Journal of Cleaner Production 574 (2026) 149110

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Data for circularity assessment: what, where, and how?

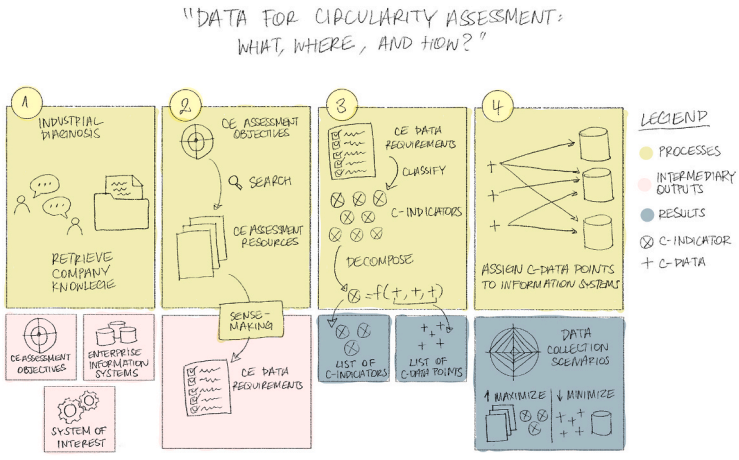
Lauren Durivault [a,b,*], Ghada Bouillass [a], Michael Saidani [a,c], Bernard Yannou [a], Abdelhamid Boujarif [b], Robert Heidsieck [b]

[a] Laboratoire Genie Industriel, CentraleSupélec, Université Paris-Saclay, France
[b] GE HealthCare, France
[c] Department of Systems Engineering, École de Technologie Supérieure, University of Quebec, Canada

HIGHLIGHTS

- A four-phase approach is proposed to facilitate circularity assessment in manufacturing.
- The approach is applied to a multinational medical imaging system manufacturer.
- 69 circularity indicators (c-indicators) are decomposed into 91 circularity data (c-data) points.
- 25% of c-indicators can be computed using only 1 of 8 information systems.
- Collecting only 13% of c-data enables the computation of 25% of c-indicators.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Circular economy
Corporate sustainability reporting directive
Enterprise information systems
Data collection
Sustainable manufacturing
Optimization

ABSTRACT

The growing need for circular economy (CE) assessment in manufacturing enterprises is driven by increasing regulatory and market pressures. However, existing approaches provide limited support for identifying and collecting the required data to compute circularity indicators. The main contribution of this paper is a structured method that links circularity indicators to collectable data and formalizes data collection as a decision problem. CE assessment is operationalized through a four-phase, data-driven approach comprising (1) an industrial diagnosis to define objectives, scope, and relevant information systems, (2) a systematic sense-making process to translate CE assessment resources into structured data requirements, (3) a decomposition of circularity indicators into data points, referred to as c-data, and (4) a mixed-integer linear programming model to determine an efficient data collection strategy. Applied to a medical radiology system manufacturer case study, 69 target indicators are decomposed into 91 c-data points distributed across eight information systems. Building on this, the optimization model shows that accessing only a limited subset of systems can be sufficient to compute a substantial share of indicators, thereby revealing trade-offs between implementation effort and assessment

* Corresponding author. Laboratoire Genie Industriel, CentraleSupélec, Université Paris-Saclay, France.
E-mail address: lauren.durivault@centralesupelec.fr (L. Durivault).

https://doi.org/10.1016/j.jclepro.2026.149110
Received 5 May 2026; Received in revised form 16 July 2026; Accepted 28 July 2026
Available online 6 August 2026
0959-6526/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

coverage. In this context, three alternative data collection strategies are identified for the company. Notably, one of these strategies demonstrates that accessing just one of eight information systems makes it possible to collect 13% of eligible data points, which in turn enables the computation of 25% of CE indicators. The approach supports the transition from high-level assessment requirements to actionable data sourcing strategies and is extendable to other sustainability assessment contexts.

1. Introduction

Circular economy (CE) is proposed as an alternative to the traditional linear "take-make-dispose" model. The adoption of CE strategies that slow, close, and narrow material loops (Bocken et al., 2016) may help reach sustainable development goals (Schroeder et al., 2019; Vann Yaroson et al., 2024). Manufacturing firms adopt CE to improve resource efficiency (Barros et al., 2021) and reduce costs (Park et al., 2010), enabling new business models such as product-service systems and take-back systems (Barros et al., 2021; Pieroni et al., 2019) that strengthen their competitiveness (Geissdoerfer et al., 2018). To implement and manage CE, companies rely on circularity indicators, referred to in the present paper as "c-indicators", supporting decision-making and monitoring progress (Moraga et al., 2019; Roos Lindgreen et al., 2022; Saidani et al., 2019). CE assessment, defined by ISO 59004:2024 as "the evaluation and interpretation of results derived from circularity measurement" (ISO 59004, 2024), has thus emerged as a structured means of evaluating circular performance within a defined system. As regulatory and institutional pressures increase, CE assessment and reporting are increasingly required through corporate compliance, as reflected by the Corporate Sustainability Reporting Directive (CSRD) (European Commission, 2022), and the Ecodesign for Sustainable Products Regulation (ESPR) (European Commission, 2024), which enforces the implementation of the Digital Product Passport (DPP) (European Commission, 2023). In this context, manufacturers are responsible for creating and maintaining product-level data, making them the primary actors in circularity data governance, placing them at the center of the data ecosystem required for circularity assessment.

Despite the growing need and interest for CE assessment, its operationalization in the industry remains challenging. First, ambiguity persists regarding *what* should be measured, as the lack of a consensual definition of CE leads to unclear and heterogeneous indicator selection (Kirchherr et al., 2023; Amicarelli et al., 2023; Kristensen and Mosgaard, 2020). Second, even when indicators are identified, challenges remain in determining *what* underlying data should be collected to compute them (Saidani et al., 2019; Pomp et al., 2023). Lastly, in cases where these latter two points are clearly established, data collection itself may present significant barriers, both in terms of *where* relevant data resides – often fragmented across lifecycle stages, organizational functions, and value chain actors, with dispersed information systems and incompatible data structures (Acerbi et al., 2022; Matos et al., 2023; Mulhall et al., 2022) – and *how* to approach its collection.

Companies may face a trade-off regarding the quantity of data to be collected: larger datasets entail higher collection, processing, and maintenance costs, whereas more limited datasets may constrain indicator computation (Brint et al., 2021). To structure these barriers, the present study draws on Krasikov and Legner (2023), whose data sourcing framework was developed in the context of corporate sustainability initiatives. They define data sourcing as encompassing three practices: sense-making, which translates regulatory and normative requirements into concrete data requirements; data collection, which retrieves those requirements from internal and external sources; and data reconciliation, which harmonizes heterogeneous data to ease computation. A growing body of literature has proposed frameworks that explicitly or implicitly engage with data sourcing practices for CE assessment, hereinafter referred to as data-driven CE assessment frameworks.

These contributions span multiple sectors and scales. In the built environment, frameworks have addressed data needs through material passports (Çetin et al., 2023), knowledge graphs linking building data to CE strategies (Keena et al., 2025), DPP-integrated lifecycle assessment (Morganti et al., 2024), ontology-based DPP structuring (Kebede et al., 2024), and BIM libraries combining lifecycle, cost, and circularity metrics (Pibal et al., 2025). In other industrial sectors, ontology models have been proposed to link c-indicators to data requirements in the automotive industry (Pidikiti et al., 2023) and to characterize DPP data needs across lifecycle actors in mechatronics (Jensen et al., 2023). Several contributions aim to be cross-sectoral: Mulhall et al. (2022) propose the Product Circularity Data Sheet, recently formalized through ISO 59040 (ISO, 2025); Sileryte et al. (2023) develop aligned ontologies for shared CE terminology; Jansen et al. (2024) present a core ontology network for semantic interoperability across DPP implementations; Kühn et al. (2025) demonstrate a standards-based DPP model using the Asset Administration Shell. Most recently, contributions have begun to focus on the structure and definition of CE data itself: Araujo et al. (2025) propose a typology of eight dimensions of CE data, and Kahandawa et al. (2025) introduce a standardized information framework mapping c-indicators to their underlying data needs.

Reviewing these works through the lens of the three data sourcing practices reveals some gaps. Data reconciliation has been addressed more than the other two, with contributions encompassing semantic alignment, interoperability, and harmonization across data sources (Acerbi et al., 2022; Sileryte et al., 2023; Kühn et al., 2025; Jansen et al., 2025). The first two practices, however, remain systematically underaddressed. On sense-making, none of the existing frameworks provides a method for translating a regulatory or normative corpus into a structured list of data requirements (Durivault et al., 2026). Concerning data collection, while some frameworks acknowledge the need to retrieve data from organizational sources, none provide a practical, structured approach that accounts for organizations' existing information systems. In fact, the importance of linking enterprise information systems (EIS) and CE data collection has been previously noted in the literature (Polenghi et al., 2021; Serody et al., 2026). Overall, data requirements of CE assessment frameworks remain vague or poorly specified (Roos Lindgreen et al., 2022; Saidani et al., 2019), and no structured method exists for identifying the specific data points needed to compute a given set of c-indicators in a given organizational context (Saidani et al., 2019; Pidikiti et al., 2023). These gaps are also reflected in grey literature. The Global Circularity Protocol (WBCSD, 2025) acknowledges the complexity of CE data collection due to fragmented systems and supply chains, and does not provide any method for companies to make sense of their regulatory context into indicators. ISO 59020 (ISO, 2024) mentions data acquisition as a step of the CE assessment process, but does not specify how to determine the required data. In the case of missing data, it suggests adapting indicators that may be unsuitable for compulsory compliance. ISO 59040, through the Product Circularity Data Sheet (ISO, 2025), improves the structuring and exchange of CE data, but remains limited to product-level CE assessment, and does not define calculation methods.

Against this background, the present paper addresses the following research question: How can manufacturing organizations operationalize and facilitate CE assessment in a data-intensive environment? To answer this question, a top-down four-phase approach is proposed and illustrated through a case study conducted within a large original equipment manufacturer of complex medical imaging systems. The approach combines an industrial diagnosis, a systematic sense-making of relevant

CE guidance documents, a recursive decomposition of c-indicators into c-data points, and the design of an optimized data collection strategy. The remainder of the paper is structured as follows: Section 2 presents the theoretical and conceptual background, Section 3 details the proposed approach and case study context, Section 4 presents the results, Section 5 discusses contributions, scalability, and limitations, and Section 6 concludes.

2. Theoretical and conceptual background

2.1. CE assessment frameworks, c-indicators, and c-data

Reviews of CE assessment methods define it as a heterogeneous set of indicators, tools, and methodological approaches aimed at measuring circularity performance across various scales, such as material, product, company, and national levels (Roos Lindgreen et al., 2022; Sassanelli et al., 2019). In the present research, the focal point is the computation of c-indicators, defined as quantitative or qualitative variables measuring achievement, change, or performance (Moraga et al., 2019; Saidani et al., 2019). Following the taxonomy proposed by Saidani et al. (2019) and the classification proposed by Moraga et al. (2019), the scope of the study is limited to micro-level, assessing services, products, and companies, as they are most fit in the context of a manufacturing enterprise. More generally, indicators are used in various fields to summarize or describe complex systems into communicable measures suitable for monitoring and decision-making (Flowers et al., 2005; Mecca et al., 2023).

As represented in Fig. 1, the relationship between indicators and the data they require can be framed through the Data-Information-Knowledge-Wisdom (DIKW) hierarchy (Ackoff, 1989; Zins, 2007). In this framework, data corresponds to raw observations, information to structured data within a given context, knowledge to interpreted information that enables understanding, and wisdom to informed judgment that guides action. Indicators correspond to the knowledge level: they enable diagnosis or understanding at a given scale and scope (Kristoffersen et al., 2020). In this research, c-data (i.e., circularity data) designates the required data points for c-indicators computation, representing the lowest tier in the DIKW hierarchy. Accordingly, CE assessment is conceptualized here as the computation of c-indicators through the use and collection of c-data points.

2.2. Information management in enterprises

Enterprise Information Systems (EIS) are integrated digital architectures coordinating organizational and inter-organizational processes.

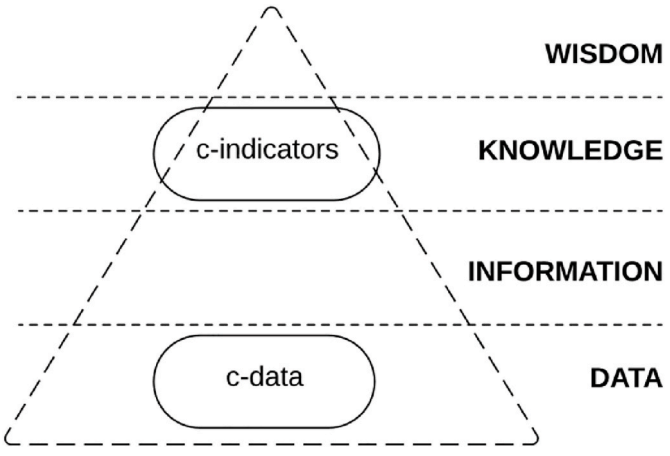


Fig. 1. Positioning of c-data and c-indicators in the Data-Information-Knowledge-Wisdom concept hierarchy, adapted from Zins (2007) and Ackoff (1989).

They support functions such as supply chain, production, logistics, customer management, and the product lifecycle, increasingly enhanced by digital technologies (Romero and Vernadat, 2016; Zdravković et al., 2022; Xu, 2011). EIS enable structured data sharing and integrated process coordination across the enterprise (Daneshvar Kakhki and Gargeya, 2019; Núñez-Merino et al., 2020), making them central to sustainability and CE implementation, which rely on consistent data sourcing, integration, and governance (Krasikov and Legner, 2023; Duong et al., 2025). Table 1 summarizes common EIS in manufacturing supply chains, across product lifecycle stages, highlighting their relevance for circularity assessment.

3. Materials and methods

The following section presents the proposed approach to tackle CE assessment in a large manufacturing enterprise, and the chosen case study for its demonstration.

3.1. Proposed top-down approach

As depicted in Fig. 2, the proposed approach consists of four phases: (1) industrial diagnosis, (2) systematic sense-making of CE assessment resources, (3) decomposition of c-indicators into c-data, and (4) design of a data collection strategy.

Phase 1 – Industrial Diagnosis: The first phase consists of an industrial diagnosis aimed at establishing the organizational context for CE assessment. It relies on participatory approaches involving the organization's stakeholders and internal documentation to produce three outputs: the identification of the organization's objectives for CE assessment, the definition of the SOI, and an inventory of relevant EIS. These outputs provide the contextual foundation for the subsequent phases.

Phase 2 – Making sense of CE assessment resources: The second phase translates the CE assessment objectives identified in Phase 1 into concrete data requirements through a systematic sense-making process. A targeted corpus of external or internal documents providing guidance on CE assessment is constructed and analyzed. From this analysis, a set of CE data requirements is extracted, reformulated, and unified.

Phase 3 – From c-indicators to c-data: Then, during the third phase, a subset of target c-indicators is selected based on a readiness assessment that accounts for regulatory priority, data availability, and modeling complexity. Each selected indicator is then recursively decomposed into its underlying data dependencies until no further decomposition is possible within the defined system boundaries, using a directed acyclic graph. The resulting atomic data points, referred to as c-data, are formalized as the graph's leaf nodes, providing a complete and traceable set of data required for indicator computation.

Phase 4 – Strategic data collection: The fourth phase addresses the planning of data collection within the organization. Each c-data point is mapped to one or more candidate EIS based on stakeholder knowledge and system descriptions. A binary mixed-integer linear programming model is then formulated to evaluate alternative data collection scenarios, considering both assessment performance, in terms of computable indicators and satisfied CE assessment resources, and implementation effort, in terms of accessed systems and collected data points. The model yields an optimal data collection strategy, specifying which systems to access and which c-data to collect.

3.1.1. Phase 1 – Industrial diagnosis for CE assessment

Phase 1 studies the industrial context for CE assessment through a stakeholder-based diagnosis. The format is left to the implementer and may include interviews (Roos Lindgreen et al., 2022; Çetin et al., 2023; Nguyen et al., 2024), workshops (Mendoza and Pigosso, 2023; Coutinho et al., 2018; Droege et al., 2021), or other collaborative approaches. Consequently, inputs include access to relevant practitioners across functions such as engineering, operations, IT, and sustainability, as well

Table 1
List of enterprise information systems commonly found in manufacturing supply chains.

Lifecycle stage	Information System Acronym	Information System full name	Description	Key references
Design & Development	PLM	Product Lifecycle Management	Manages product definitions, materials, and bills of materials (BOMs).	(Romero and Vernadat, 2016; Zdravković et al., 2022; Panagiotidis et al., 2022)
	CAD/CAE/CAM	Computer-Aided Design/Engineering/ Manufacturing	Supports design, engineering analysis, and manufacturing.	(Polenghi et al., 2021; Gunasekaran and Ngai, 2004)
Manufacturing	MES	Manufacturing Execution System	Controls and monitors shop-floor production and execution.	(Polenghi et al., 2021; Romero and Vernadat, 2016; Panagiotidis et al., 2022)
	ERP	Enterprise Resource Planning	Manages production planning and inventory.	(Polenghi et al., 2021; Romero and Vernadat, 2016; Zdravković et al., 2022; Panagiotidis et al., 2022; Gunasekaran and Ngai, 2004)
Distribution & logistics	SCM	Supply Chain Management	Coordinates sourcing and distribution.	(Romero and Vernadat, 2016; Zdravković et al., 2022; Panagiotidis et al., 2022)
	WMS	Warehouse Management System	Manages warehouse inventory and order fulfillment.	(Mason et al., 2003; Hamdy et al., 2018; Minashkina and Happonen, 2023)
	TMS	Transportation Management System	Plans and tracks transportation and delivery operations.	(Mason et al., 2003; Romagnoli et al., 2023)
Use & service	CRM	Customer Relationship Management	Manages customer interactions and after-sales.	(Romero and Vernadat, 2016; Zdravković et al., 2022; Panagiotidis et al., 2022; Gunasekaran and Ngai, 2004)
	CMMS	Computerized Maintenance Management System	Tracks maintenance, repair, and service operations.	(Polenghi et al., 2021; Fumagalli et al., 2009; Wienker et al., 2016)
	IoT/OT	Internet of Things/Operational Technology platforms	Collects real-time operational data from products in the field.	(Xu, 2011)
End-of-life	EHS/EIS/EMIS	Environment, Health, and Safety/ Environmental (Management) Information System	Manages waste, hazardous substances, and compliance data.	(Krasikov and Legner, 2023; Frysinger, 2001; El-Gayar and Fritz, 2006)

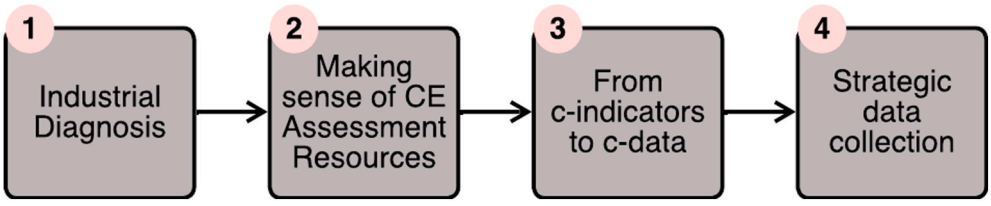


Fig. 2. Workflow of the proposed approach.

as internal documentation. Rather than prescribing a procedure, the approach specifies expected outputs that document the organization's rationale, scope, and data context for CE assessment. These outputs are developed iteratively, as insights on objectives, data needs, information systems, and scope mutually inform and refine one another.

Output 1 – Identification of the organization's objectives for CE assessment

Building on the data perspective on sustainability initiatives developed by Krasikov and Legner (2023), the first output identifies and formalizes the organization's rationale and objectives for CE assessment. Objectives are seen as responses to institutional pressures: (i) regulative, stemming from laws, policies, or mandatory reporting; (ii) normative, reflecting expectations from customers, investors, industry bodies, or society; and (iii) cultural-cognitive, driven by competitive alignment with peers or industry practices. Clarifying these objectives makes explicit why circularity is assessed and guides the selection of indicators aligned with operational needs.

Output 2 – Definition and modeling of the system-of-interest

The second output formalizes the chosen scope, or system of interest (SOI). This consists of delimiting the system, which is the object of the CE assessment, i.e., listing the relevant products, processes, lifecycle stages, organizational units, flows, and their interrelations. A consistent set of terms and concepts should be defined to reduce ambiguity and structure subsequent steps. Modeling the SOI may rely on internal, organizational concepts, or external resources such as meta-models, ontologies, or taxonomies, e.g., CirDEF (Kahandawa et al., 2025), an automotive ontology (Pidikiti et al., 2023), a built environment ontology (Kebede et al., 2024), or a healthcare taxonomy (Hoveling et al., 2026).

Output 3 – Identification of existing information systems relative to the chosen scope

The third output identifies the EIS that may store c-data points relative to the defined scope. Table 1 lists typical EIS in large manufacturing organizations, differentiated by product lifecycle stage. This inventory is intended to guide discussions with stakeholders and to identify the organization's own EIS.

3.1.2. Phase 2 – Systematic sense-making of CE assessment resources

Step 1 – Identification of relevant CE assessment resources

Phase 2 begins by identifying CE assessment resources aligned with the objectives defined in Phase 1 (Section 3.1.1). CE assessment resources are documents produced by CE enablers – academia, policymakers, industry bodies, or consumers (Kirchherr et al., 2023) – providing guidance, requirements, or reference frameworks for assessing circularity. These include peer-reviewed literature, regulations, international standards, certifications, guidelines, and other formal or semi-formal documents. The aim is to select reference documents that specify what should be assessed, monitored, or reported in relation to

CE, reflecting evolving industry expectations and obligations. The resulting corpus is constructed in a targeted manner to cover regulatory, normative, and operational perspectives relevant to the organization. While not exhaustive, it is designed to capture a representative set of requirements aligned with the identified objectives. Consequently, the CE data requirements derived from this corpus reflect the selected sources and may evolve if additional or alternative resources are considered. For each objective identified in the first output of Phase 1, one or more relevant resources are selected. A single resource may suffice for narrowly defined objectives, such as a specific regulatory requirement, whereas broader objectives may require several complementary resources. For instance, compliance with the CSRD (European Commission, 2022) requires consultation of the relevant CE reporting standards (EFRAG, 2023; EFRAG, 2024), whereas integrating product-level circular strategies may draw on existing methodologies for measuring circularity, such as the Closing Slowing Future Past Quadrant Model (Shevchenko et al., 2022) or the Ellen MacArthur Foundation's framework (Goddin et al., 2019).

Step 2 – Translation of the corpus into CE data requirements through sense-making

Once the corpus of CE assessment resources is defined, it is translated into CE data requirements through a structured sense-making workflow. Following Krasikov and Legner (2023), sense-making refers to identifying "data objects and attributes […] which should be collected in the next data sourcing phase." The workflow operationalizing this concept in the context of CE assessment resources was developed and formalized by Durivault et al. (2026), and is directly applied here to extract tangible indicators or data points required for CE assessment, referred to as CE data requirements.

The workflow comprises three steps. (i) Selecting relevant sections. CE assessment resources are often not designed for data sourcing and may be unstructured or semi-structured. They can include contextual guidance, administrative metadata (e.g., template identifiers or version numbers), or content outside the defined SOI (e.g., social sustainability, specific products or services beyond the SOI's bounds). Such elements are systematically excluded. (ii) Excluding non-quantifiable content. The remaining sections are screened for quantifiable elements. Content is retained if it includes quantifiable language, i.e., references to trends (e.g., "increase", "decrease"), limits (e.g., "minimum", "maximum"), computed outputs (e.g., "percentage", "rate"), or explicit measurement units (e.g., "kg", "L"). The CE data typology proposed by Araujo et al. (2025), which distinguishes unit types such as volume, energy, and weight, can support this step. (iii) Reformulating into CE data requirements.

Selected sections are reformulated into concise statements describing data to be collected or indicators to be measured, computed, or monitored. Reformulations should preserve the original meaning and scope of the source content and avoid interpretative assumptions.

Step 3 – Unification of the CE data requirements

The CE data requirements obtained from the previous steps may contain redundancies, overlaps, or variations in terminology. Duplicate or semantically equivalent data requirements are identified and consolidated, and terminology is harmonized to ensure consistent and unique requirements. This harmonization is performed using the terms, definitions, and naming conventions established for the SOI in Phase 1 (section 3.1.1), in order to maintain alignment with the organization's context. Depending on the size and heterogeneity of the CE data requirements, this process may be supported by natural language processing techniques, such as similarity analysis or semantic clustering.

3.1.3. Phase 3 – Breaking down c-indicators into c-data

Step 1 – Identification and selection of target c-indicators

Within the set of CE data requirements, a distinction is first made between elements that correspond to c-indicators and those representing intermediate information or c-data. Let $R = \{r_1, r_2, \ldots, r_n\}$ denote the set of requirements, and $I \subseteq R$ the subset corresponding to c-indicators as defined in section 2.1. C-indicators are distinguished as they denote ratios, indexes, or composites, following the classification framework proposed by Moraga et al. (2019). In a supply chain context, implementing a large set of indicators may be inefficient, as it leads to information overload and complicates monitoring and decision-making (Chae, 2009). As noted by Brint et al. (2021), larger sets of indicators increase the quantity of data requirements, leading to higher costs and efforts (Almeida and Calistru, 2013). It is therefore necessary to filter the set of c-indicators and define a subset as the focus of an initial implementation phase.

This selection is based on the readiness level of each indicator, comprising several criteria, such as regulatory urgency, data availability, or modeling complexity. Indicators dictated by regulations are compulsory and therefore typically constitute a high priority. Readiness may also distinguish quantitative c-indicators from qualitative ones, as the former may be more straightforward to model mathematically, making their underlying data requirements easier to identify and operationalize. Readiness may also be opportunistic, based on organizational context and data availability. Readiness is, however, not an intrinsic property of an indicator but depends on the organization conducting the assessment. For example, a design team applying the approach may prioritize qualitative, design-oriented indicators, such as "design for disassembly" or "design for circularity", as they may have prior knowledge of available design or material data. Conversely, environmental footprints require complex life cycle assessment modeling, yet an organization with mature LCA comprehension and established access to the corresponding data could assign them a high readiness level and address them early. Each c-indicator $i \in I$ is therefore assigned a discrete readiness level:

$$P(i) \in \{1, 2, \ldots, L\}$$

The subset of target c-indicators to be addressed first is then defined as $I^* = \{i \in I | P(i) \leq p_{\max}\}$ where $p_{\max}$ reflects the chosen readiness threshold for the current implementation phase. This subset represents the first iteration of an incremental implementation strategy. Importantly, indicators not included in the initial subset are not considered less relevant; rather, they are deferred to subsequent implementation waves to reduce effort, limit complexity, and maintain focus for practitioners. The ultimate objective remains the progressive modeling of the complete set of c-indicators.

As illustrated in Fig. 3, the approach is designed as a sequence of successive implementation waves. Between iterations, organizations should undergo a consolidation phase aimed at strengthening their assessment capabilities and preparing for the next readiness level. This may involve targeted literature reviews, consultation with domain experts or benchmarking of industrial practices. These activities support the refinement of indicator definitions, and more generally, the gradual expansion of the assessment scope toward the full set of c-indicators.

Step 2 – Recursive decomposition of target c-indicators into data dependencies

Once the target c-indicators have been selected, the next step is to identify the data required to compute them. Each target c-indicator $i \in I^*$ is first expressed in terms of the elements required for its calculation:

$$i = f(d_1, d_2, \ldots, d_m)$$

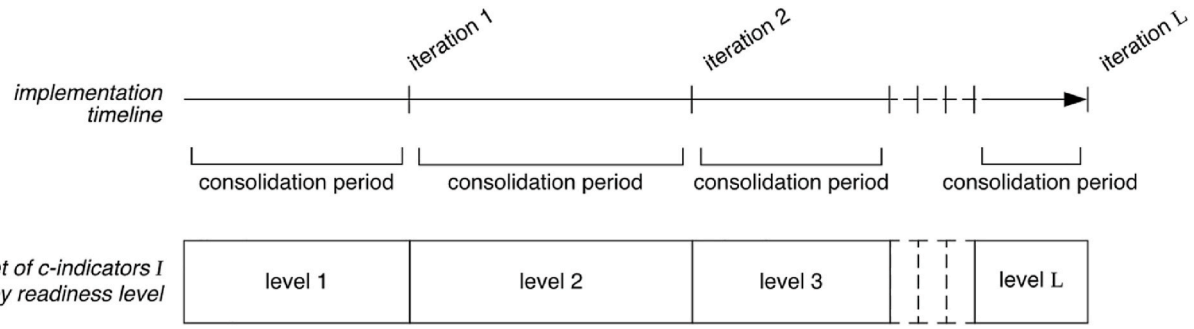


Fig. 3. Generic projection timeline for tackling all identified c-indicators, with L: = highest level of readiness P(i), and I: = the full set of c-indicators.

where the d_k represent the variables necessary for computing *i*. For each element d_k, it is assessed whether a decomposition exists within the boundaries of the SOI. If such a decomposition exists, the element is expressed as:

$$d_k = g_k\left(d_{k1}, d_{k2}, \ldots, d_{kp}\right)$$

where the d_{kj} denote lower-level contributing variables. If no such decomposition exists within the SOI, that is, if further expansion would require introducing elements, relationships, or variables outside the defined system boundaries, the element d_k is not decomposed further and is declared "atomic data", or c-data. The same procedure is applied recursively to each non-atomic element d_{kj}. The expansion continues until every branch terminates in elements that admit no further decomposition within the SOI. At that point, each target indicator $i \in I^*$ is expressible exclusively as a function of c-data obtained through successive substitutions of the decomposed elements. To maintain consistency and avoid ambiguity across multiple indicators, the decomposition of all $i \in I^*$ is structured as a directed acyclic graph:

$$G = (V, E)$$

where:

- $V = I^* \cup \left\{d_{k_1}, d_{k_1k_2}, d_{k_1k_2k_3}, \ldots\right\}$ is the set of c-indicators, c-data and intermediary variables needed to compute all c-indicators
- $E \subseteq V \times V$ represents directed dependencies. A directed edge $(u, v) \in E$ indicates that element u depends on element v for its computation.

During the graph construction, one should ensure that identical elements required by multiple indicators are represented only once, preventing duplication and preserving consistency of definitions. Consider a node $u \in V$ currently being decomposed. For each contributing element v identified in the decomposition of u, membership in the existing node set V is verified. If $v \in V$, the element is not recreated; only the corresponding dependency edge from u to v is added:

$$E \leftarrow E \cup \{(u, v)\}$$

If $v \notin V$, the element is first inserted into the node set, then the dependency in the edge set.

$$V \leftarrow V \cup \{v\}, E \leftarrow E \cup \{(u, v)\}$$

By construction, the resulting dependency graph satisfies several fundamental structural properties. (1) **Hierarchy**. The graph is hierarchically organized. The selected c-indicators I^* form the root nodes of the structure, while c-data points form its leaf nodes. Intermediate nodes correspond to aggregated variables introduced during recursive decomposition. (2) **Acyclicity**. Decomposition always proceeds toward lower levels of aggregation and never reintroduces higher-level elements as dependencies. Formally, there does not exist any $v \in V$ such that v depends directly or indirectly on itself. The graph is therefore a directed acyclic graph, ensuring logical consistency and preventing circular definitions between indicators and their underlying data. (3) **Traceability**. Let $\mathrm{Reach}(i) \subseteq V$ denote the set of nodes reachable from a given indicator $i \in I^*$. For each c-data element a, there exists at least one $i \in I^*$ such that $a \in \mathrm{Reach}(i)$. This guarantees that every atomic data element included in the structure contributes to at least one indicator and that no collected data point is disconnected from the CE assessment. (4) **Uniqueness**. Each element appears only once in the node set V. When multiple indicators depend on the same data element, this shared dependency is represented through multiple incoming edges rather than by duplicating nodes.

Result 1 – List of c-data points to collect within the organization

At this point, the first result of the approach is obtained. The list of c-data points to collect within the organization's EIS is given by the leaf nodes of the dependency graph $G = (V, E)$. Let

$$D = \{v \in V | \nexists\, w \in V \text{ such that } (v, w) \in E\}.$$

The set D constitutes the complete list of data points that must be measured, collected, or made available within the organization in order to compute the selected c-indicators.

3.1.4. Phase 4 – Building a data collection strategy

While the identification of c-data facilitates CE assessment, it does not resolve the practical challenge of organizing and operationalizing data collection within the organization. Required data may be distributed across multiple EIS, partially available, redundantly stored, or costly to extract. Access to EIS is not necessarily guaranteed, as practitioners may face organizational, technical, or governance constraints that limit data accessibility. Collecting all potentially relevant data maximizes indicator computability but significantly increases implementation effort, including time and coordination. If the collected data should be reused to develop a dedicated database supporting future CE assessments, additional burdens arise in terms of data storage, design, and long-term maintenance. Phase 4, therefore, addresses data collection and balances both the implementation progress and effort of the CE assessment.

Step 1 – Hypothetical mapping of c-data to EIS

Before initiating data collection, each c-data point $d \in D$ is mapped to one or more EIS expected to contain it. This mapping is established based on two sources of information: the industrial diagnosis conducted in Phase 1, including stakeholder interviews, documentation, and knowledge of existing EIS, and generic descriptions of EIS identified in

the literature. The hypothesis is based on the definition of the c-data (e.g., data type, unit, granularity, and SOI scope), and the description of the EIS (e.g., system name and typical usage by practitioners). This mapping is performed manually by the research team in collaboration with practitioners and reflects a plausible approximation of data locations rather than a direct verification of system content. Let S denote the set of EIS. For each c-data point $d \in D$, a candidate set of systems is defined as:

$$S(d) \subseteq S$$

where $s \in S(d)$ indicates that system s is considered a potential source for retrieving d. This formulation enables the exploration of data collection strategies under realistic but partially uncertain conditions. To reduce the uncertainty associated with this mapping, a final validation step is conducted for the most critical c-data points, e.g., the most frequently required across the selected c-indicators. Their mapping is reviewed with an internal practitioner with direct knowledge of the relevant data and information systems, such as a system owner, data steward, or data engineer.

Step 2 – Modeling EIS access and c-data collection

The model is formulated as a binary Mixed-Integer Linear Programming problem (MILP). Let:

- S denote the set of EIS within the organization identified in Phase 1
- D denote the set of c-data identified as the leaf nodes of the dependency graph in Phase 3
- I denote the set of c-indicators under consideration
- F denote the set of solicited CE assessment resources for sense-making in Phase 2

In this context, a *data collection scenario* is defined as a specific configuration of accessed EIS, and collected c-data points, determining which c-indicators can be computed and which CE assessment resources can be satisfied.

Input parameters. To formalize the relationships between c-data, c-indicators, EIS, and CE assessment resources, the following binary parameters are defined:

- The relationship between systems and data availability is represented by a binary parameter:

$$A_{sd} = \begin{cases} 1 & \text{if data point } d \in D \text{ is available in system } s \in S \\ 0 & \text{otherwise} \end{cases}$$

- The dependency between indicators and data, derived from the graph constructed in Phase 3, is defined by:

$$B_{di} = \begin{cases} 1 & \text{if indicator } i \in I \text{ requires data } d \in D \\ 0 & \text{otherwise} \end{cases}$$

- The contribution of an indicator to a CE assessment resource, as retrieved from Phase 2, is represented by:

$$C_{if} = \begin{cases} 1 & \text{if indicator } i \in I \text{ contributes to CE assessment resource } f \in F, \\ 0 & \text{otherwise} \end{cases}$$

Let:

$$I_f = \{i \in I | C_{if} = 1\}$$

denote the subset of indicators associated with CE assessment resource f.

Decision variables. Binary decision variables are defined as follows:

$$\mathrm{x_s} = \begin{cases} 1 & \text{if system s} \in \text{S is accessed} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{y_d} = \begin{cases} 1 & \text{if data point d} \in \text{D is collected} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{z_i} = \begin{cases} 1 & \text{if indicator i} \in \text{I is computable} \\ 0 & \text{otherwise} \end{cases}$$

$$\theta_\mathrm{f} = \begin{cases} 1 & \text{if CE assessment resource f} \in \text{F is fully satisfied} \\ 0 & \text{otherwise} \end{cases}$$

Constraints. The decision problem is subject to the following constraints, which formalize data availability, indicator computability, and CE assessment resource completion:

- A data point is collectable if at least one accessed system contains it:

$$\forall d \in D,\ y_d \leq \sum_{s \in S} A_{sd} x_s$$

- An indicator is computable only if all required data are collected:

$$\forall i \in I, \forall d \in D \text{ such that } B_{di} = 1 : z_i \leq y_d$$

- A CE assessment resource is considered to be fully completable if and only if all of its indicators are computable:

$$\forall f \in F, \sum_{j \in J_f} z_j \geq |J_f| \theta_f$$

Objective functions. To evaluate alternative data collection scenarios, two objective functions are defined as follows:

- Performance represents two complementary dimensions of the assessment's coverage: indicator-level coverage reflects the direct quantity of computable indicators, while resource-level coverage reflects the degree to which organizational objectives, each tied to a specific CE assessment resource, are fully met. It is defined as:

$$P = \frac{1}{2}\left(\frac{\sum_{i \in I} z_i}{|I|} + \frac{\sum_{f \in F} \theta_f}{|F|}\right), P \in [0, 0.5],$$

- Effort represents two distinct sources of implementation burden: access to EIS, which is not systematically granted to practitioners, and the quantity of collected data points, which, when increased, raises costs related to data extraction, processing, storage, and maintenance (Almeida and Calistru, 2013; Brint et al., 2021). It is defined as:

$$E = \frac{1}{2}\left(\frac{\sum_{s \in S} x_s}{|S|} + \frac{\sum_{d \in D} y_d}{|D|}\right), E \in [0, 0.5],$$

Both objective functions are normalized to ensure comparability between performance and effort dimensions and to express the final objective function within a bounded range. The trade-off between CE assessment progress and implementation effort is modeled through a weighted linear scalarization. This formulation reflects a standard approach for exploring trade-offs between competing objectives and enables systematic sensitivity analysis through variation of the weighting parameter α. The equal weighting within each dimension provides a balanced representation in the absence of predefined preferences.

$$\text{maximize } \alpha P - (1 - \alpha) E, \alpha \in [0, 1].$$

Result 2 – Choice of the optimal scenario

The second result of the approach corresponds to the identification of an optimal data collection scenario obtained by solving the binary Mixed-Integer Linear problem. The optimization model determines the combination of EIS to access and c-data points to collect that maximizes CE assessment progress while minimizing implementation effort, according to the selected trade-off parameter α. The resulting solution specifies which c-indicators become computable and which CE assessment resources can be fully addressed under the chosen configuration. Since the optimal configuration depends on the weighting parameter α, sensitivity analyses should be conducted by varying $\alpha \in [0, 1]$ to explore alternative trade-offs between assessment progress and implementation effort.

3.2. Case study: radiology system manufacturing

3.2.1. General context and motivation

The proposed approach is illustrated through a case study conducted within a large, multinational original equipment manufacturer (OEM) of complex medical systems, such as magnetic resonance imaging and computed tomography scanners, as shown in Fig. 4. The organization's activities encompass the manufacturing and maintenance of these systems through service operations, resulting in a technically complex and globally distributed supply chain. The organization has long implemented practices related to maintenance, life extension, refurbishment, spare part recovery, and recycling, initially driven by operational reliability and resource management needs. More recently, these practices have been reconsidered within broader CE and sustainability perspectives, with increased attention to material flows and environmental performance (El Bechari et al., 2025; Shevchenko et al., 2026).

However, the organization currently lacks a structured view and characterization of material flows across its supply chain, which limits its ability to consistently quantify circularity and, more importantly, to prioritize circular strategies, identify hotspots, and support decision-making. This context provides a relevant setting to apply the proposed approach, as the organization combines multiple sources of complexity that directly challenge CE assessment in practice. The presence of complex products, multiple lifecycle stages, existing but partially articulated circular strategies, and fragmented EIS are representative of large industrial organizations facing CE transition challenges and therefore calls for a structured approach to CE assessment.

3.2.2. Complexity and specificities of the case study

The case study combines several sources of complexity at both the product and supply chain levels. At the product level, the systems present a multi-level architecture composed of subassemblies, assemblies, parts, and components, with individual subsystems being themselves multi-component units subject to structural and economic dependencies. These are durable, material-intensive products built largely from steel, aluminum, electronic components, plastic, and reliant on critical resources (The Shift Project, 2025). They are deployed at large scale – approximately four million units across more than 160 countries – and typically operate beyond ten years using extended-life management strategies.

At the supply chain level, manufacturing is discrete and globally distributed across multinational facilities. The organization operates multiple circular loops, including reuse, repair, refurbishment, remanufacturing, recycling, and the harvesting of systems retrieved from the market to extract reusable parts. Spare parts in particular follow a closed-loop supply chain in which failed units are recovered, repaired, and reintegrated through a central distribution center sourcing from both new suppliers and repair centers. This configuration is compounded by fragmented data, as maintenance and logistic information is dispersed across multiple systems and the repeated reallocation of parts makes lifetime data difficult to gather, reflecting the broader difficulty of obtaining and structuring CE data in this context.

Beyond the specificities of GE HealthCare, the healthcare sector presents conditions that make CE assessment particularly challenging. It is a highly heterogeneous industry, covering more than 20,000 product types ranging from single-use consumables to complex capital equipment, and relies on a globalized value chain involving numerous subcontractors and a strong dependence on imported materials and components (The Shift Project, 2025). In medtech, the environmental footprint is substantial: medical imaging devices in France are estimated to generate around up to 230 $ktCO_2e$ per year, with raw materials and manufacturing contributing to approximately 50% of this total (The Shift Project, 2025). The development of circular end-of-life pathways is further limited by structural barriers, such as limited integration of ecodesign principles and the absence of viable economic models for product recovery schemes (The Shift Project, 2025). These challenges are further hindered by difficulties in accessing reliable data, which is often confidential, fragmented across heterogeneous systems and formats, poorly structured, embedded in unstructured text, or simply unavailable (The Shift Project, 2025). Taken together, the highly data-intensive nature of the sector and its supply chain, combined with these data-related challenges, motivated the selection of this case study.

4. Results

4.1. Application of the approach to the case study

This section reports on the application of the proposed top-down approach to the radiology system manufacturing case study. The results are presented in accordance with the four phases described in



Fig. 4. GE HealthCare's (A) SIGNA sprint: 1.5T MRI scanner (B) revolution vibe CT scanner.

Section 3.1.

4.1.1. Phase 1 – Industrial diagnosis for CE assessment

To conduct the industrial diagnosis, semi-structured interviews with key stakeholders of the OEM are conducted. Ten 1-h interviews are conducted with representatives from project management, sourcing, design engineering, product installation, and information technology. Interviewees are primarily selected based on their involvement in a previous CE assessment initiative. The interviews mainly explore participants' roles, data usage, and knowledge of the OEM's data architecture, using the guiding questions listed in Table A.1.

Output 1 – Identification of the organization's objectives for CE assessment

The industrial diagnosis identified four main objectives for CE assessment:

- compliance with the upcoming Corporate Sustainability Reporting Directive (CSRD),
- assessment of organizational readiness for CE-related standards and potential certification,
- response to customer sustainability requirements,
- improve day-to-day circularity management for internal practitioners.

Output 2 – Definition and modeling of the system-of-interest

The SOI was defined by explicitly listing the elements that the organization considers within the scope of its CE assessment. As shown in Fig. 5, the SOI was organized along three complementary dimensions. First, the product lifecycle is defined across four stages: design, production, use, and end-of-life. Second, the supply chain dimension identifies the organizational processes considered within the assessment scope, including sourcing, manufacturing, transportation, installation, maintenance, buyback, harvesting, and refurbishment. Third, material flows are identified as the physical assets subject to circularity measurement. These include materials, products, accessories, spare parts, packaging, and waste streams generated throughout the lifecycle.

Output 3 – Identification of existing information systems relative to the chosen scope

In total, eight EIS are identified within the company: PLM, CAD, TMS, CRM, ERP, SCM, IoT system, and CMMS, a subset of the generic system types described in Table 1. Their names are anonymized accordingly.

4.1.2. Phase 2 – Systematic sense-making of CE assessment resources

Step 1 – Identification of relevant CE assessment resources

Based on the objectives identified during the industrial diagnosis, a targeted corpus of CE assessment resources is constructed. First, to ensure compliance with the CSRD's requirements in terms of CE, the European Sustainability Reporting Standard (ESRS), entitled "*ESRS E5: Resource Use and Circular Economy*" is analyzed. Concretely, the selected documents are the European Financial Reporting Advisory Group's (EFRAG) Implementation Guidance 3 (EFRAG, 2024), complemented by the official legal text of the directive (Official journal of the European Union, 2023). Second, to assess organizational readiness for CE-related standards and potential certification, the international standard on the Product Circularity Data Sheet, ISO 59040 (ISO, 2025), is selected. Third, to aid in responding to customer sustainability requirements, company documents compiling calls for tenders are examined. Finally, to improve day-to-day circularity management for internal practitioners, additional internal company documents are included. These documents are the result of a prior needs-analysis workshop conducted with internal experts to identify relevant c-indicators and highlight missing or inaccessible data.

Step 2 – Translation of the corpus into CE data requirements through sense-making

The CE assessment resources identified in Step 1 are translated into structured CE data requirements following the sense-making procedure described in Section 3. As summarized in Table 2, 47 requirements are extracted from the CSRD, 92 from ISO 59040, 120 from customer calls for tendering, and 65 from the internal needs-analysis workshop.

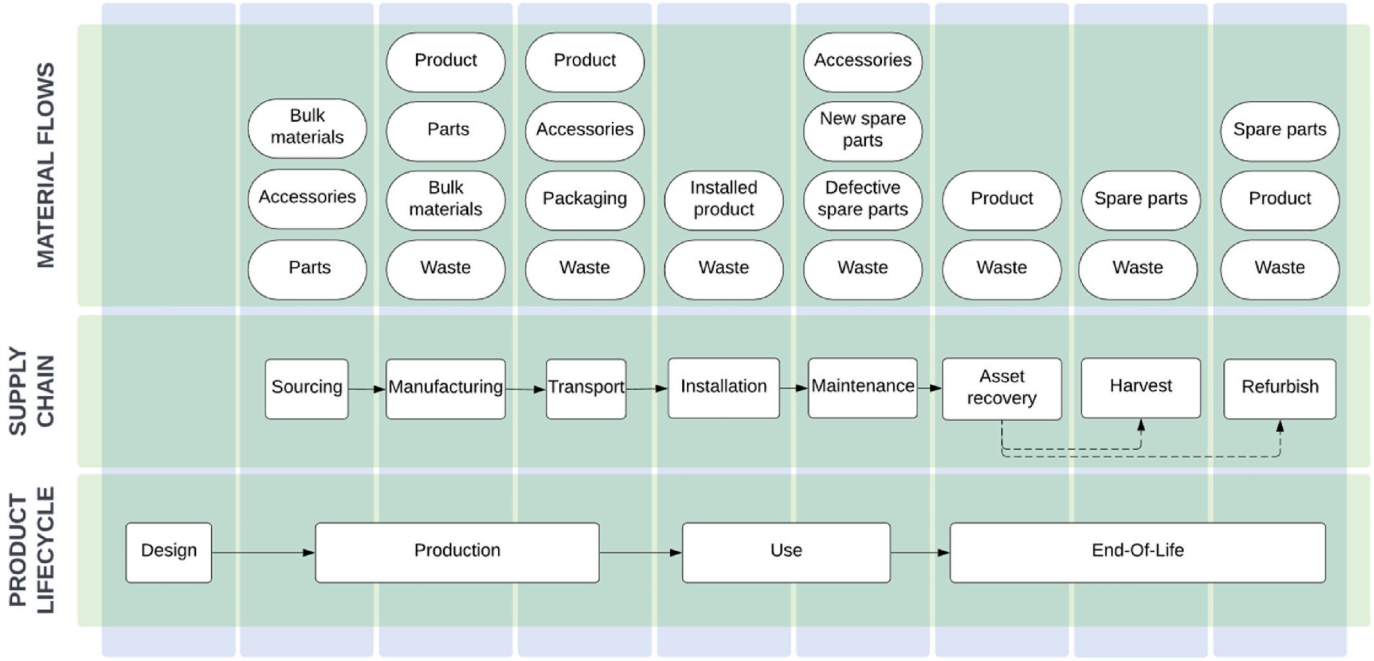


Fig. 5. Structured representation of the system-of-interest covered within the CE assessment scope.

Table 2
CE assessment resources associated with organizational objectives and resulting data requirements.

Objective	CE Assessment Resource	Document Type	Author	Number of CE data requirements	Total CE data requirements	Number of unique CE data requirements per CE Assessment Resource	Total unique CE data requirements across all CE Assessment Resources
Compliance with the CSRD	EFRAG ESRS E5	Excel + PDF	Policymaker	47	324	45	281
Assessment of CE certification readiness	ISO 59040	PDF	Policymaker + Industry + Academia	92		89	
Answer to customer sustainability requirements	Call for tenders	Excel	Consumers	120		97	
Improve practitioner CE management	Needs-analysis workshop	Excel	Industry	65		65	

CSRD: Corporate Sustainability Reporting Directive.
EFRAG: European Financial Reporting Advisory Group.
ESRS E5: European Sustainability Reporting Standard - Environmental 5.

Step 3 – Unification of the CE data requirements

Following their extraction, the CE data requirements are consolidated through a unification process aimed at removing redundancies and harmonizing terminology across sources. Semantically equivalent or overlapping requirements are identified by comparing their measurement intent, scope, and underlying variables, and are merged into a single standardized formulation. Particular attention is paid to preserving the original meaning of each requirement while ensuring consistency with the SOI defined in Phase 1. To enhance robustness and limit subjectivity, the unification process is conducted iteratively by two researchers: coding decisions are regularly compared, and ambiguous or borderline cases are systematically discussed and resolved through consensus.

This procedure ensures consistency in interpretation and reduces the risk of misclassification or loss of meaning across heterogeneous sources. For instance, requirements such as "mass fraction of recycled materials out of the total product mass (expressed in accordance with range 1 defined in 6.2)" (ISO 59040), "product percentage of recycled content" (practitioner needs), "proportion of recycled materials" (call for tenders), and "rate of injected recycled material in manufactured equipment" (call for tenders) are considered semantically equivalent, as they refer to the share of recycled material within a product. These are therefore consolidated into a single requirement labeled "percentage of recycled content in product", where "product" refers to fully manufactured radiology systems as defined in the SOI.

As shown in Table 2, the process resulted in a final set of 281 unique CE data requirements. Their distribution across all four CE assessment resources is illustrated in Fig. 6.

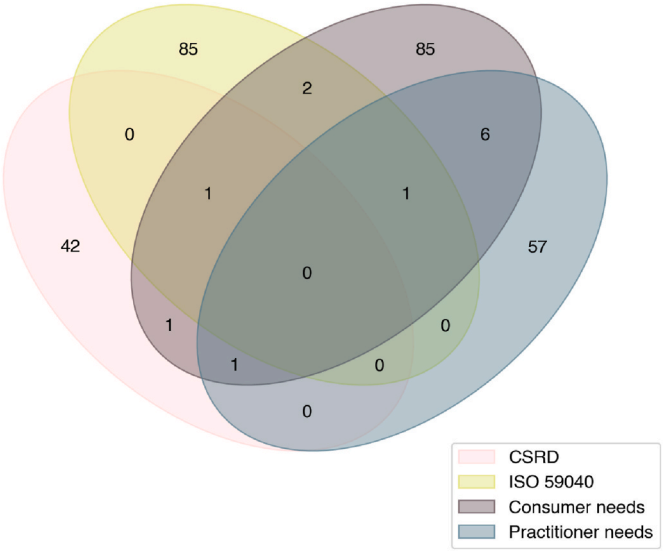


Fig. 6. CE data requirement distribution across the four CE assessment resources and their corresponding intersections.

4.1.3. Phase 3 – Breaking down c-indicators into c-data

Step 1 – Identification and selection of target c-indicators

From the unified set of CE data requirements, 170 c-indicators are identified. These indicators are then classified before decomposition, following data availability and ease of computation.

Indicators are assigned readiness levels based on explicit criteria, including regulatory priority, data availability, and modeling complexity. For instance, indicators stemming from regulatory requirements such as the CSRD are assigned the highest readiness level, $p = 1$, due to their mandatory nature. Indicators formulated qualitatively, or lacking a clearly defined measurement framework are assigned a lower readiness level, as they introduce ambiguity in operationalization.

For example, ISO 59040 refers to the "fraction of the product that is designed to be cleanly removed from the assembly where it is fixed," and the CSRD requires disclosure of "the expected durability of the products placed on the market by the undertaking, in relation to the industry average." Concepts such as "design for" or "durability" can be computed in multiple ways (e.g., through technical lifetime, warranty period, failure rate, or design specifications), leading to methodological ambiguity. Similarly, indicators with high modeling complexity, such as carbon emissions and environmental footprints, are assigned lower readiness levels due to their higher implementation effort. Indeed, their computation requires life cycle assessment modeling, making data identification substantially more complex. Although essential, they are postponed to later iterations of the approach. While this classification remains context-dependent, it follows a structured rationale aimed at ensuring feasibility and relevance in the initial implementation phase.

For the following phases of the approach, the readiness threshold is set to $p_{max} = 1$ thus, as shown in Fig. 7, 69 target c-indicators compose I^*. These indicators are listed in Table B.1.

Step 2 – Recursive decomposition of target c-indicators into data dependencies

Each target c-indicator $i \in I^*$ is decomposed to identify its underlying data dependencies, thus represented as a directed acyclic graph $G = (V, E)$, capturing both the variables involved in its computation and their

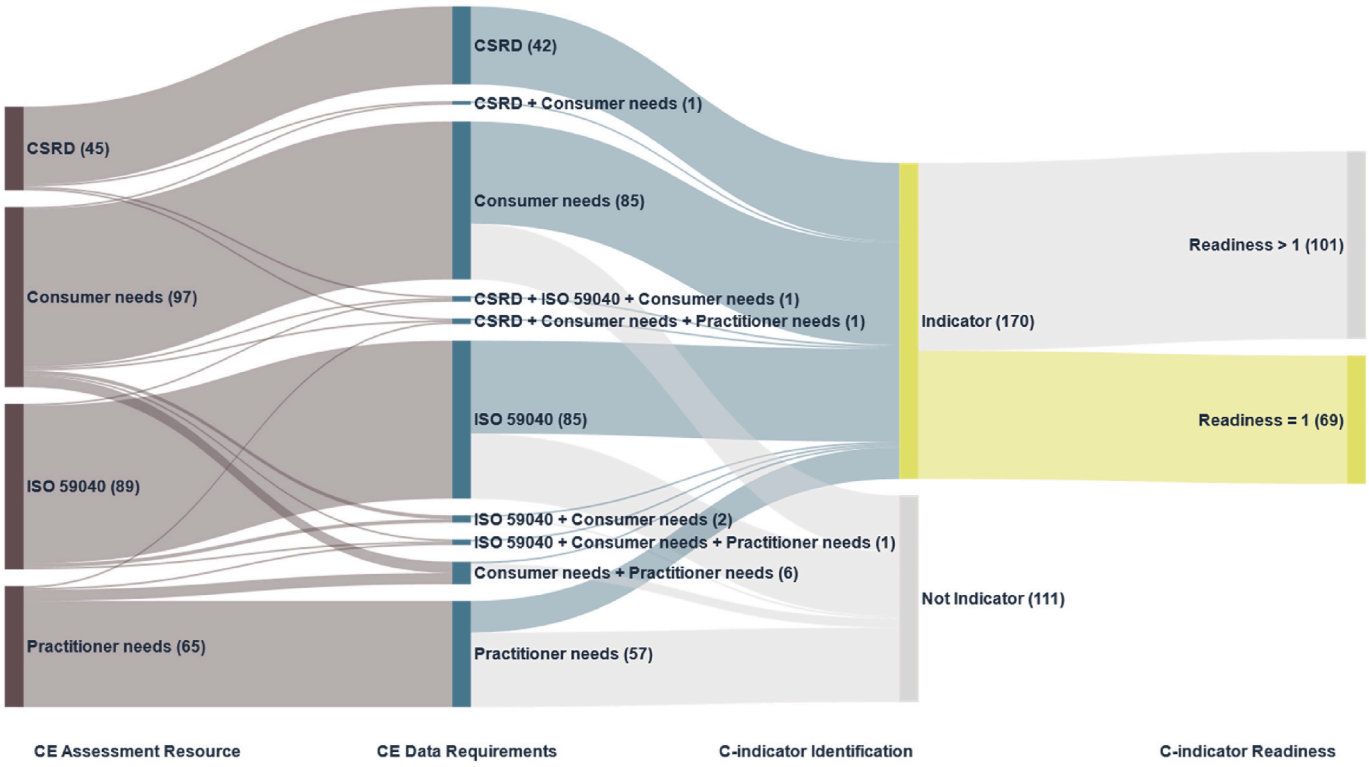


Fig. 7. From CE assessment resources to target c-indicators: filtering and readiness assignment.

dependency structure. An illustrative example is provided for the indicator *"percentage of recycled content in product"*, which can be expressed as:

$$\textit{percentage of recycled content in product} = \frac{\textit{amount of recycled content in product}}{\textit{product weight}}$$

The "*amount of recycled content in product*" is not considered an atomic data point, as it is a derived variable. Unlike "*product weight*", which is a property directly associated with the product and can be directly retrieved from EIS, the amount of recycled content cannot be obtained as a single value, as it requires knowing which are the composing materials of the product, and whether they are recycled. The following decomposition thus follows:

$$\textit{amount of recycled content in product} = \sum_{i=1}^{N} w_i \times 1_{recycled}(i)$$

With:

- w_i, the mass of material i contained in the product
- $\mathbf{1}_{\text{recycled}}(i)$, indicator function equal to 1 if material i is from a recycled source, and 0 otherwise
- N, the total number of materials composing the product

The associated graph of the c-indicator is represented in Fig. 8, with the identification of the c-data points as the nodes with no outcoming edges.

Result 1 – List of c-data points to collect within the organization

The decomposition of the 69 c-indicators resulted in the identification of 91 distinct c-data points required for their computation, which are listed in Table B.2. This constitutes the first result of the approach, allowing the organization to better understand what data they potentially need to collect for the assessment.

Fig. 9 presents the distribution of c-indicators by their number of c-data requirements, along with the most frequently used c-data points across all c-indicators. As shown in Fig. 9 (A), CSRD c-indicators are data-intensive, with 7 of them requiring at least 25 c-data points, substantially more than the other CE assessment resources, which never exceed 4 c-data points. This reflects the broader, company-level scope of the CSRD's requirements. Fig. 9 (B) shows that the most repeatedly used c-data points are weight-related such as the weight of each material composing the product, total product weights, and waste stream weights, reflecting the mass-based nature of most c-indicators in the case study, which are predominantly expressed as functions of weights. Such disparities in data requirements across different CE resources could be challenging for companies to meet. Hence, it is key to examine how data collection strategies could be designed to facilitate their practical implementation.

4.1.4. Phase 4 – Building a data collection strategy

Step 1 – Hypothetical mapping of c-data to EIS

Fig. 10 maps the distribution of c-data points across the organization's EIS and their contribution to c-indicators. The height of each data point indicates the number of indicators it contributes to (left y-axis),

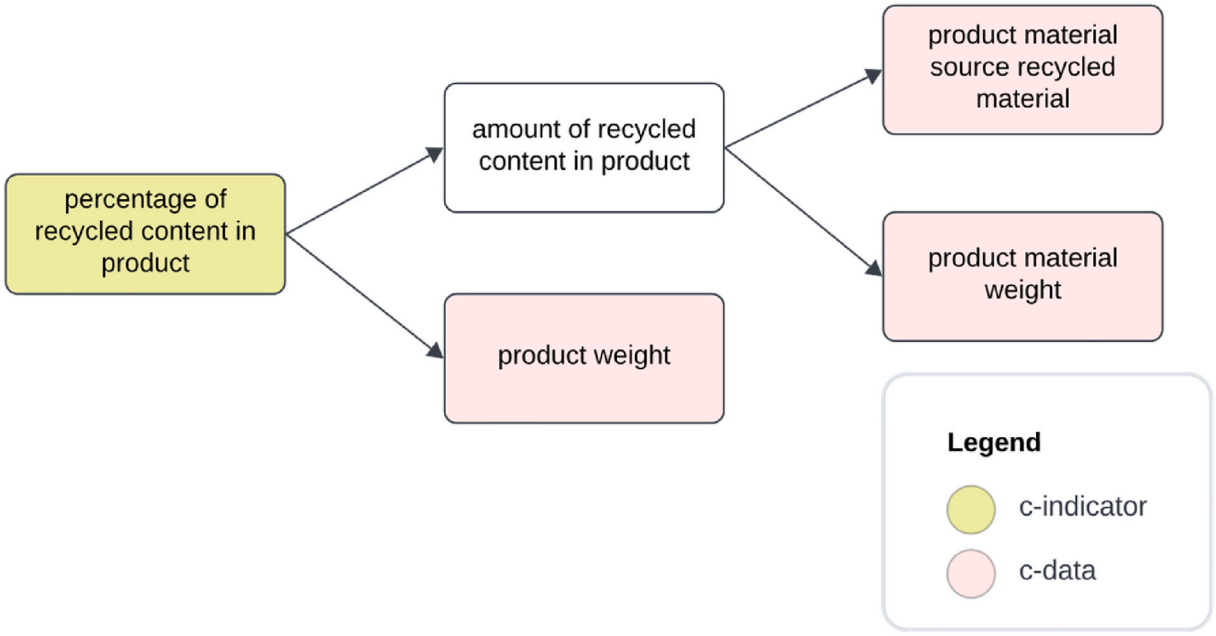


Fig. 8. Dependency graph of c-indicator "percentage of recycled content in product".

while the histogram's height represents the same information at the EIS level (right y-axis). The results show a concentration of c-data in PLM and ERP, which together support 94% of all indicators, i.e., 94% of all indicators need at least one c-data point contained in these EIS. In contrast, systems such as TMS, CRM, CAD, CMMS, SCM, and IoT contribute only marginally. 82% of c-data points are hypothesized to be accessible in more than one EIS, indicating redundant storage or cross-system availability; the remaining 18% are each associated with a single system, making their collection contingent on access to that specific system. To reduce uncertainty in these mappings, the 30 most frequently used c-data points, identified as those contributing to the highest number of c-indicators and therefore positioned highest on the y-axis in Fig. 10, were reviewed and validated with a data engineer.

Step 2 – Modeling EIS access and c-data collection

The binary MILP model is applied to the case study inputs: $|S| = 8$ EIS, $|D| = 91$ c-data points, $|I| = 69$ c-indicators, and $|F| = 4$ CE assessment resources.

Result 2 – Choice of the optimal scenario

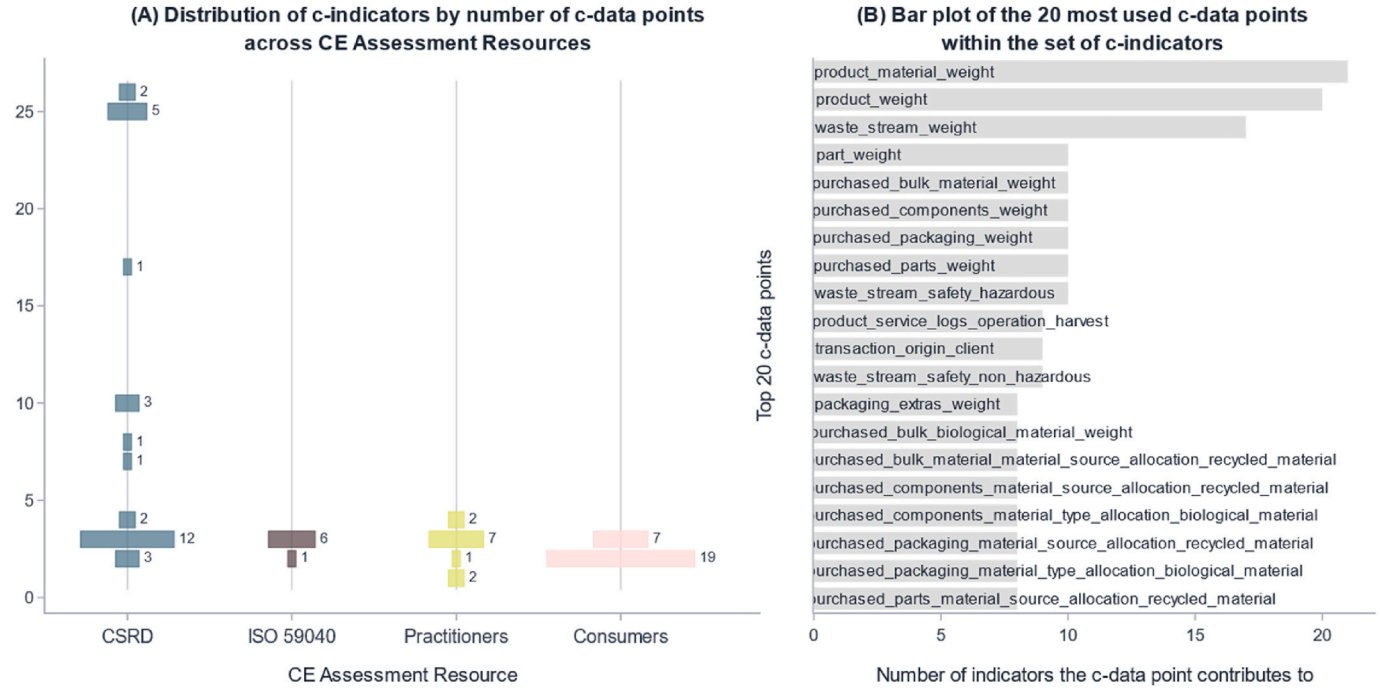


Fig. 9. (A) Distribution of c-indicators by number of c-data points across CE Assessment Resources (B) Bar plot of the 20 most used c-data points within the set of c-indicators.

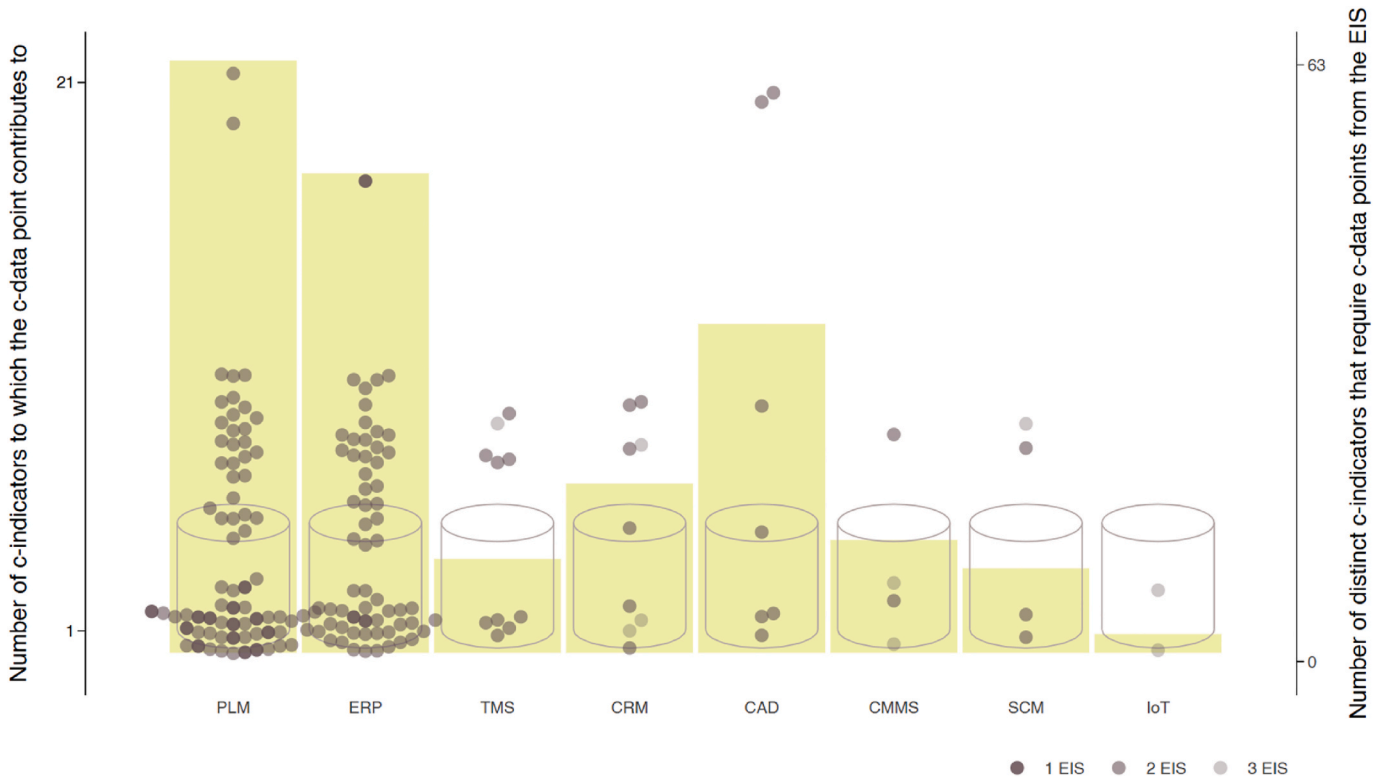


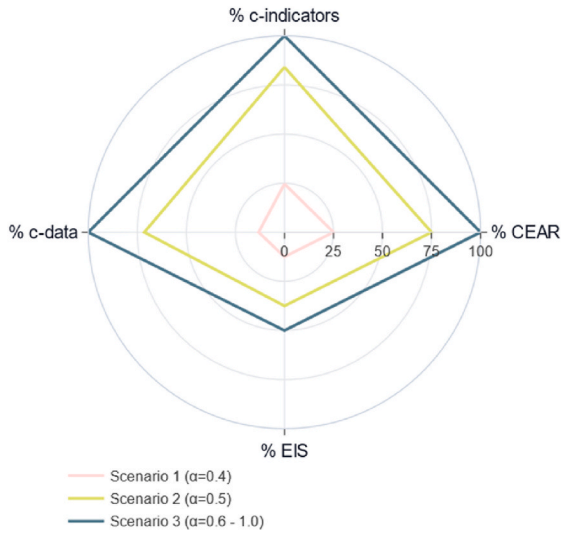
Fig. 10. Illustrative diagram of hypothetical c-data location in the organization's EIS Acronyms – EIS: Enterprise Information Systems, PLM: Product Lifecycle Management, ERP: Enterprise Resource Planning, TMS: Transport Management System, CRM: Customer Relationship Management, CAD: Computer-Aided Design, CMMS: Computerized Maintenance Management System, SCM: Supply Chain Management, IoT: Internet of Things.

The optimization is first run at $\alpha = 0.5$, reflecting equal weighting between CE assessment performance and implementation effort. This scenario is characterized as follows:

- Accessed systems: PLM, CRM, ERP (i.e., 37.5% of available EIS)
- Collected c-data points: 65 (i.e., 71.4% of all data points)
- Computable c-indicators: 58 (i.e., 84.1% of all indicators)
- Fully completable CE assessment resources: ISO 59040, consumer needs, practitioner needs (i.e., 75% of resources)

This result highlights a non-linear relationship between data collection effort and indicator computability. Accessing only three of the eight identified EIS is sufficient to fully compute over 80% of the targeted c-indicators, suggesting the presence of highly informative data sources and redundancy across enterprise information systems. This finding indicates that organizations can prioritize a limited number of high-impact systems to significantly improve assessment coverage while limiting implementation effort.

To examine how alternative configurations evolve with the performance-effort trade-off, a sensitivity analysis is conducted by varying α across [0, 1]. Fig. 11 presents the results as a radar plot and summary table, showing how the number of visited EIS, collected c-data



Scenario	α range	%c-indicators	%CEAR	%EIS	%c-data
Scenario 1	α = 0.4	24.6%	25.0%	12.5%	13.2%
Scenario 2	α = 0.5	84.1%	75.0%	37.5%	71.4%
Scenario 3	α = 0.6 - 1.0	100.0%	100.0%	50.0%	100.0%

Legend

CEAR CE Assessment Resource
EIS Enterprise Information Systems

Fig. 11. Sensitivity analysis of parameter alpha.

points, computable c-indicators, and completion of CE Assessment Resources vary across the range of α. The results yield 3 data collection scenarios.

Additionally, it is notable that not all EIS need to be accessed in the case study, as this indicator never exceeds 50% across all scenarios. Given these results, under conditions of limited time and resources, the organization may prioritize the most constrained scenario, which requires collecting only 13% of the data, relies on a single EIS, and still enables the computation of 25% of the indicators.

To examine how potential errors in the hypothetical mapping of c-data to EIS affect these results, a sensitivity analysis is conducted. Mapping errors are modeled as misplacements and parameterized by an error rate $\in [0,1]$: for each unvalidated c-data point, a proportion ϵ of its mappings is randomly reassigned to a different system, preserving the total number of mappings in the matrix. The 30 most frequently used c-data points, whose mappings were validated with a data engineer, are kept fixed. Three error levels are tested: low ($\epsilon = 0.15$), medium ($\epsilon = 0.50$), and high ($\epsilon = 0.75$). For each error level, 100 Monte Carlo iterations are run for each value of α, the weighting parameter balancing CE assessment effort and performance. This number was determined through a preliminary convergence analysis, which showed that the mean metric values stabilized after 65 iterations. The mean values of the four metrics are computed across iterations and reported in Fig. 12.

Fig. 12 (A) presents the set of baseline scenarios as depicted in Fig. 11. The performed sensitivity analysis allows to investigate three error levels – low, medium, and high – represented accordingly in Fig. 12 (B), (C), and (D). At low error rates, the optimizer continues to identify strategies in which not all EIS need to be accessed to compute all c-indicators, a finding consistent with the baseline result. At higher error rates, the number of EIS accesses increases substantially.

5. Discussion

5.1. Contributions of the proposed approach

This paper addresses the research question: "How can manufacturing organizations operationalize and facilitate CE assessment in a data-intensive environment?". The proposed four-phase top-down approach provides a structured framework, which may guide organizations from clarifying their CE assessment objectives to selecting an optimal data collection strategy within their information systems. To answer the established lack of guidance concerning the data perspective for CE assessment (Roos Lindgreen et al., 2022; Krasikov and Legner, 2023) – the *"what, where, and how?"* – the framework and associated case study illustrate how the approach may help organizations to identify *what* c-indicators are relevant in their context, *what* underlying c-data points

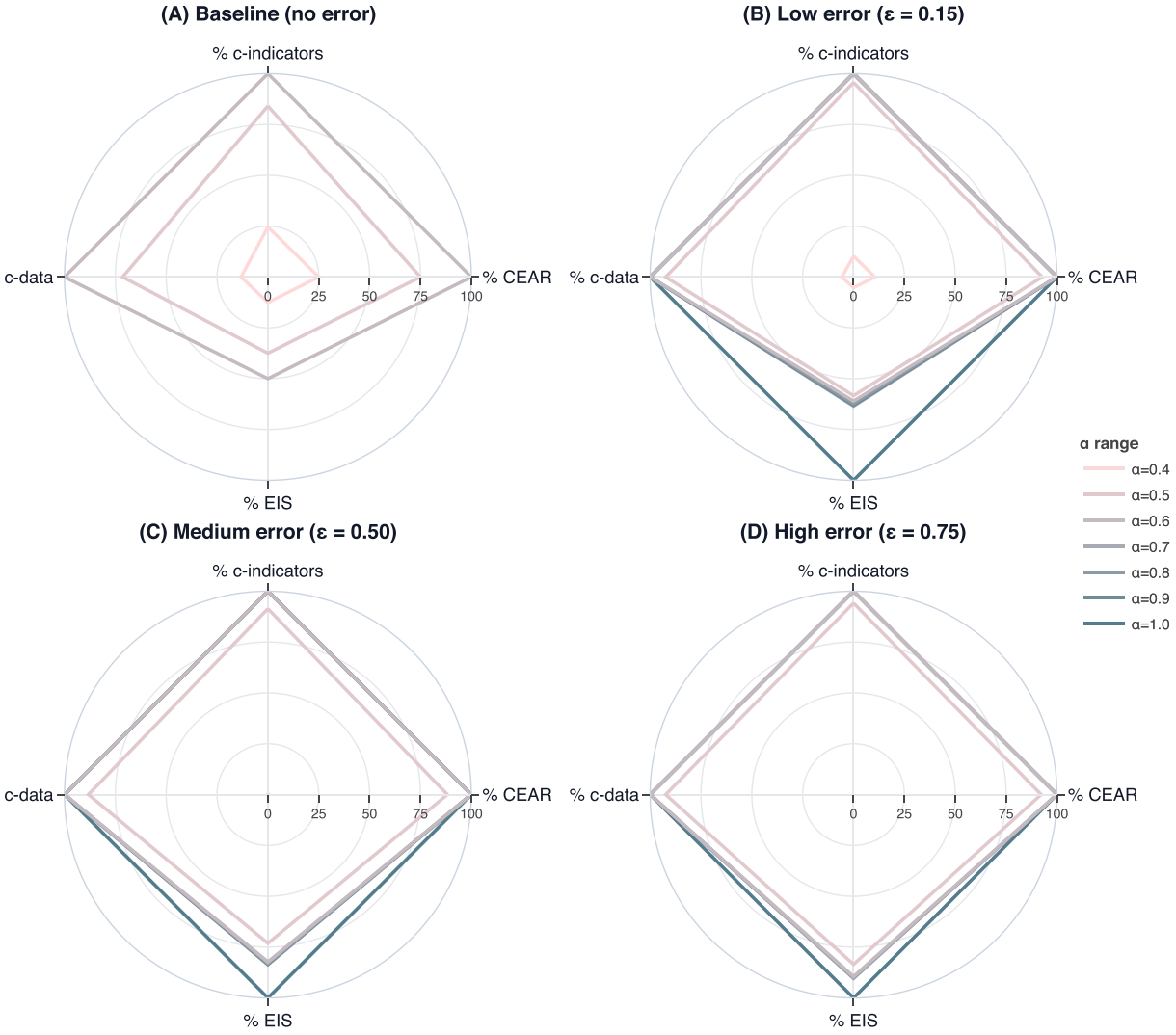


Fig. 12. – Sensitivity of data collection scenarios to c-data to EIS mapping errors (A) Baseline scenario (B) Low error (C) Medium error (D) High error. Acronyms – EIS: Enterprise Information Systems, CEAR: CE Assessment Resource.

are needed, *where* the c-data resides within the EIS, and *how* to tackle data collection. Beyond its core methodological contribution, the paper introduced the c-data concept as a way of distinguishing collectable data points from higher-level c-indicators. The notion of CE data has been explored in the literature, most notably by Araujo et al. (2025), who deconstruct 194 c-indicators from 26 reference frameworks into 334 distinct CE data points organized across eight typological dimensions. Their multi-level structure – framework, indicator, CE data – is conceptually aligned with the present approach. However, two important differences distinguish the c-data concept introduced here from the CE data points identified by Araujo et al. First, their research aims to define a typology of CE data, it fails to provide a systematic method for identifying such data or guidance on data collection in practice. Second, a significant share of their identified CE data points are aggregated values and are considered as c-indicators in the present research. For example, the "Total weight of waste generated", "Number of circular economy jobs created or retained", or "Total weight of recycled materials (secondary raw materials)" lack guidance to be directly computed or reported. This limitation motivates the introduction of the c-data concept, which focuses on granular, collectable data points within a manufacturing supply chain, corresponding to measurable properties or attributes of the products, components, or processes constituting the system of interest.

5.2. Generalizability and scalability

Although the approach was demonstrated in a single industrial case study, it shows several features that support its potential applicability across different contexts. First, the workflow in Phase 2 is designed to accommodate different CE assessment resource corpora (Durivault et al., 2026), suggesting that it could remain applicable as regulatory and organizational requirements evolve. Second, it is indicator-agnostic in principle: the decomposition logic is not tied to any specific indicator set, it may extend to other types of sustainability indicators, including environmental, social, or economic ones, provided they can be decomposed into well-defined data requirements. Third, the optimization model was solved to optimality in the case study, indicating that the approach can be implemented with reasonable computational effort at the scale of a large OEM. However, its applicability depends on several contextual conditions, including the presence of enterprise information systems, access to knowledgeable stakeholders, and the ability to define a consistent system of interest. While the approach can be extended to small and medium-sized enterprises or multi-organizational value chains, such extensions may require adaptations to account for differences in data infrastructure, governance, and data-sharing capabilities (Jäger-Roschko and Petersen, 2022; Neri et al., 2023).

Given the suitability of the proposed framework to data-intensive environments, the approach may also be relevant beyond manufacturing, particularly for waste management organizations. Such organizations play an important role in the CE as they collect, treat and recover end-of-life material flows. In many manufacturing supply chains, they are directly involved in the end-of-life processing of products, components, and materials generated during production and use, playing a key role in reverse logistics and closed-loop supply chains (Mallick et al., 2023). Their data can therefore contribute to circular performance assessment at two levels: the waste management organization's own operations and the broader value chain to which it contributes.

Similar to the focus of the present research, waste management organizations face important data-related barriers (Salmenperä et al., 2021; Zhang et al., 2026). Classification systems record where waste originates and what it is made of, yet omit the quality and contamination attributes that determine whether a material can be recovered, so they reveal little about recovery potential. This shortcoming is reinforced by inconsistent terminology, uneven data quality, and weak interoperability between datasets. The four-phase approach could therefore be adapted to this context. The industrial diagnosis would characterize the organization's SOI: waste streams, treatment facilities, operational processes, and information systems. The sense-making phase would translate relevant regulations, such as the EU Waste Framework Directive (European Commission, 2008) or the CSRD's ESRS E5 (EFRAG, 2024) waste-related disclosure requirements, into structured CE data requirements. Phases 3 and 4 would, in theory, remain similar to the present case study.

Such an extension would require adaptations to reflect the specific features of waste management. These include the multi-actor nature of waste data governance, as they might not have dedicated internal EIS, and have a greater reliance on external data sources, making stakeholder data sharing more critical than in the present case study.

Beyond waste management, the proposed approach may be of interest to a broad range of stakeholders involved in value chains where material and resource flows are managed. Other actors, including remanufacturers, recyclers, and service providers, may also benefit from the ability to link data requirements to c-indicators.

More broadly, the framework may also be valuable for third-party organizations that support circularity assessment and reporting, such as consulting firms and certification bodies. As corporations face increasing reporting obligations toward governmental authorities and policymakers, these intermediaries are becoming increasingly involved in identifying, collecting, and validating the data required for compliance. Applying the approach may facilitate the systematic identification of the data needed to support regulatory reporting while maintaining traceability between data points and reporting requirements. This approach could thus serve as a foundation to develop tools facilitating the anticipation and operationalization of new reporting requirements by leveraging indicators and associated data that are already collected and reported within the organization.

5.3. Limitations and future research

The proposed approach has several limitations that need to be addressed in future research.

Concerning the optimization model, it includes some simplifications that limit its ability to fully capture the complexity of the data collection process. First, the final scenarios rely on data availability assumptions, as the mapping between c-data and EIS is in part hypothetical and may not hold when systems are actually queried. These hypotheses rely on business knowledge but could be enhanced with a hybrid LLM-based approach that leverages context reasoning, considering the names of the data points and detailed descriptions of the organization's EIS. Strengthening the assignment of data points to the EIS would increase the accuracy of the data collection strategy and reduce additional costs and effort.

To assess the effect of this first limitation, the mapping uncertainty analysis conducted in Section 4.1.4 studies how sensitive the resulting scenarios are to errors in the c-data to EIS mapping. At low error rates, c-indicator and CEAR coverage remain consistently high across all values of α, and the optimizer continues to identify strategies in which not all EIS need to be accessed to compute all indicators, a finding consistent with the baseline result. At higher error rates, the number of EIS accesses increases substantially. However, this increase should be interpreted with caution, as the perturbation model does not constrain misplacements to plausible system-data combinations, which may artificially scatter data points across systems and inflate the number of systems the optimizer needs to access. Since the mappings are grounded in structured stakeholder interviews, EIS documentation, and partial validation with a data engineer, lower error rates may better reflect the case study conditions. Therefore, under the current model formulation, mapping uncertainty should be reduced by validating as many mappings as possible before implementation. This can be reinforced by consulting system owners, or by directly querying the EIS to inspect available data fields. This would increase the reliability of the resulting data collection

strategy and provide an empirical basis for defining confidence levels in future probabilistic formulations.

Nevertheless, this analysis suggests directions for future model development. First, the binary mapping assumption could be replaced by a probabilistic formulation, where each mapping is associated with a confidence level based on expert knowledge or system documentation. This would allow the model to account for mapping uncertainty directly in the decision process and generate data collection strategies that consider uncertainty. This formulation could also restrict possible mappings to realistic combinations of systems and data. For example, design-related data is unlikely to be found in a logistics system. This would ensure that uncertainty is modeled within plausible boundaries rather than across all possible system assignments. The model could also be extended using risk-averse models, where the objective function penalizes solutions that are highly sensitive to mapping errors (Cotton and Ntaimo, 2015). This would favor data collection strategies that remain robust under different possible mapping scenarios.

Beyond uncertainty in the mapping matrix, other simplifications concern the objective function. It assumes equal importance across CE assessment resources, although, in practice, organizations may give priority to some requirements over others. For example, assessing circularity in the context of regulatory compliance – for example under the CSRD (European Commission, 2022) – is mandatory, whereas internal practitioner requirements or certification initiatives are voluntary-based. Future versions of the model could introduce priority weights based on regulatory context, time sensitivity, or strategic importance.

On the definition of "effort", EIS access and data collection are weighted equally, although they involve different types of costs. Accessing a new EIS usually involves a one-time organizational and technical cost, while data collection effort depends on the volume and complexity of the extracted data.

Additionally, the model does not account for data ownership or access rights. In practice, data collection depends on who generates, owns, and is authorized to use the data. IT governance constraints may prevent access to certain EIS, even when the data technically exists within them. This limitation is especially relevant in large multinational organizations, where EIS ownership may be distributed across business units, and where data sharing may require formal interdepartmental agreements or legal clearance (Silvola et al., 2011; Vilminko-Heikkinen and Pekkola, 2019). Future work could refine the effort function by distinguishing fixed EIS access costs from variable data collection costs, and by introducing role-based access constraints. In such an extension, the model could distinguish between "data owners", who generate, manage, or control access to a given dataset or EIS, and "data users", who need access to this data for CE assessment.

Regarding decision variables, data collectability is modeled as binary. In practice, however, the existence of a relevant field in an accessible EIS does not guarantee that the required data is available or reliable. The field may be empty, incomplete, inconsistent, or populated only for a subset of products, sites, or time periods. For example, product weights may be recorded for only part of the product portfolio, material composition may be known for more recent products but not for legacy products, and data manually entered by field operators may contain errors or inconsistencies. A further extension could include simulation-based methods to estimate missing data points, allowing c-indicators to be computed even when data is incomplete (Zargar et al., 2022). This would move the current collect-or-not formulation toward a probabilistic one, where the decision to access a given EIS depends not only on the data it contains, but also on how much of this data is available and how reliably missing values can be estimated.

Further limitations concern the approach as a whole. First, it is demonstrated through a single case study in a large OEM. While this provides realistic industrial complexity, it limits transferability to small and medium-sized enterprises or other sectors with different EIS maturity, regulatory context, or resource constraints. Second, Phase 3 focuses on a subset of c-indicators based on a certain level of readiness, which contains a level of subjectivity. While the "readiness-to-assess" of a c-indicator may have high variability depending on the implementer's knowledge and may lead to the exclusion of critical c-indicators, it is important to note that the remaining ones are equally important to consider in future iterations of the approach, as noted in Section 3.1.3. In fact, a single iteration of the approach would not be sufficient to guarantee that the organization has assessed the most relevant c-indicators for their context. In this regard, although organizations have an increased interest in measuring CE due to sustainability reporting obligations (Roos Lindgreen et al., 2022), the resulting assessment should be linked with concrete CE strategies to identify hotspots and facilitate decision-making, contributing to reducing environmental impacts and sustainable manufacturing.

6. Conclusion

This paper explored the challenge of operationalizing CE assessment in manufacturing organizations through the proposal and demonstration of a structured, data-driven approach. The four phases link CE assessment objectives to data collection within EIS, providing a clear pathway from regulatory and organizational requirements to computable indicators. Applied to a radiology system manufacturing case, the case study demonstrated how the approach can be used to systematically identify data requirements, decomposing 69 target c-indicators into 91 collectable data points, while the optimization model identified efficient data collection configurations, showing that a limited subset of information systems can support a large share of indicator computation. The main contribution is the proposal of a workflow intended to help bridge the gap between organizations' growing interest in conducting CE assessment and its practical implementation. By combining sense-making, graph modeling, and optimization, the approach offers an integrated method to support and structure data sourcing practices for CE assessment. However, the approach relies on assumptions regarding data availability, which may limit direct applicability without further validation. Future work should focus on the latter, reinforcing and validating the link between c-data and EIS, and refining the optimization model to better represent implementation constraints, and extending the approach to multi-organizational supply chains where data governance becomes critical. Future research could also explore how the resulting c-data inventory can support the development of internal databases to structure the data, facilitating c-indicator computation, and reducing effort for future assessments.

Funding

This work was supported by GE HealthCare and the French Ministry of Higher Education, Research and Innovation through the CIFRE individual fellowship (grant number 2023/0794).

CRediT authorship contribution statement

Lauren Durivault: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ghada Bouillass:** Conceptualization, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Michael Saidani:** Conceptualization, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Bernard Yannou:** Conceptualization, Funding acquisition, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Abdelhamid Boujarif:** Conceptualization, Data curation, Methodology, Supervision, Validation, Writing – review & editing. **Robert Heidsieck:** Conceptualization, Funding acquisition, Resources, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lauren Durivault reports financial support was provided by GE HealthCare. Abdelhamid Boujarif reports financial support was provided by GE HealthCare. Robert Heidsieck reports financial support was provided by GE HealthCare. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank GE HealthCare and the CircularIT Alliance for their support and for sharing their expertise.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.149110.

Data availability

Data will be made available on request.

References

Acerbi, F., Sassanelli, C., Taisch, M., 2022. A conceptual data model promoting data-driven circular manufacturing. Oper. Manag. Res. 15 (3), 838–857. https://doi.org/10.1007/s12063-022-00271-x.

Ackoff, R.L., 1989. From data to wisdom. J. Appl. Syst. Anal. 16, 8.

Almeida, F.L.F., Calistru, C., 2013. The main challenges and issues of big data management. Int. J. Res. Stud. Comput. 2 (1). https://doi.org/10.5861/ijrsc.2012.209.

Amicarelli, V., Primiceri, M., Misino, E., Bux, C., 2023. An application of the UNI/TS 11820:2022 on the measurement of circularity in an electrical equipment manufacturing organization in Italy. J. Clean. Prod. 420, 138439. https://doi.org/10.1016/j.jclepro.2023.138439.

Araujo, J.B., et al., 2025. A typology for circular economy data. J. Circ. Econ. 3 (1). https://doi.org/10.55845/UXBM6358.

Barros, M.V., Salvador, R., do Prado, G.F., de Francisco, A.C., Piekarski, C.M., 2021. Circular economy as a driver to sustainable businesses. Clean. Environ. Syst. 2, 100006. https://doi.org/10.1016/j.cesys.2020.100006.

Bocken, N.M.P., de Pauw, I., Bakker, C., van der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 33 (5), 308–320. https://doi.org/10.1080/21681015.2016.1172124.

Brint, A., Genovese, A., Piccolo, C., Taboada-Perez, G.J., 2021. Reducing data requirements when selecting key performance indicators for supply chain management: the case of a multinational automotive component manufacturer. Int. J. Prod. Econ. 233, 107967. https://doi.org/10.1016/j.ijpe.2020.107967.

Chae, B. (Kevin), 2009. Developing key performance indicators for supply chain: an industry perspective. Supply Chain Manag. Int. J. 14 (6), 422–428. https://doi.org/10.1108/13598540910995192.

Cotton, T.G., Ntaimo, L., 2015. Computational study of decomposition algorithms for mean-risk stochastic linear programs. Math. Program. Comput. 7 (4), 471–499. https://doi.org/10.1007/s12532-015-0088-0.

Coutinho, V., et al., 2018. Employee-driven sustainability performance assessment in public organisations. Corp. Soc. Responsib. Environ. Manag. 25 (1), 29–46. https://doi.org/10.1002/csr.1438.

Daneshvar Kakhki, M., Gargeya, V.B., 2019. Information systems for supply chain management: a systematic literature analysis. Int. J. Prod. Res. 57 (15–16), 5318–5339. https://doi.org/10.1080/00207543.2019.1570376.

Droege, H., Raggi, A., Ramos, T.B., 2021. Co-development of a framework for circular economy assessment in organisations: learnings from the public sector. Corp. Soc. Responsib. Environ. Manag. 28 (6), 1715–1729. https://doi.org/10.1002/csr.2140.

Duong, A., et al., 2025. Driving carbon neutrality and socioeconomic sustainability through supply chain quality management 4.0: an enterprise information perspective. J. Enterprise Inf. Manag. 1–30. https://doi.org/10.1108/JEIM-04-2025-0249.

Durivault, L., Bouillass, G., Saidani, M., Yannou, B., Boujarif, A., Heidsieck, R., 2026. Bridging the gap between circularity assessment and data governance. Proced. CIRP 140, 251–256. https://doi.org/10.1016/j.procir.2026.05.043.

European Commission and European Financial Reporting Advisory Group (EFRAG), 2023. Commission Delegated Regulation (EU) 2023/2772 of 31 July 2023 supplementing Directive 2013/34/EU of the European Parliament and of the Council as regards sustainability reporting standards [Online]. Available: https://eur-lex.europa.eu/eli/reg_del/2023/2772/oj/eng. (Accessed 18 July 2025).

European Financial Reporting Advisory Group (EFRAG), 2024. Implementation Guidance 3 List of Datapoints - ESRS E5 [Excel]. Available: https://www.efrag.org/en/projects/esrs-implementation-guidance-documents. (Accessed 8 September 2025).

El Bechari, S., Bouillass, G., Yannou, B., Saidani, M., Volanschi, A., Heidsieck, R., 2025. Measuring and enhancing circularity of the healthcare sector: the circularity model of products and spare parts. In: Zimmermann, R., Rodrigues, J.C., Simoes, A., Dalmarco, G. (Eds.), Human-Centred Technology Management for a Sustainable Future. Springer Nature Switzerland, Cham, pp. 217–228. https://doi.org/10.1007/978-3-031-72490-9_21.

El-Gayar, O., Fritz, B.D., 2006. Environmental Management Information Systems (EMIS) for sustainable development: a conceptual overview. Commun. Assoc. Inf. Syst. 17 (1). https://doi.org/10.17705/1CAIS.01734.

Çetin, S., Raghu, D., Honic, M., Straub, A., Gruis, V., 2023. Data requirements and availabilities for material passports: a digitally enabled framework for improving the circularity of existing buildings. Sustain. Prod. Consum. 40, 422–437. https://doi.org/10.1016/j.spc.2023.07.011.

European Commission, 2008. Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives (Text with EEA relevance) [Online]. Available: http://data.europa.eu/eli/dir/2008/98/oj. (Accessed 14 June 2026).

European Commission, 2022. Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) no 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate sustainability reporting (text with EEA relevance) [Online]. Available: http://data.europa.eu/eli/dir/2022/2464/oj/eng. (Accessed 31 January 2024).

European Commission, 2023. Digital product passport [Online]. Available: https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/topic-details/digital-2023-cloud-data-04-digipass. (Accessed 31 January 2024).

European Commission, 2024. Regulation (EU) 2024/1781 of the European Parliament and of the Council of 13 June 2024 establishing a framework for the setting of ecodesign requirements for sustainable products, amending Directive (EU) 2020/1828 and Regulation (EU) 2023/1542 and repealing Directive 2009/125/EC (text with EEA relevance) [Online]. Available: http://data.europa.eu/eli/reg/2024/1781/oj. (Accessed 4 April 2026).

Flowers, J., Hall, P., Pencheon, D., 2005. Public health indicators. Public Health 119 (4), 239–245. https://doi.org/10.1016/j.puhe.2005.01.003.

Frysinger, S.P., 2001. An integrated environmental information system (IEIS) for corporate environmental management. Adv. Environ. Res. 5 (4), 361–367. https://doi.org/10.1016/S1093-0191(01)00087-9.

Fumagalli, L., Macchi, M., Rapaccini, M., 2009. Computerized Maintenance Management Systems in SMEs: a survey in Italy and some remarks for the implementation of condition based maintenance. IFAC Proc 42 (4), 1615–1619. https://doi.org/10.3182/20090603-3-RU-2001.0416.

Geissdoerfer, M., Morioka, S.N., de Carvalho, M.M., Evans, S., 2018. Business models and supply chains for the circular economy. J. Clean. Prod. 190, 712–721. https://doi.org/10.1016/j.jclepro.2018.04.159.

Goddin, J., et al., 2019. Circularity Indicators: An Approach to Measuring Circularity, Methodology. https://doi.org/10.13140/RG.2.2.29213.84962.

Gunasekaran, A., Ngai, E.W.T., 2004. Information systems in supply chain integration and management. Eur. J. Oper. Res. 159 (2), 269–295. https://doi.org/10.1016/j.ejor.2003.08.016.

Hamdy, W., Mostafa, N., Elawady, H., 2018. Towards a Smart Warehouse Management System.

Hoveling, T., et al., 2026. Mapping circular economy product and material flows in healthcare: a visual taxonomy. J. Clean. Prod. 538, 147258. https://doi.org/10.1016/j.jclepro.2025.147258.

ISO, 2024. ISO 59020 [Online]. Available: https://www.iso.org/standard/80650.html. (Accessed 25 July 2025).

ISO, 2025. ISO 59040 [Online]. Available: https://www.iso.org/standard/82339.html. (Accessed 25 July 2025).

ISO 59004 [Online]. Available: https://www.iso.org/fr/standard/80648.html–. (Accessed 16 October 2024).

Jansen, M., et al., 2024. Modelling digital product passports for the circular economy. In: Proceedings of the the 2nd International Workshop on Knowledge Graphs for Sustainability (KG4S 2024). Hersonissos, Greece: CEUR [Online]. Available: https://ceur-ws.org/Vol-3753/paper2.pdf.

Jansen, M., et al., 2025. Designing an ontology network for digital product passports. In: Meroño Peñuela, A., Corcho, O., Groth, P., Simperl, E., Tamma, V., Nuzzolese, A.G., Poveda-Villalón, M., Sabou, M., Presutti, V., Celino, I., Revenko, A., Raad, J., Sartini, B., Lisena, P. (Eds.), The Semantic Web: ESWC 2024 Satellite Events. Springer Nature Switzerland, Cham, pp. 220–237. https://doi.org/10.1007/978-3-031-78955-7_19.

Jensen, S.F., Kristensen, J.H., Adamsen, S., Christensen, A., Waehrens, B.V., 2023. Digital product passports for a circular economy: data needs for product life cycle decision-making. Sustain. Prod. Consum. 37, 242–255. https://doi.org/10.1016/j.spc.2023.02.021.

Jäger-Roschko, M., Petersen, M., 2022. Advancing the circular economy through information sharing: a systematic literature review. J. Clean. Prod. 369, 133210. https://doi.org/10.1016/j.jclepro.2022.133210.

Kahandawa, R., Jayasinghe, R.S., Gomis, K., 2025. CirDEF: standardised information framework to address the information needs of circularity indicators. J. Clean. Prod. 510, 145611. https://doi.org/10.1016/j.jclepro.2025.145611.

Kebede, R., Moscati, A., Tan, H., Johansson, P., 2024. A modular ontology modeling approach to developing digital product passports to promote circular economy in the built environment. Sustain. Prod. Consum. https://doi.org/10.1016/j.spc.2024.05.007.
Keena, N., et al., 2025. Housing passport knowledge graph: promoting a circular economy in urban residential buildings. Sustain. Cities Soc. 119, 106050. https://doi.org/10.1016/j.scs.2024.106050.
Kühn, M., Baumann, M., Volz, F., Stojanovic, L., 2025. Digital product passport design supporting the circular economy based on the asset administration shell. Sustainability 17 (3), 3. https://doi.org/10.3390/su17030969.
Kirchherr, J., Yang, N.-H.N., Schulze-Spüntrup, F., Heerink, M.J., Hartley, K., 2023. Conceptualizing the circular economy (Revisited): an analysis of 221 definitions. Resour. Conserv. Recycl. 194, 107001. https://doi.org/10.1016/j.resconrec.2023.107001.
Krasikov, P., Legner, C., 2023. Introducing a data perspective to sustainability: how companies develop data sourcing practices for sustainability initiatives. Commun. Assoc. Inf. Syst. 53, 162–188. https://doi.org/10.17705/1CAIS.05307.
Kristensen, H.S., Mosgaard, M.A., 2020. A review of micro level indicators for a circular economy – moving away from the three dimensions of sustainability? J. Clean. Prod. 243, 118531. https://doi.org/10.1016/j.jclepro.2019.118531.
Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J., 2020. The smart circular economy: a digital-enabled circular strategies framework for manufacturing companies. J. Bus. Res. 120, 241–261. https://doi.org/10.1016/j.jbusres.2020.07.044.
Mallick, P.K., Salling, K.B., Pigosso, D.C.A., McAloone, T.C., 2023. Closing the loop: establishing reverse logistics for a circular economy, a systematic review. J. Environ. Manag. 328, 117017. https://doi.org/10.1016/j.jenvman.2022.117017.
Mason, S.J., Mauricio Ribera, P., Farris, J.A., Kirk, R.G., 2003. Integrating the warehousing and transportation functions of the supply chain. Transp. Res. Part E Logist. Transp. Rev. 39 (2), 141–159. https://doi.org/10.1016/S1366-5545(02)00043-1.
Matos, J., Martins, C., Simões, C.L., Simoes, R., 2023. Comparative analysis of micro level indicators for evaluating the progress towards a circular economy. Sustain. Prod. Consum. 39, 521–533. https://doi.org/10.1016/j.spc.2023.06.002.
Mecca, B., Gaballo, M., Todella, E., 2023. Measuring and evaluating urban sustainability [Misurare e valutare la sostenibilità urbana]. Valori E Valutazioni 32, 17–29. https://doi.org/10.48264/vvsiev-20233203.
Mendoza, J.M.F., Pigosso, D.C.A., 2023. How ready is the wind energy industry for the circular economy? Sustain. Prod. Consum. 43, 62–76. https://doi.org/10.1016/j.spc.2023.10.016.
Minashkina, D., Happonen, A., 2023. Warehouse management systems for social and environmental sustainability: a systematic literature review and bibliometric analysis. Logistics 7 (3), 40. https://doi.org/10.3390/logistics7030040.
Moraga, G.L., et al., 2019. Circular economy indicators: what do they measure? Resour. Conserv. Recycl. 146, 452–461. https://doi.org/10.1016/j.resconrec.2019.03.045.
Morganti, L., et al., 2024. Data-driven and LCA-based framework for environmental and circular assessment of modular curtain walls. J. Facade Des. Eng. 12 (1), 9–42. https://doi.org/10.47982/jfde.2024.305.
Mulhall, D., Ayed, A.-C., Schroeder, J., Hansen, K., Wautelet, T., 2022. The product circularity data sheet—A standardized digital fingerprint for circular economy data about products. Energies 15 (9), 9. https://doi.org/10.3390/en15093397.
Neri, A., et al., 2023. The role of digital technologies in supporting the implementation of circular economy practices by industrial small and medium enterprises. Bus. Strat. Environ. 32 (7), 4693–4718. https://doi.org/10.1002/bse.3388.
Núñez-Merino, M., Maqueira-Marín, J.M., Moyano-Fuentes, J., Martínez-Jurado, P.J., 2020. Information and digital technologies of industry 4.0 and Lean supply chain management: a systematic literature review. Int. J. Prod. Res. 58 (16), 5034–5061. https://doi.org/10.1080/00207543.2020.1743896.
Nguyen, J., Bouillass, G., Saidani, M., Yannou, B., Graff, P., Ouisse, H., 2024. Applying the building blocks framework for circular economy progress in heavy-duty vehicle manufacturing. In: ICEER 2024 - the 11th International Conference on Energy and Environment Research. Coimbra, Portugal. https://hal.science/hal-04768586. (Accessed 19 December 2024).
Official journal of the European Union. Legislation, 2023. "ANNEX I to Commission Delegated Regulation (EU) 2023/2772 supplementing Directive 2013/34/EU of the European Parliament and of the Council as regards sustainability reporting standards. Off. J. Eur. Union published in the Official Journal of the European Union on 22 December 2023 and including the corrigendum published on 18 April 2024.". https://xbrl.efrag.org/e-esrs/esrs-set1-2023.html#d1e24283-3-1. (Accessed 4 October 2024).
Panagiotidis, K., Tsolakis, N., Tsigkas, A., 2022. Overcoming critical failure factors in enterprise information systems implementation: a viable system model framework for manufacturing firms. J. Oper. Res. Soc. 74, 1670–1689. https://doi.org/10.1080/01605682.2022.2108734.
Park, J., Sarkis, J., Wu, Z., 2010. Creating integrated business and environmental value within the context of China's circular economy and ecological modernization. J. Clean. Prod. 18 (15), 1494–1501. https://doi.org/10.1016/j.jclepro.2010.06.001.
Pibal, S.S., Bittner, R., Kovacic, I., 2025. A BIM-based framework for life cycle, cost, and circularity data integration in environmental impact assessment. Sustainability 17 (6). https://doi.org/10.3390/su17062656.
Pidikiti, V.S., Vijaya, A., Valilai, O.F., Wicaksono, H., 2023. An ontology model to facilitate the semantic interoperability in assessing the circular economy performance of the automotive industry. Proced. CIRP 120, 1351–1356. https://doi.org/10.1016/j.procir.2023.09.175.
Pieroni, M.P.P., McAloone, T.C., Pigosso, D.C.A., 2019. Business model innovation for circular economy and sustainability: a review of approaches. J. Clean. Prod. 215, 198–216. https://doi.org/10.1016/j.jclepro.2019.01.036.
Polenghi, A., Acerbi, F., Roda, I., Macchi, M., Taisch, M., 2021. Enterprise information systems interoperability for asset lifecycle management to enhance circular manufacturing. IFAC-Pap. 54 (1), 361–366. https://doi.org/10.1016/j.ifacol.2021.08.162.
Pomp, A., Jansen, M., Berg, H., Meisen, T., 2023. SPACE_DS: towards a circular economy data space. In: Companion Proceedings of the ACM Web Conference 2023. Association for Computing Machinery, New York, NY, USA, pp. 1500–1501. https://doi.org/10.1145/3543873.3587685. WWW '23 Companion.
Romagnoli, S., Tarabu', C., Maleki Vishkaei, B., De Giovanni, P., 2023. The impact of digital technologies and sustainable practices on circular supply chain management. Logistics 7 (1), 1. https://doi.org/10.3390/logistics7010001.
Romero, D., Vernadat, F., 2016. Enterprise information systems state of the art: past, present and future trends. Comput. Ind. 79, 3–13. https://doi.org/10.1016/j.compind.2016.03.001.
Roos Lindgreen, E., et al., 2022. Exploring assessment practices of companies actively engaged with circular economy. Bus. Strat. Environ. 31 (4), 1414–1438. https://doi.org/10.1002/bse.2962.
Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., Kendall, A., 2019. A taxonomy of circular economy indicators. J. Clean. Prod. 207, 542–559. https://doi.org/10.1016/j.jclepro.2018.10.014.
Salmenperä, H., Pitkänen, K., Kautto, P., Saikku, L., 2021. Critical factors for enhancing the circular economy in waste management. J. Clean. Prod. 280, 124339. https://doi.org/10.1016/j.jclepro.2020.124339.
Sassanelli, C., Rosa, P., Rocca, R., Terzi, S., 2019. Circular economy performance assessment methods: a systematic literature review. J. Clean. Prod. 229, 440–453. https://doi.org/10.1016/j.jclepro.2019.05.019.
Schroeder, P., Anggraeni, K., Weber, U., 2019. The relevance of circular economy practices to the sustainable development goals. J. Ind. Ecol. 23 (1), 77–95. https://doi.org/10.1111/jiec.12732.
Serody, T., Le Duigou, J., Gaha, R., Eynard, B., 2026. Preliminary research work for sustainability assessments integrated within enterprise information systems. In: Mas, F., Del Valle, C., Eynard, B., Rivest, L., Bouras, A. (Eds.), Product Lifecycle Management. PLM in the Age of Model-based Engineering in Industry. Springer Nature Switzerland, Cham, pp. 396–405. https://doi.org/10.1007/978-3-032-09700-2_39.
Shevchenko, T., et al., 2022. Product-level circularity metrics based on the 'Closing–Slowing Future–Past' quadrant model. Sustain. Prod. Consum. 34, 395–411. https://doi.org/10.1016/j.spc.2022.09.024.
Shevchenko, T., et al., 2026. Circular economy in the healthcare industry: developing a circularity assessment tool for complex medical devices. Bus. Strat. Environ. n/a (n/a). https://doi.org/10.1002/bse.70647.
Sileryte, R., Wandl, A., van Timmeren, A., 2023. A bottom-up ontology-based approach to monitor circular economy: aligning user expectations, tools, data and theory. J. Ind. Ecol. 27 (2), 395–407. https://doi.org/10.1111/jiec.13350.
Silvola, R., Jaaskelainen, O., Kropsu-Vehkapera, H., Haapasalo, H., 2011. Managing one master data – challenges and preconditions. Ind. Manag. Data Syst. 111 (1), 146–162. https://doi.org/10.1108/02635571111099776.
The Shift Project, 2025. Décarbonons Les Industries Des Dispositifs Médicaux [Online]. Available: https://theshiftproject.org/app/uploads/2025/11/TSP-Decarbonons-les-industries-des-DM-RF.pdf. (Accessed 13 April 2026).
Vann Yaroson, E., Chowdhury, S., Mangla, S.K., Dey, P., Chan, F.T.S., Roux, M., 2024. A systematic literature review exploring and linking circular economy and sustainable development goals in the past three decades (1991–2022). Int. J. Prod. Res. 62 (4), 1399–1433. https://doi.org/10.1080/00207543.2023.2270586.
Vilminko-Heikkinen, R., Pekkola, S., 2019. Changes in roles, responsibilities and ownership in organizing master data management. Int. J. Inf. Manag. 47, 76–87. https://doi.org/10.1016/j.ijinfomgt.2018.12.017.
World Business Council For Sustainable Development, 2025. Global Circularity Protocol (GCP) for business [Online]. Available: https://www.wbcsd.org/actions/global-circularity-protocol-for-business-gcp/. (Accessed 6 April 2026).
Wienker, M., Henderson, K., Volkerts, J., 2016. The computerized maintenance management system an essential tool for world class maintenance. Procedia Eng. 138, 413–420. https://doi.org/10.1016/j.proeng.2016.02.100.
Xu, L., 2011. Information architecture for supply chain quality management. Int. J. Prod. Res. 49, 183–198. https://doi.org/10.1080/00207543.2010.508944.
Zargar, S., Yao, Y., Tu, Q., 2022. A review of inventory modeling methods for missing data in life cycle assessment. J. Ind. Ecol. 26 (5), 1676–1689. https://doi.org/10.1111/jiec.13305.
Zdravković, M., Panetto, H., Weichhart, G., 2022. AI-enabled enterprise information systems for manufacturing. Enterp. Inf. Syst. 16 (4), 668–720. https://doi.org/10.1080/17517575.2021.1941275.
Zhang, C., Noumbissié, L.T., Zhang, J., Zhang, C., van Ewijk, S., Stegemann, J.A., 2026. Collection and reporting of waste data to support waste management policies. Npj Mater. Sustain. 4 (1), 6. https://doi.org/10.1038/s44296-025-00092-6.
Zins, C., 2007. Conceptual approaches for defining data, information, and knowledge. J. Am. Soc. Inf. Sci. Technol. 58 (4), 479–493. https://doi.org/10.1002/asi.20508.