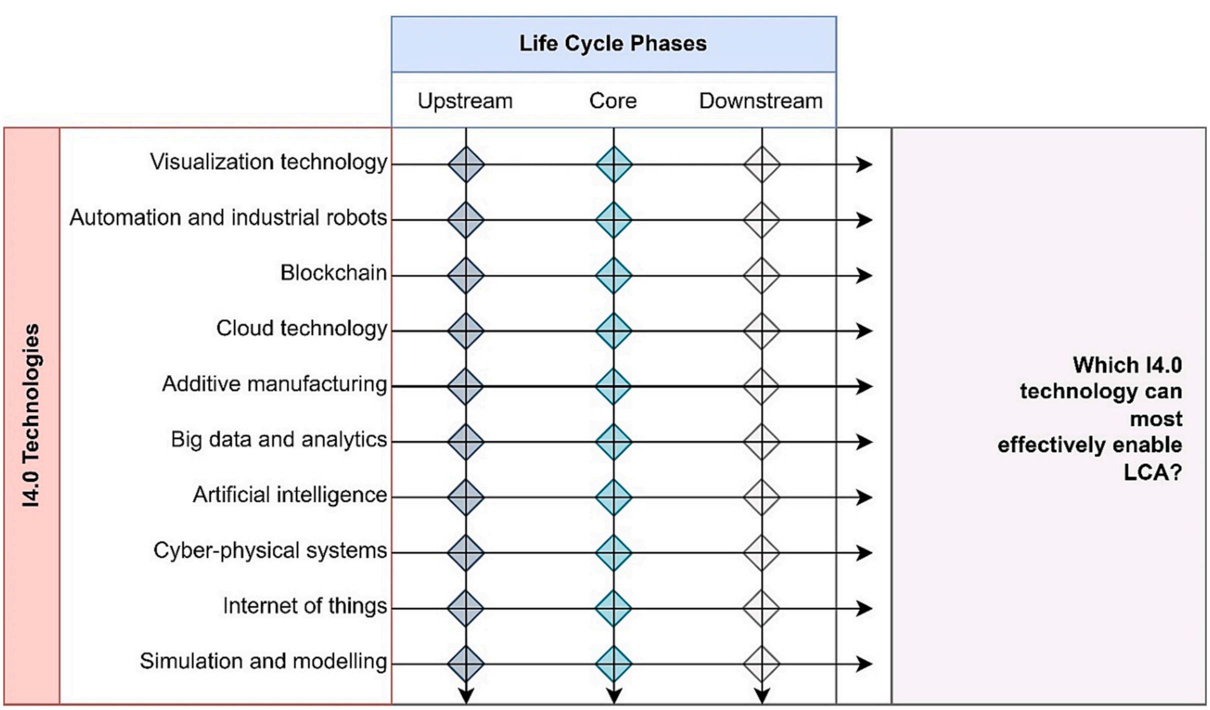

Fig. 1. Conceptual framework of the analysis.

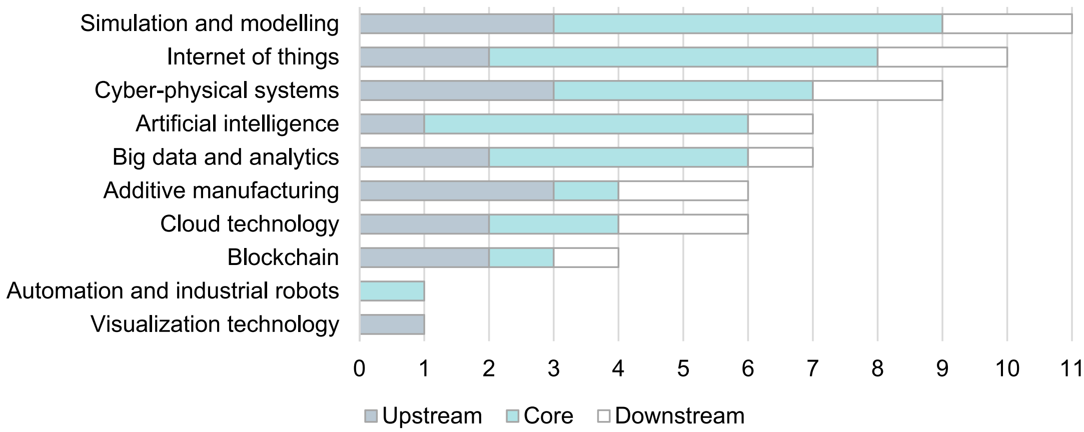

Fig. 2. Assessment results.

available on a certain issue to close knowledge gaps and improve the field of study. To generate the original database, the following set of keywords were entered into Scopus and Web of Science (WoS):

TITLE – ABS – KEY (industry 4.0) AND TITLE – ABS – KEY (manufacturing) AND TITLE – ABS – KEY (application) AND TITLE – ABS – KEY (technologies)

1.637 publications were gathered as a result of the data source-building phase, including 739 from Scopus and 898 from WoS. The data source was updated on December 31, 2022. Papers were screened after the initial database was created using the databases' common filtering fields. This phase only included articles written in English. Book chapters, conference papers, proceedings, and other non-refereed publications were excluded, because only peer-reviewed journal articles were included. This technique is typical in systematic reviews, because it works as a quality assurance tool that validates the information provided by the included articles (Light and Pillemer, 2009). Duplicate articles from the two databases were removed after merging the content from both databases. The results summarized in Table 1 were obtained from a single database consisting of 1.101 papers.

The authors carried out a first selection step, which consisted of reviewing the titles and abstracts of each publication to reject those that were beyond the scope of the research and to accomplish the research objectives based on the conceptual framework produced. In particular, studies looking into the 4.0 phenomena in general and without a specific mention of an I4.0 enabling technology were not taken into consideration. Articles that primarily focused vertically on a single technology and did not mention its utilization in manufacturing were also removed. As a result, 798 papers were deemed to be "outside the scope of this study." Consequently, 303 articles remained in the sample after the reading procedure. Reading the entire paper was a part of the second selection procedure. In this scenario, all publications that did not mention manufacturing-related processes were disregarded, in addition to the criteria listed above. Papers outside the purview of the manufacturing sector were excluded. Ultimately, 198 publications were deemed to be appropriate for this review. The selected articles were read, examined, and categorized according to the diagram in Fig. 1 using Mendeley and Microsoft Excel. According to the established purpose, the different technologies and business processes underpinning the table were identified, in accordance with Zheng et al. (Zheng et al., 2021) categorization based on the scientific and managerial literature. As there is no established taxonomy in the scientific literature, this served as the starting point. Consequently, all articles in the aforementioned scientific review were considered and read in the present study. Specifically, a list of ten technology clusters described in Table 2 was adopted, and the manufacturing business processes are listed in Table 3, where the corresponding life cycle phases were associated based on the information deducible from the definition provided.

3. Calculation

In this section, the results of the study conducted to assess compliance with the specified criteria and assign justifiable scores is presented. The scores in the following tables play a crucial role in the result presentation, helping to identify the I4.0 technology that could impact Life Cycle Assessment (LCA) development. Furthermore, the contribution of I4.0 technologies to data collection in each life cycle phase is analyzed.

The formula (1) employed for determining the results at paragraph 4 is as follows:

$$I4.0\ tecnology'score = \sum_{i=1}^{3} \sum_{j=1}^{n_i} x_{ij} \tag{1}$$

Here, x_{ij} represents the score for the jth Manufacturing business process in the ith life cycle phase. Consequently, $\sum_{j=1}^{n_i} x_{ij}$ quantifies the score for each phase of the life cycle, while $\sum_{i=1}^{3} \sum_{j=1}^{n_i} x_{ij}$ provides the total result obtained from the considered I4.0 technology. This

Table 1
Articles and resources identified.

Database	Fields of search	Language	Subject Area	Document Types	Years	Total	Total Both	Duplicate	Remaining
Scopus	TITLE-ABS-KEY	English	No restriction	Article and review	2013-2022	739	1.637	536	1.101
Web of science	TITLE-ABS-KEY	English	No restriction	Article and review	2013-2022	898			

Table 2
Summary of I4.0 technologies.

Technology	Description
Cyber-physical systems	CPS is a set of transformational technologies that integrates physical asset operations with computational capabilities. The primary goal is to monitor physical systems while also constructing a virtual clone of them. (Monostori et al., 2016; Lee et al., 2015; Alguliyev et al., 2018)
Internet of things	Sensors, machines, vehicles, buildings, and other physical objects can interact and work together as part of an information network that enables data collection and exchange. (Trappey et al., 2016; Oztemel and Gursev, 2020a; Atzori et al., 2010)
Big data and analytics	Gathering and analysis of a vast quantity of data available, with information processed at bigger volumes, faster rates, and with a wider range of approaches to filter, capture, and report insights. (Vera-Baquero et al., 2014; Fosso Wamba et al., 2015; Buhl et al., 2013)
Cloud technology	System that offers online storage services for all data, programs, and applications on a virtual server without the need for installation. (Xu, 2012; Tao et al., 2011)
Artificial intelligence	Intelligent machines that use natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotics to think like humans and rationally. (Russell and Peter, 2016; Monostori, 2003)
Blockchain	A database that generates a decentralized, impenetrable digital log of transactions, complete with timestamps for every block that each participating node maintains. (Viriyasitavat et al., 2020; Sikorski et al., 2017a; Sikorski et al., 2017b)
Simulation and modelling	Technology that replicate elements of the actual world—such as equipment, objects, and people—in a virtual setting with the goal of making system design, development, testing, and live operation simpler and more affordable. (Kocian et al., 2012; Higashino et al., 2016; Ghobakhloo, 2018)
Visualization technology (augmented and virtual reality)	A collection of cutting-edge Human Computer Interaction (HCI) approaches that allow virtual things to be embedded and live with the actual world; Virtual reality is the use of computer technology to create an interactive environment that gives the user real-time control over every aspect of the virtual world. (Yew et al., 2016; Wang et al., 2016; Reif and Walch, 2008; Regenbrecht et al., 2005; Mujber et al., 2004; Azuma, 1997)
Automation and industrial robots	Automation tools and equipment that include collaborative robotics, which enables interaction between humans and robots in a shared learning environment. (Oztemel and Gursev, 2020b; Cherubini et al., 2016)
Additive manufacturing	Making items from 3D model data by merging materials in consecutive layers allows for greater design flexibility and the possibility of mass customisation. (Esmaeilian et al., 2016; Durão et al., 2017)

formulation allows for a comprehensive evaluation of the impact of I4.0 technologies on each life cycle phase and offers a consolidated score for the entire technological consideration.

3.1. Cyber-physical systems

The primary focus of CPS design problems is the pursuit of an integrated multidomain, multidisciplinary design over the course of the product development process (Azuma, 1997). This paradigm tends to make industrial locations adjust quickly, while still being profitable.

Table 3
Summary of manufacturing business processes.

Manufacturing business processes	Description	Life cycle phase
New product development	Before a product is produced and marketed, it must first go through design, testing, and prototyping. Moreover, conception and potential redesign of future product iterations are included in this phase.	Upstream
Supply chain configuration	Making decisions related to the strategic choices often made at the managerial level with relation to the network design (number of levels, supplier selection, manufacture or purchase strategy), as well as the factory architecture, which includes material flows management and asset placement.	Upstream
Integrated supply chain planning	Demand planning, demand forecasting, distribution planning, sourcing planning, inventory planning, positioning of materials along the supply chain, and production planning are the main areas of focus (master production scheduling).	Upstream
Internal logistics	Operations logistics for storage, internal product handling, and production enslavement in factories.	Core
Production scheduling and control	Procedure that combines production monitoring and control with factory scheduling (such as machine load management and batch allocation).	Core
Energy management	The resources utilized for production and for the overall operation of the firm are monitored and controlled (e.g. raw materials, energy, utilities).	Core
Quality management	Activities carried out in factories to manage production in terms of both goods (such as product flaws) and procedures (e.g. production parameters).	Core
Maintenance management	Administration of the factory's planning and upkeep of its assets (including both breakdown and preventive or predictive maintenance).	Core
Customer relationship management	Process that includes all actions including contact with clients (for example, to understand their habits or any product customizations). It also covers the creation, administration, and delivery of services that are directly related to the physical product, including customized services.	Downstream
After-sales management	Administration of the after-sales process, which includes tasks mostly related to technical support and product upkeep, spare parts management, product recovery, and product disposal at the end of its useful life.	Downstream

This situation enables decentralization of production through autonomous tasks based on cyber-physical production systems, improving quality control, and reducing inventories. The capacity to produce personalized goods at the cost of mass production, creation of highly flexible and adaptable manufacturing processes, and integration of seamless digital workflows across the product lifecycle are major challenges. Furthermore, the upcoming CPS will enhance the capability of maintaining individual systems and even components through monitoring (Roy et al., 2016). Table 3 presents the functions offered by CPS and an assessment of the potential exploitability of the data in the inventory analysis.

3.2. Internet of things

IoT is used to integrate the underlying equipment resources into the creation of smart factories. Consequently, the production system

Table 4
Cyber-physical systems assessment.

	Manufacturing business processes	Cyber-physical systems	Score	Rationale
Upstream	New product development	Smart product development (Miranda et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
	Supply chain configuration	Distributed production of spare parts (Durão et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
		Supply chain risk management (Ivanov et al., 2019)	0	Qualitative information not included in the criteria
	Integrated supply chain planning	Supply chain integration and automation (Nagy et al., 2018; Hofmann and Rüsch, 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs,
Core	Internal logistics	–	–	–
	Production scheduling and control	Cyber-physical production system scheduling and control (Monostori et al., 2016; Tao et al., 2011; Ghobakhloo, 2018; Diez-Olivan et al., 2019; Fatorachian and Kazemi, 2018; Tao and Qi, 2019; Chen et al., 2018; Zhang et al., 2019a)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil
		Manufacturing resource virtualization (Shafiq et al., 2016; Lu and Xu, 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs,
	Energy management	Service-oriented energy management (Bonilla et al., 2018; Diaz and Ocampo-Martinez, 2019; Mohamed et al., 2019)	1	Information on ancillary inputs, other physical inputs
	Quality management	–	–	–
	Maintenance management	Industrial data acquisition and structuralizing for maintenance analytics (Ansari et al., 2019; Caggiano, 2018; Fumagalli et al., 2019; Guizzi et al., 2019; Redelinghuys et al., 2020; Turner et al., 2019; da Xu and Duan, 2019)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	Advanced services (Kiel et al., 2017; de Sousa Jabbour et al., 2018; Strandhagen et al., 2017; Weking et al., 2020)	0	Do not provide data included in the criteria
	After-sales management	Product-in-use monitoring (Roy et al., 2016)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil
		Reverse logistics management and control (Dev et al., 2020)	1	Information on ancillary inputs, other physical inputs, products,

Table 5
Internet of things assessment.

	Manufacturing business processes	Internet of things	Score	Rationale
Upstream	New product development	Data collection for product design improvements (Tao and Qi, 2019; Chen et al., 2018; Bressanelli et al., 2018; Ang et al., 2017)	0	Do not provide data included in the criteria
	Supply chain configuration	Smart purchasing and supply management (Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs
	Integrated supply chain planning	Data collection for advanced demand assessment and forecasting (Hofmann and Rüsch, 2017; Kamble et al., 2018; Wan et al., 2016)	1	Information on raw material inputs, ancillary inputs, other physical inputs
		Supply chain information exchange and visualization (Hofmann and Rüsch, 2017; Ben-Daya et al., 2019; Gružauskas et al., 2018)	0	Do not provide data included in the criteria
		Supply chain integration and automation (Schroeder et al., 2019; Patel et al., 2018; Manavalan and Jayakrishna, 2019; Garay-Rondero et al., 2019; Bienhaus and Haddud, 2018; Ardito et al., 2019)	0	Do not provide data included in the criteria
Core	Internal logistics	Material identification and tracking (Hofmann and Rüsch, 2017; Zhang et al., 2019b)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products, waste
		Automation of internal transportation, line feeding and material handling (Strandhagen et al., 2017; Wan et al., 2016)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products, waste
	Production scheduling and control	Data collection from production processes and resources (Tao et al., 2011; Tao and Qi, 2019; Zhong et al., 2017; Lalanda et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products, waste
		Smart connected factory formalization (Ghobakhloo, 2018; Fatorachian and Kazemi, 2018; Zhang et al., 2019a; Strandhagen et al., 2017; Wan et al., 2016; Zhang et al., 2019b)	0	Do not provide data included in the criteria
	Energy management	Energy consumption monitoring (Bonilla et al., 2018; Diaz and Ocampo-Martinez, 2019; Mohamed et al., 2019; Kumar et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs, releases to air, water and soil
	Quality management	Product quality defect detection (Illa and Padhi, 2018)	1	Information on products, co-products and waste
	Maintenance management	Industrial data acquisition and structuralizing for maintenance analytics (Diez-Olivan et al., 2019; Ansari et al., 2019; Caggiano, 2018; Redelinghuys et al., 2020; Turner et al., 2019; da Xu and Duan, 2019; Ang et al., 2017)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	Customized and advanced services (Frank et al., 2019; Tao and Qi, 2019; Kiel et al., 2017; de Sousa Jabbour et al., 2018; Weking et al., 2020; Bressanelli et al., 2018; Ardito et al., 2019; Anshari et al., 2019; Ardolino et al., 2018; Müller, 2019)	0	Do not provide data included in the criteria
	After-sales management	Product-in-use monitoring (Roy et al., 2016; Strandhagen et al., 2017; Ben-Daya et al., 2019)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil
		Reverse logistics management and control (Dev et al., 2020; Ben-Daya et al., 2019)	1	Information on ancillary inputs, other physical inputs, products,

Table 6
Big data and analytics assessment.

	Manufacturing business processes	Big data and analytics	Score	Rationale
Upstream	New product development	Data processing and analysis for product design improvements (Tao and Qi, 2019; Chen et al., 2018; Bressanelli et al., 2018; Ang et al., 2017)	0	Do not provide data included in the criteria
	Supply chain configuration	Supply chain risk assessment (Ivanov et al., 2019; Queiroz and Telles, 2018)	0	Do not provide data included in the criteria
		Factory layout design and evaluation (Zhang et al., 2019a; Kumar et al., 2018)	0	Do not provide data included in the criteria
		Smart purchasing and supply management (Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs
	Integrated supply chain planning	Advanced demand assessment and forecasting (Hofmann and Rüsch, 2017; Kamble et al., 2018; Wan et al., 2016; Patel et al., 2018; Garay-Rondero et al., 2019)	0	Do not provide data included in the criteria
		Supply chain information exchange and visualization (Hofmann and Rüsch, 2017; Ben-Daya et al., 2019; Gružauskas et al., 2018)	0	Do not provide data included in the criteria
		Supply chain integration and automation (Nagy et al., 2018; Srai and Lorentz, 2019; Patel et al., 2018; Manavalan and Jayakrishna, 2019; Garay-Rondero et al., 2019; Bienhaus and Haddud, 2018; Ardito et al., 2019)	0	Do not provide data included in the criteria
		Distribution planning (Strandhagen et al., 2017; Gružauskas et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs
Core	Internal logistics	–	–	–
	Production scheduling and control	Automated resource allocation and scheduling (Tao and Qi, 2019; Ang et al., 2017; Kamble et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs
	Energy management	Energy performance and consumption forecasting (Bonilla et al., 2018; Kumar et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs, releases to air, water and soil
	Quality management	Manufacturing process quality monitoring and control (Tao and Qi, 2019)	1	Information on products, co-products and waste
	Maintenance management	Diagnosis and predictive maintenance analytics (Diez-Olivan et al., 2019; Tao and Qi, 2019; Ang et al., 2017; Illa and Padhi, 2018)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	Customer profiling & service innovation (Frank et al., 2019; Bressanelli et al., 2018; Ardito et al., 2019; Anshari et al., 2019; Zaki et al., 2019; Zheng et al., 2018)	0	Do not provide data included in the criteria
	After-sales management	Product-in-use assessment (Roy et al., 2016; Strandhagen et al., 2017; Bressanelli et al., 2018; Kerin and Pham, 2019)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil

includes perceptions, connectivity, and data integration capabilities. In a smart factory, production scheduling, equipment maintenance, and product quality control are accomplished through data analysis and scientific decision making. The worldwide collaborative process of intelligent manufacturing tailored to the order-driven market is produced through human-machine interaction (Tao and Qi, 2019; Chen et al., 2018; Bressanelli et al., 2018; Ang et al., 2017). In addition, IoT services influence supply chain delivery procedures and are used in reverse logistics (Dev et al., 2020; Ben-Daya et al., 2019). Table 5 shows the potential impact of IoT on data collection from a life cycle perspective.

3.3. Big data and analytics

As data analysis has become a crucial method for manufacturing to advance intelligence, big data (BD) has become a cornerstone of smart manufacturing. A large amount of data created throughout the production process can be sensed, gathered, and analyzed using a universal interface. From the standpoint of application scenarios, smart applications based on big data are present in all elements of the manufacturing processes (Tao and Qi, 2019; Chen et al., 2018; Bressanelli et al., 2018; Ang et al., 2017). Real-time data collection from numerous sources, thorough analysis of the data, and real-time decision making are made possible by big data analytics and technology. This improves the manufacturing flexibility, product quality, energy efficiency, and equipment services through preventative maintenance (Hofmann and Rüsch, 2017; Kamble et al., 2018; Wan et al., 2016; Patel et al., 2018; Garay-Rondero et al., 2019).

3.4. Cloud technology

Supply chain experts believe that CT solutions improve the informational-physical integration of the supply chain, operational performance, end-to-end supply chain visibility, manufacturing scalability, and coordinated service delivery. An interoperable cloud marketplace that addresses the requirements of standards, vendor selection, and order allocation in cloud-based manufacturing is an example of a cloud application for interconnectivity (Ang et al., 2017; Rao and Prasad, 2018). Condition data from diverse engineering system modules dispersed across several sites can be gathered and combined using cloud-based data fusion and data analytics. To accomplish a closed-loop design process, knowledge about the system functioning can then be sent back to the design team (Roy et al., 2016; de Sousa Jabbour et al., 2018).

3.5. Artificial intelligence

Artificial intelligence (AI) is defined as a computer field that attempts to mimic or simulate so-called intelligent human activities such as perception, decision-making, and comprehension. The notion of AI represents Industry 4.0's digital brain and is its driving force. This entails the use of machine learning, which allows machines to independently forecast their future activities and learn from their experience. It also enables communication between machines and interfaces through the use of distributed AI in a multiagent system. AI enables the capture of each machine's energy usage, analysis of maintenance cycles, and optimization during the following phase (Diez-Olivan et al., 2019; Ansari et al., 2019; Turner et al., 2019; Sharp et al., 2018; Wan et al., 2018). Moreover, AI creates an optimal setting for reinforcing circular solutions, such as remanufacturing and recycling, while improving maintainability and extending the lifecycle and value of items (Rajput and Singh, 2019).

Table 7
Cloud technology assessment.

	Manufacturing business processes	Cloud technology	Score	Rationale
Upstream	New product development	Distributed and collaborative design (Ang et al., 2017; Rao and Prasad, 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
	Supply chain configuration	Smart purchasing and supply management (Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
	Integrated supply chain planning	Advanced data repository to carry out demand assessment and forecasting (Wan et al., 2016; Garay-Rondero et al., 2019; Ardito et al., 2019)	0	Do not provide data included in the criteria
		Supply chain information exchange and visualization (Hofmann and Rüsch, 2017; Ben-Daya et al., 2019; Gružauskas et al., 2018)	0	Do not provide data included in the criteria
		Supply chain integration and automation (Srai and Lorentz, 2019; Manavalan and Jayakrishna, 2019; Garay-Rondero et al., 2019)	0	Do not provide data included in the criteria
		Cloud manufacturing service platform for collaboration (Hofmann and Rüsch, 2017; Strandhagen et al., 2017; Bienhaus and Haddud, 2018; Rao and Prasad, 2018)	0	Do not provide data included in the criteria
Core	Internal logistics	–	–	–
	Production scheduling and control	Storage and computation capacities for smart connected factories (Ghobakhloo, 2018; Fatorachian and Kazemi, 2018; Zhang et al., 2019a; Strandhagen et al., 2017; Lalanda et al., 2017)	0	Do not provide data included in the criteria
		Smart machining implementation (Kim et al., 2018)	0	Do not provide data included in the criteria
	Energy management	Service-oriented energy management (Mohamed et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, releases to air, water and soil
	Quality management	–	–	–
	Maintenance management	Storage and computation capacity for maintenance analytics (Diez-Olivan et al., 2019; Caggiano, 2018; Redelinghuys et al., 2020)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	Cloud service platform (Frank et al., 2019; de Sousa Jabbour et al., 2018; Strandhagen et al., 2017; Ardito et al., 2019; Zheng et al., 2018)	0	Do not provide data included in the criteria
	After-sales management	Product-in-use data storage and processing (Roy et al., 2016; de Sousa Jabbour et al., 2018)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil
		Reverse logistics management and control (Dev et al., 2020)	1	Information on ancillary inputs, other physical inputs, products,

3.6. Blockchain

Smart contracts, flexible interconnections of autonomous purchasing systems, and machine-to-machine communication may be made possible using blockchain technology. This may also aid information transparency by making a product's history transparent, including its sources, how it was handled, and travel paths (Srai and Lorentz, 2019). Consequently, Blockchain technology aids in problem resolution by tracking important information on spare components in a shared ledger that is accessible to all the concerned parties (Alladi et al., 2019).

3.7. Simulation and modelling

Simulation and modelling (S&M) allows data and information to be exchanged between remote emulation, simulation, and physical reality. The physical production system and its digital twin are key building elements of fully connected and adaptable systems that can learn and adapt to new demands. At this point, ideas concerning the value and purpose of the digital twin are still evolving. Some digital twin positions rely on the capabilities shared by all roles. These essential digital twin skills can be summarized as follows: acquiring a physical twin state, maintaining an information repository, simulating the operation, and emulating the operation (Guizzi et al., 2019; Redelinghuys et al., 2020; Turner et al., 2019; Ang et al., 2017). However, proper data management and synchronization of a physical product and its digital twin enables the management and assessment of information concerning product life and remanufacturing (Kerin and Pham, 2019).

3.8. Visualization technology

In smart purchasing and supply management, visualization technology (VT) can be viewed as a 'cognitive procurement assistant' through cloud and cognitive computing. Given the possible greater usage of approved catalogs and procurement channels, such an application may be envisioned to enable more efficient transactions as well as coordination and control of purchases. (Srai and Lorentz, 2019).

3.9. Automation and industrial robots

There is a significant opportunity for automation and robots to assist in internal logistics and increase the flexibility and agility of production operations. Industrial automation can reduce the operational complexity of assembly stations when used in conjunction with a production prioritizing strategy. Furthermore, the use of automated guided vehicles can improve internal logistics by reducing the loading/unloading and material transfer times between workstations (Strandhagen et al., 2017; Novais et al., 2019).

3.10. Additive manufacturing

One of the key enablers of mass personalization and supply chain flexibility is additive manufacturing (AM). The co-creation of individualized items is made possible by 3D manufacturing, which provides additional material alternatives, increased processing speeds, and higher production autonomy (Strandhagen et al., 2017; Novais et al., 2019). Because of its adaptability and reliance on digitally accessible designs, AM can also be used once a product is in the middle of its useful life (MoL) to support quick design changes in the event of an unexpected failure or behavior, or to support repair and remanufacturing activities that provide after-sales services for businesses (Kerin and Pham, 2019).

4. Results

The subsequent table and accompanying graph offer a

Table 8
Artificial intelligence assessment.

	Manufacturing business processes	Artificial intelligence	Score	Rationale
Upstream	New product development	Data processing and analysis for product design improvements (Ang et al., 2017)	0	Do not provide data included in the criteria
	Supply chain configuration	Factory layout design and evaluation (Kumar et al., 2018)	0	Do not provide data included in the criteria
		Smart purchasing and supply management (Diez-Olivan et al., 2019; Ghadimi et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
		Supply chain risk management (Ivanov et al., 2019)	0	Do not provide data included in the criteria
	Integrated supply chain planning	Multi-criteria inventory classification (Lolli et al., 2019)	0	Do not provide data included in the criteria
		Advanced demand assessment and forecasting (Garay-Rondero et al., 2019)	0	Do not provide data included in the criteria
		Supply chain integration and automation (Srai and Lorentz, 2019; Bienhaus and Haddud, 2018)	0	Do not provide data included in the criteria
Core	Internal logistics	Order picking management (Lee et al., 2018)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste
	Production scheduling and control	Automated resource allocation and scheduling (Sharp et al., 2018; Cohen et al., 2019; González Rodríguez et al., 2020; Moussa and ElMaraghy, 2019; Zhang et al., 2019c)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil
		Smart machining implementation (Kim et al., 2018)	0	Do not provide data included in the criteria
		Semantic applications for production systems (Lu and Xu, 2018; Patel et al., 2018)	0	Do not provide data included in the criteria
		Multi-agent applications for production systems (Wan et al., 2018; Tan et al., 2019; Jiang et al., 2018; Rojas and Rauch, 2019)	0	Do not provide data included in the criteria
	Energy management	–	–	–
	Quality management	Assembly defect detection (Kucukoglu et al., 2018)	1	Information on products, co-products and waste
		Product quality defect detection (Carvajal Soto et al., 2019)	1	Information on products, co-products and waste
	Maintenance management	Diagnosis and predictive maintenance analytics (Diez-Olivan et al., 2019; Ansari et al., 2019; Turner et al., 2019; Sharp et al., 2018; Wan et al., 2018)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	–	–	–
	After-sales management	Product-in-use assessment (Rajput and Singh, 2019)	1	Information on ancillary inputs, other physical inputs, products, co-products, waste, releases to air, water and soil

comprehensive overview of the analysis results. The graph serves as a visual representation of the data presented in the table, providing a concise summary of the assessment. It outlines the cumulative contributions of the considered Industry 4.0 technologies for each life cycle phase. These contributions are meticulously calculated using Formula (1), as specified in paragraph 3. Together, the table and graph provide a clear and detailed portrayal of the impact of I4.0 technologies throughout various stages of the life cycle. The results are in line with the purpose of the research to identify the I4.0 technology that could have an impact on LCA development, emphasizing which life cycle phase the technologies help in data collection, and allocating a score that clearly identifies which technology can most effectively enable LCA.

5. Discussion

The analysis results demonstrated how several I4.0 technologies can contribute in various ways to the creation of the LCI and, in turn, make it easier to produce an LCA. Focusing on the overall score, it becomes possible to identify three technology clusters that can distinguish I4.0 technologies based on their potential impact on LCI. S&M, IoT, and CPS constitute the first class. CT, AM, BD, and AI constitute the middle class. Blockchain, automation, industrial robots, and VT constitute the last class. The difference between the classes is first caused by the different amounts of usable data in the core phase of the life cycle, and second by the greater contribution to the downstream phase. I4.0 technology provides data collection support in the core phase, which allows us to examine:

- Organization and control of production;
- Energy and consumption management;
- Product quality and machinery maintenance.

After IoT and S&M, the technologies that offer the most opportunities for data collection at this stage of the life cycle are AI, BD, and CPS.

Regarding the downstream phase, I4.0, allows us to acquire data that have historically been difficult to precisely define. S&M, IoT, CPS, AM, and CT are technologies that stand out from the results, and by implementing them, it is possible to obtain information on

- Product-in-use monitoring;
- Reverse logistics management and control;
- Spare part tracking;
- Remanufacturing operation.

Finally, the upstream phase data collection provides a similar contribution among the I4.0 technologies, except for automation and industrial robots. Distinguishing between the two main contributions of these technologies is important. The first examines the supply chain, while the second uses virtual product modelling to ascertain the quantity and materials used in the product.

Finally, it is important to note that the concepts of sensing and smart are combined for technologies with higher total scores, and thus, a better potentiality for LCI implementation. These technologies combine the ability to check the efficiency of a process and use it in design, thereby enabling a networked organization. Consequently, these systems provide rapidly growing opportunities for new functionality, increased reliability, higher product utilization, and capabilities that cross and transcend traditional product boundaries, enabling the provision of data related to the product lifecycle that can be used to define the product eco-profile.

In the context of the transformative potential discussed above, a standout innovation belonging to S&M is the concept of Digital Twin, elevating the integration of sensing and smart technologies to a more

Table 9
Blockchain assessment.

	Manufacturing business processes	Blockchain	Score	Rationale
Upstream	New product development	–	–	–
	Supply chain configuration	Smart purchasing and supply management (Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs
	Integrated supply chain planning	Real-time materials identification and tracking (Ivanov et al., 2019; Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs
		Cross-organizational collaboration among stakeholders (Viriyasitavat et al., 2020; Ghobakhloo, 2018; Ivanov et al., 2019; Hofmann and Rüsch, 2017)	0	Do not provide data included in the criteria
Core	Internal logistics	–	–	–
	Production scheduling and control	–	–	–
	Energy management	Smart contract for energy supply and consumption (Mohamed et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, releases to air, water and soil
	Quality management	–	–	–
	Maintenance management	–	–	–
Downstream	Customer relationship management	Customized and advanced services (Fraga-Lamas and Fernandez-Carames, 2019)	0	Do not provide data included in the criteria
	After-sales management	Spare part tracking (Alladi et al., 2019)	1	Information on products, co-products and waste

sophisticated level (Grieves, 2014). Functioning as a virtual replica of a physical system, a Digital Twin represents a pivotal advancement in seamlessly merging sensing and smart technologies (Jones et al., 2020). By replicating real-world processes and products within a virtual environment, Digital Twins offer real-time insights, enabling continuous monitoring, predictive modelling, and dynamic adaptations. Within the domain of Life Cycle Assessment (LCA), Digital Twins are poised to revolutionize the acquisition and utilization of data across the product lifecycle, making a substantial contribution to the definition of comprehensive eco-profiles. As explored, the relationship between Digital Twin and Life Cycle Assessment (LCA) in the upcoming rows, becomes apparent that their role surpasses mere replication, presenting a compelling intersection of technologies aimed at enhancing sustainability practices (Kritzinger et al., 2018; Lee et al., 2013; Rosen et al.,

Table 10
Simulation and modelling assessment.

	Manufacturing business processes	Simulation and modelling	Score	Rationale
Upstream	New product development	Virtual prototyping (Ang et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
		Technical product assessment (Miranda et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
		Digital product representation (Tao and Qi, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
	Supply chain configuration	Factory layout design and evaluation (Zhang et al., 2019a; Kumar et al., 2018)	0	Do not provide data included in the criteria
		Supply chain risk assessment (Ivanov et al., 2019; Vieira et al., 2019)	0	Do not provide data included in the criteria
	Integrated supply chain planning	–	–	–
Core	Internal logistics	Material flow simulation in factories and warehouses (Hofmann and Rüsch, 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
	Production scheduling and control	Manufacturing resources virtualization (Shafiq et al., 2016; Lu and Xu, 2018; Benotsmane et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
		Production planning preview and performances evaluation (Tao et al., 2011; Zhang et al., 2019a; Guizzi et al., 2019; Zhang et al., 2019c; Cimino et al., 2019; Kaihara et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
	Energy management	Energy performance and consumption forecasting (Kumar et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs, releases to air, water and soil
	Quality management	Product quality defects detection (Carvajal Soto et al., 2019)	1	Information on products, co-products and waste
	Maintenance management	Workshop machinery health monitoring (Guizzi et al., 2019; Redelinghuys et al., 2020; Turner et al., 2019; Ang et al., 2017)	1	Information on ancillary inputs, other physical inputs
Downstream	Customer relationship management	Customized and advanced services (Zheng et al., 2018)	0	Do not provide data included in the criteria
	After-sales management	Remanufacturing operation (Kerin and Pham, 2019)	1	Information on products, co-products and waste
		Reverse logistics management and control (Dev et al., 2020)	1	Information on ancillary inputs, other physical inputs, products,

Table 11
Visualization technology assessment.

	Manufacturing business processes	Visualization technology	Score	Rationale
Upstream	New product development	Augmented design (Zhong et al., 2017)	0	Do not provide data included in the criteria
	Supply chain configuration	Smart purchasing and supply management (Srai and Lorentz, 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
	Integrated supply chain planning	–	–	–
Core	Internal logistics	Pick-by vision (Strandhagen et al., 2017)	0	Do not provide data included in the criteria
		Material allocation guidance (Blanco-Novoa et al., 2018)	0	Do not provide data included in the criteria
	Production scheduling and control	Shop floor visualization (Turner et al., 2016)	0	Do not provide data included in the criteria
		Automated guidance for operators' manual tasks (Wang et al., 2016; Ang et al., 2017; Kamble et al., 2018; Cohen et al., 2019; Blanco-Novoa et al., 2018)	0	Do not provide data included in the criteria
	Energy management	–		
	Quality management	Digital visual quality control (Nagy et al., 2018; Avalle et al., 2019)	0	Do not provide data included in the criteria
	Maintenance management	Maintenance task guidance (Nagy et al., 2018; Turner et al., 2019; Blanco-Novoa et al., 2018)	0	Do not provide data included in the criteria
		Maintenance training guidance (Roy et al., 2016)	0	Do not provide data included in the criteria
Downstream	Customer relationship management	–	–	–
	After-sales management	Remote maintenance support (Blanco-Novoa et al., 2018)	0	Do not provide data included in the criteria

2015; Tao and Zhang, 2017).

- Real-time data for precision: Digital Twins, as virtual replicas of physical systems or processes, provide real-time data and insights throughout the entire life cycle of a product or system. Integrating Digital Twin technology with LCA enhances the accuracy and granularity of data used in sustainability assessments, ensuring precise measurement of environmental impacts under real-world conditions and variations.
- Continuous monitoring and analysis: Digital Twins enable continuous monitoring and analysis of assets or processes, aligning with the temporal aspect of life cycle thinking in LCA. This dynamic and real-time nature allows for the identification of environmental hotspots and assessment of environmental performance over time.
- Predictive modelling for informed decisions: Incorporating predictive modelling capabilities, Digital Twins facilitate forecasting environmental impacts of design changes, material substitutions, or process optimizations in LCA. Simulation of scenarios empowers organizations to make informed decisions, minimizing ecological footprints during a product or system's life cycle.
- Design for Environment (DfE) Principles: Integrating Digital Twin technology into the design phase supports Design for Environment (DfE) principles. Real-time environmental data informs decisions about materials, manufacturing processes, and product configurations, optimizing for reduced environmental impact before physical prototypes are created.
- Holistic supply chain visibility: Digital Twins extend their reach into the supply chain, providing a holistic view of the entire life cycle network. This transparency aids in tracing and assessing the environmental impact of raw materials, components, and suppliers, facilitating sustainable choices early in the life cycle.
- Adaptability for continuous improvement: The adaptability and dynamic nature of Digital Twins ensure that environmental data remains relevant and up-to-date throughout the life cycle. This aligns with the life cycle perspective in LCA, allowing organizations to adapt and refine sustainability strategies in response to changes in technology, regulations, or market conditions.

Table 12
Automation and industrial robots' assessment.

	Manufacturing business processes	Automation and industrial robots	Score	Rationale
Upstream	New product development	–	–	–
	Supply chain configuration	Back shoring (Savastano et al., 2019)	0	Do not provide data included in the criteria
	Integrated supply chain planning	–	–	–
Core	Internal logistics	Automation of internal transportation, line feeding and material handling (Strandhagen et al., 2017; Novais et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
	Production scheduling and control	Collaborative operations with humans (Strandhagen et al., 2017; Kamble et al., 2018; Benotsmane et al., 2019)	0	Do not provide data included in the criteria
		Production process automation (Ghobakhloo, 2018; Zhang et al., 2019a; Strandhagen et al., 2017; Kamble et al., 2018)	0	Do not provide data included in the criteria
	Energy management	–	–	–
	Quality management	–	–	–
	Maintenance management	–	–	–
Downstream	Customer relationship management	–	–	–
	After-sales management	–	–	–

Table 13
Additive manufacturing assessment.

	Manufacturing business processes	Additive manufacturing	Score	Rationale
Upstream	New product development	Digital complex design (Chen et al., 2018; Ang et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
		Rapid prototyping (Ghobakhloo, 2018; Chong et al., 2018)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products and waste
	Supply chain configuration	Distributed production of spare parts (Durão et al., 2017)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
		Insourcing/back sourcing strategy (Ivanov et al., 2019)	0	Do not provide data included in the criteria
		Back shoring (Savastano et al., 2019)	0	Do not provide data included in the criteria
	Integrated supply chain planning	–	–	–
Core	Internal logistics	–	–	–
	Production scheduling and control	JIT and advanced pull system management (Cohen et al., 2019)	1	Information on raw material inputs, ancillary inputs, other physical inputs, products, co-products
	Energy management	–	–	–
	Quality management	–	–	–
	Maintenance management	–	–	–
	Customer relationship management	Product customization and individualization (Ghobakhloo, 2018; de Sousa Jabbour et al., 2018; Strandhagen et al., 2017; Kamble et al., 2018; Novais et al., 2019)	0	Do not provide data included in the criteria
Downstream	After-sales management	Spare part management (Pelantova and Cecak, 2018)	1	Information on products, co-products and waste
		Remanufacturing operation (Kerin and Pham, 2019)	1	Information on products, co-products and waste

In essence, the integration of sensing and smart technologies (S&M), and notably Digital Twin technology, with LCA not only enhances the precision of environmental impact assessments but also promotes a proactive and data-driven approach to sustainability.

6. Conclusions

With regard to the effects of I4.0 on the LCA setting, this research aimed to organize a corpus of existing scientific knowledge. The research project was created in particular to close a gap in the scientific literature by examining how the various I4.0 technologies can help construct the LCI and subsequently make it easier to develop an LCA. The research started by developing a functional research framework for carrying out the research itself and for presenting the data in a way that highlights the different contributions that I4.0 might have on the LCI constitution at different life cycle phases. The second stage of the research activity involved a comprehensive review of scientific literature. In light of the fact that there is no accepted taxonomy in the scientific literature, a list of the key I4.0 technologies and business activities was created in accordance with the Zheng et al. (Zheng et al., 2021) classification. The key applications in the various business processes for each technology were studied, analyzed, and appraised to determine whether they offered key headings for LCI in accordance with ISO 14044. The results demonstrated how various technologies can contribute in different ways to the collection of LCI data, and that it is possible to perform clustering into three macro families of technologies. The amount of data provided by various technologies in the core and downstream phases distinguishes these three levels, whereas the upstream phase contribution is uniform across all technologies. Owing to their ability to create an interconnected data network, S&M, IoT, and CPS have been found to be the best solutions for supporting LCI implementation. These three technologies, often categorized as sensing and smart technologies, form the cornerstone of Industry 4.0's impact on Life Cycle Assessment (LCA). In addition, emerging technologies, including the innovative concept of Digital Twin, contribute to the synergy of sensing and smart capabilities. Digital Twin, as a virtual replica of physical systems, further enhances the connectivity and data-driven insights within the LCA framework. The integration of sensing and smart technologies, along with advancements like Digital Twin, not only refines LCI implementation but also marks a paradigm shift towards a more sustainable and data-centric approach in environmental assessments.

Table 14
Assessment results.

I4.0 technology	Upstream	Core	Downstream	Total
Visualization technology	1	0	0	1
Automation and industrial robots	0	1	0	1
Blockchain	2	1	1	4
Cloud technology	2	2	2	6
Additive manufacturing	3	1	2	6
Big data and analytics	2	4	1	7
Artificial intelligence	1	5	1	7
Cyber-physical systems	3	4	2	9
Internet of things	2	6	2	10
Simulation and modelling	3	6	2	11

This study has some limitations similar to those of other types of research. The study framework in particular, since it belongs to an ever-changing state of the art, not all potential I4.0 options have been addressed. However, this study provides a preliminary effort on a topic that is currently unexplored in the literature by referring to a scientifically acknowledged categorization of technologies and industrial processes. This finding, in addition to offering fresh research breakthroughs, may serve as a guide for practitioners seeking to adopt one or more technologies in industrial activity and assess the potential environmental impacts from a life cycle perspective.

Building upon the insights gained, it is essential to acknowledge the potential improvements and future directions for this work, including policy and managerial implications. While the present study presents a pioneering effort to explore the influence of I4.0 on the LCA setting, there are opportunities for further refinement. The dynamic nature of the I4.0 landscape suggests that not all potential options have been exhaustively addressed within our study. As the field continues to evolve, future iterations of this research should consider integrating emerging I4.0 options into the framework.

The absence of an accepted taxonomy in the scientific literature prompted the creation of a key taxonomy aligned with Zheng et al.

(Zheng et al., 2021). Future research could delve deeper into the development of a standardized taxonomy, addressing the evolving nature of I4.0 technologies and providing a common foundation for researchers and practitioners. This standardized taxonomy could, in turn, facilitate policy development by offering a structured framework for regulatory bodies to categorize and oversee the integration of I4.0 technologies in various industries.

Second, while ten macro families of technologies were identified here, further investigations could explore the interplay and synergies between these families, offering a nuanced understanding of how combined I4.0 solutions might enhance LCI implementation. From a managerial standpoint, this knowledge could guide organizations in strategically adopting synergistic I4.0 solutions for optimal environmental sustainability.

Finally, since the study's focus on the environmental impacts from a life cycle perspective opens avenues for future research to consider broader sustainability aspects, it also invites attention to the policy realm. Exploring social and economic dimensions within the context of I4.0 technologies could contribute to a more comprehensive understanding of their overall impact and inform policies that align with sustainable development goals.

Despite these potential areas for improvement, the present paper offers a preliminary exploration of a topic that remains largely unexplored in the literature. By referencing a scientifically acknowledged categorization of technologies and industrial processes, the findings provide a valuable guide for practitioners seeking to adopt I4.0 technologies and assess their potential environmental impacts from a life cycle perspective.

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CRediT authorship contribution statement

Mirco Piron: Conceptualization, Data curation, Methodology, Writing – original draft. **Junzhang Wu:** Validation, Writing – review & editing. **Andrea Fedele:** Validation, Writing – review & editing. **Alessandro Manzardo:** Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

Data availability

Data will be made available on request.

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