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Review

Systematic Literature Review on Dynamic Life Cycle Inventory: Towards Industry 4.0 Applications

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Abstract: Life cycle assessment (LCA) is a well-established methodology to quantify the environmental impacts of products, processes, and services. An advanced branch of this methodology, dynamic LCA, is increasingly used to reflect the variation in such potential impacts over time. The most common form of dynamic LCA focuses on the dynamism of the life cycle inventory (LCI) phase, which can be enabled by digital models or sensors for a continuous data collection. We adopt a systematic literature review with the aim to support practitioners looking to apply dynamic LCI, particularly in Industry 4.0 applications. We select 67 publications related to dynamic LCI studies to analyze their goal and scope phase and how the dynamic element is integrated in the studies. We describe and discuss methods and applications for dynamic LCI, particularly those involving continuous data collection. Electricity consumption and/or electricity technology mixes are the most used dynamic components in the LCI, with 39 publications in total. This interest can be explained by variability over time and the relevance of electricity consumption as a driver of environmental impacts. Finally, we highlight eight research gaps that, when successfully addressed, could benefit the diffusion and development of sound dynamic LCI studies.

Keywords: dynamic life cycle assessment; temporal differentiation; temporal; dynamic modeling; real-time

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1. Introduction

Life cycle assessment (LCA) is a quantitative methodology to evaluate the potential environmental impacts related to a product, a process, or a service [1,2]. It can be used to consider the impacts of something that took place in the past, or in a prospective manner to assess potential evolution pathways of a system. In both cases, practitioners tend to make the hypothesis that the system is in a deterministic state, even though this is often not the case. Practically, this leads to work with aggregate temporal averages in all phases of the LCA, something that is highlighted as a limitation of the methodology [3,4]. This is particularly significant for the life cycle inventory (LCI) and life cycle impact assessment (LCIA) phases. To overcome this limitation, dynamic LCA (DLCA) is proposed as a solution to be able to account for the dynamic of systems and for the temporal differentiation for each flow in the technosphere as well as in the ecosphere, which are, respectively, related to the LCI and the LCIA [5].

Industry 4.0, or the fourth industrial revolution, is expected to drive change based on data-driven approaches [6]. Machine learning, additive manufacturing, CAD/CAM, cloud services, big data collection and analysis, sensoring, and digital product–service systems are among the technologies referred to as Industry 4.0 technologies [7]. Various studies address the potential interaction between Industry 4.0 and the sustainability trend. As a matter of fact, even if the original document of Industry 4.0 mentions the LCA methodology, it does not provide guidelines on how to integrate it [6]. Industry 4.0 can present different opportunities for sustainable manufacturing, both at the macro and at the micro level [8]. Both positive and negative impacts on environmental and social sustainability can be expected from Industry 4.0 activities, with the resulting balance often difficult to predict, due to the relevance of the implementation and operational phase [9,10]. An extensive review on the impact of digitalization on environmental sustainability in manufacturing validates this finding [11]. Indeed, a life cycle perspective is seen as necessary to correctly quantify the environmental impact of digitalization in manufacturing [11]. When dealing with Industry-of-Things (IoT) sensors and cyber-physical systems (CPSs) especially, the inclusion of temporally distributed data is one of the common trends within Industry 4.0 technologies. Since LCA is seen as the prominent methodology to quantify potential environmental impacts, DLCA seems to be well-suited for this task. However, there is no consensus on which characteristics a DLCA model would require to fit this application, let alone the consensus on a DLCA model altogether. The majority of DLCA studies include some form of dynamic LCI (DLCI). Sohn et al. [12] report that 70% of DLCA studies contain dynamic flows within the process inventory and that 45% contemplate the change of the unit process [12].

To the best of our knowledge, four literature reviews on DLCA have recently been published. Sohn et al. [12] identify five types of LCA dynamism: dynamic process inventory, dynamic systems, dynamic characterization, dynamic scope, and dynamic weighting [12]. While the first three are assessed in detail as they are used in the literature, the last two are proposed by the authors. Lueddeckens et al. [13] write a systematic literature review that defines and analyzes six temporal issues: time horizon, discounting, temporal resolution of the inventory, time-dependent characterization, dynamic weighting, and time-dependent normalization [13]. Beloin-Saint-Pierre et al. [5] build on the findings of the two previous reviews to propose a standardized glossary for DLCA. The approach of this review is to address temporal consideration based on their purpose and not on predefined classifications of temporal considerations [5]. The purposes of using DLCA are grouped under four classes: the goal and scope definition phase, the system modeling phase, the LCI computation phase, and the LCIA phase [5]. Finally, Su et al. [14] review the assessment models used to conduct DLCA studies of buildings, a widely studied topic due to factors such as the long lifetime of buildings and the importance of carbon storage [14]. The review focuses on eleven dynamic variables to highlight current limitations and to recommend research directions [14]. Both Lueddeckens et al. [13] and Beloin-Saint-Pierre et al. [5] dedicate a detailed section to DLCI, describing the state of the art and current remaining issues. However, none of the four literature reviews tackle how DLCI could be supported from or integrated through Industry 4.0 tools.

In this paper, a systematic literature review is carried out to identify, select, and analyze research studies dealing with DLCI in evolving systems. The aim of the systematic literature review is to answer the following research question: "How is DLCI implemented in the literature, particularly in Industry 4.0 applications?". First, we describe and explain the systematic literature review process, aiming for transparency and reproducibility of the process. Then, we discuss the goal and scope phase, which is the first of the four phases of LCA [1,2], for the selected studies. The discussion serves to understand how the DLCI can be useful to address different purposes. Finally, we analyze the structure of the models used to integrate DLCI. This shows the relevance of the dynamic component in the LCI on key parameters such as the temporal resolution. Even if the focus is on those studies that can implement digital transformation tools, we also consider more traditional studies. This is to provide readers with a fuller picture of the studies on DLCI, which helps locate more robust insights. Therefore, this review aims at supporting life cycle practitioners in understanding the panorama of past studies, analyzing current trends, and identifying potential research gaps.

2. Methods

As this is a qualitative literature review, we adopt the systematic literature review methodology [15]. This aims to ensure the transparency and replicability of the process. The systematic literature review methodology [15] is composed of the following five steps:

- question formulation;
- locating studies;
- study selection and evaluation;
- analysis and synthesis;
- reporting and using the results.

The first four steps are discussed in Sections 2.1–2.4, while the last step is covered in the Results, Section 3.

2.1. Question Formulation

The use of DLCI has grown increasingly popular, yet it is not clear how the differences among the various available methodologies impact their application. Particularly, there is no meta-assessment of the effectiveness of such methodologies in terms of LCA impact reduction. Therefore, the primary question that we aim at addressing with this literature review is: How is DLCI implemented in the literature, particularly in Industry 4.0 applications?

The supporting questions to further analyze the scientific literature on the applications of the DLCI are the following:

1. What are the goals and scopes of the assessed studies?
2. How are existing methodologies able to integrate DLCI in LCA studies?
3. What are the characteristics of the proposed solutions and what are the opportunities for further development?

The first supporting question seeks to report the description of the first phase of LCA studies, the goal and scope [1,2]. This is useful to understand the aims and the case studies that are prevalent in the assessed literature. The second supporting question aims to dive into technical aspects regarding the integration of dynamic components into the LCI. Finally, the third supporting question looks at the differences among the methodologies assessed with the previous supporting questions. To provide useful insights to the scientific community, we discuss the characteristics of the methodologies and opportunities for further development.

2.2. Locating Studies

To identify the relevant scientific publications, we selected the Web of Science Core Collection and Scopus databases. The keywords used in the surveyed literature are not well established and tend to vary significantly depending on the focus of the article, with the most common being variations of the keywords “dynamic”, “temporal”, and “time”. An iterative process is therefore adopted to define and improve the search string, testing the relevance and the number of works connected to a keyword. The final search string is ((“live life cycle assessment” OR “live LCA” OR “shop-floor LCA” OR “shop-floor life cycle assessment”) OR (“life cycle assessment” OR lca OR “life cycle inventory” OR lci) AND (“real time” OR dynamic OR hour*))). The first half of the string contains technical keywords found to be relevant in the literature, i.e., “shop-floor LCA”. The second half of the string then combines common keywords such as “LCA” and “LCI” with three keywords that are used to signal that the study takes into account the temporal dimension.

2.3. Study Selection and Evaluation

Figure 1 describes the step-by-step process of study selection and evaluation. The search string is used with regards to title, abstract, and author keywords sections for the Scopus database, yielding 1963 publications as of 25 February 2022. The search in the Web of Science Core Collection on the same date resulted in 2400 publications. The difference can be attributed to a different database catalogue, as well as to the fact that the search in Web of Science Core Collection is performed as a "topic search", which includes title, abstract, and author keywords as well as the proprietary "KeyWords Plus" sections. The latter are automatically generated by the company that runs the database by scanning the paper and its references to find common phrases and keywords that are not listed in the article itself. Therefore, the total initial number of studies is 4363. No limitations are imposed on the date of publication or on kind of publication (e.g., journal paper, conference proceedings, or book chapter), leaving the assessment of the relevance and the quality of the studies to a further stage. After the removal of duplicates and a first screening of titles and abstracts, we are left with 166 studies for evaluation.

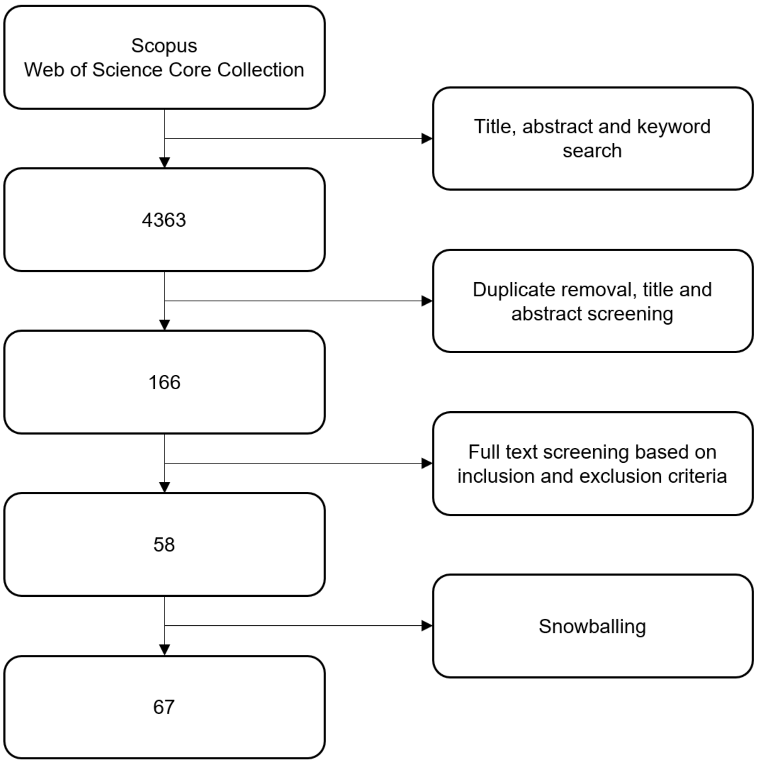

Figure 1. Overview of the sorting, exclusion, and inclusion process followed to obtain the final selection of the literature during the study selection and evaluation step.

However, the detailed aim of this review required a further selection. Therefore, we introduce inclusion and exclusion criteria, summarized in Table 1, to structure a full text screening of the remaining studies. We include studies that focus on dynamic LCI to structure the current understanding in the phase of data collection. Therefore, we limit our search to two of the types of LCA dynamism described by Sohn et al. [12], namely the dynamic process inventory (DPI) and the dynamic systems inventory (DSys). As the names suggests, the former leads to dynamic inventories for single processes, while the latter aims at creating dynamic inventories for the system. The second inclusion criterion stems from the main research question. Studies dealing with DLCI and Industry 4.0 applications should be selected. The third inclusion criterion wants to include previous literature reviews on dynamic LCA because, even if they would fail the second criterion, they are useful to understand the scientific landscape for the subject. The first exclusion criterion is a consequence of the first inclusion criterion. In the second exclusion criterion, the cut-off for the smallest temporal resolution is set at 1 year. This value would mostly lead to a more precise accounting, rather than to insights for LCA impacts reduction for existing systems.

Table 1. Inclusion and exclusion criteria used for selecting the studies.

Inclusion Criteria	Exclusion Criteria
Focus on DLCI Involvement of Industry 4.0 applications Literature review on DLCA	Focus on dynamic LCIA The smallest temporal resolution of DLCI is 1 year or more

To conclude, nine studies are added in the snowballing step, bringing the final number of studies under consideration for this review to 67. In this step, studies are searched within the references of the selected studies, within Google Scholar profiles of the first authors, and within publications published in the current special issue.

2.4. Analysis and Synthesis

To analyze the reviewed literature, we define the following data extraction forms for each publication:

- Bibliographic information:
  - Title;
  - Authors;
  - Year of publication;
  - Journal;
- Goal and scope of the study:
  - Goal;
  - Type of the assessment: retrospective, scenario analysis, or forecast;
  - Static or continuous data collection;
  - Attributional or consequential modeling;
- Integration of dynamic LCI:
  - Modeling: white-box, gray-box, or black-box;
  - Dynamic component in the LCI;
  - Temporal resolution.

Data extraction forms are defined by iteration with the aim of providing meaningful, coherent, and reproducible knowledge that should help in answering the research questions. To do so, the gathered knowledge is described, analyzed, and discussed throughout Section 3.

Figure 2 describes the growing interest with time in the subjects related to dynamic LCI, while also differentiating by scientific journals and conference proceedings. Indeed, the distribution of publications among the reviewed literature by year of publication shows a clear increasing trend. The years 2012, 2014, and 2020 are the only ones in which this trend is not verified. We argue that this variability can be explained by the natural volatility of the rhythm of the publication process. With regard to the year 2014, we should highlight that 3 papers published that year are part of a thematic special issue by the International Journal of Life Cycle Assessment.

Figure 3 shows that the International Journal of Life Cycle Assessment and the Journal of Cleaner Production account for the largest number of reviewed publications, both with 8. Procedia CIRP and Science of the Total Environment host 4 publications each, while other well-known names to the LCA community such as Applied Energy, Journal of Industrial Ecology, and Sustainability contribute with 3 articles each. However, 34 publications, or 51% of the total, are part of the category “Others” since they are hosted by journals, proceedings, or book chapters that contributed with only 1 or 2 publication(s).

According to Google Scholar, in April 2022 63% of the selected publications had more than 10 citations. As expected, most of the publications that do not reach this threshold were produced in the last few years. Moreover, 49% of the publications have at least 20 citations and 18% surpass the 50 citations threshold. Finally, only 5 publications collect more than

100 citations, helped by a relatively early publication date and by highly researched case studies such as electric cars [16–19] and IoT [20].

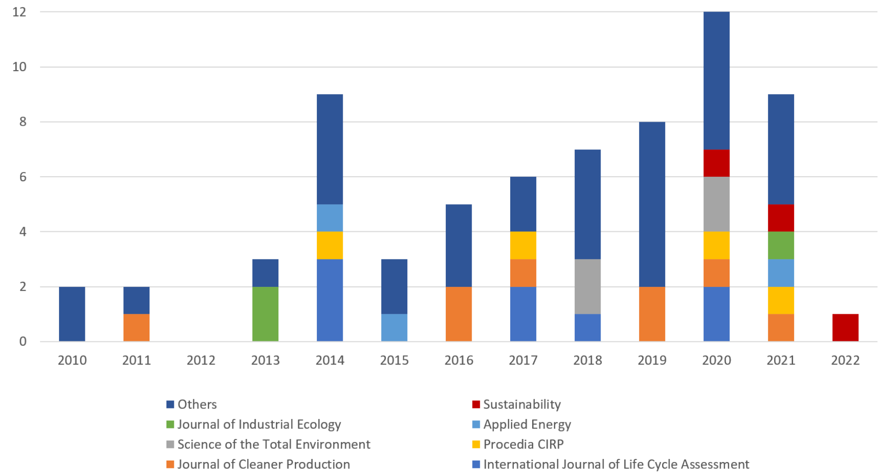

Figure 2. Distribution of the reviewed literature by year of publication and among scientific journals and conference proceedings. Journals, proceedings, and book chapters with 1 or 2 contribution(s) are assigned to the category 'Others'.

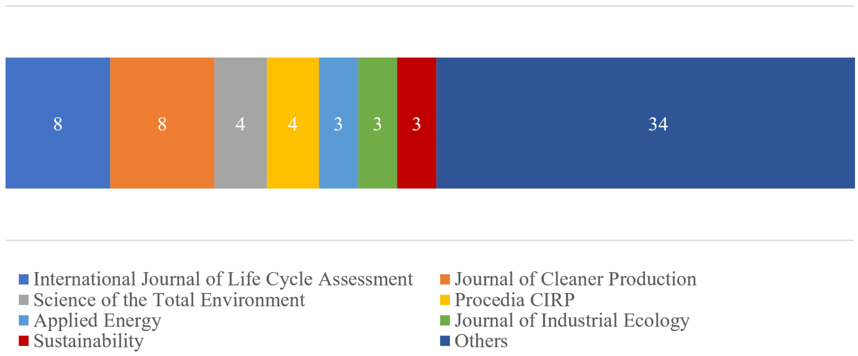

Figure 3. Distribution of the reviewed literature among scientific journals and conference proceedings. Journals, proceedings, and book chapters with 1 or 2 contribution(s) are assigned to the category 'Others'.

3. Results

In Section 3.1, we analyze and discuss the literature relative to the goal and scope phase based on two classifications. In the first classification, we consider whether assessments can be considered retrospective, scenario analysis, forecast, and the relationship to the data collection process. In the second, we provide six more detailed classes for the goal of each publication, while taking into account the choice between attributional and consequential LCA. This section should help LCA practitioners aiming to develop DLCI projects to find projects that could be relevant due to goal and scope similarity.

While Section 3.1 deals with the "what" and "why" within the reviewed publications, Section 3.2 focuses on the "how". Section 3.2 aims at describing the existing methodologies employing DLCI, which components of the LCI are considered dynamic, and what temporal resolution is adopted in each study. Therefore, this section supports LCA practitioners aiming to develop DLCI projects looking for a more technical understanding. While other classifications might have been pursued, e.g., by sectors of the economy that are involved, we believe that the dynamic component in the LCI and the temporal resolution provide more immediate insights and are better at highlighting the most relevant studies.

Finally, Section 3.3 summarizes the research gaps that are found throughout this literature review. Therefore, this section should be useful for researchers who are interested in understanding which are the future research needs we have identified.

3.1. Goal and Scope

In Table 2, studies are classified for the goal of using a DLCI in three kinds of alternative assessments: retrospective assessments, scenario analyses, and forecasts. Depending on the chosen temporal scope, retrospective assessments can include periods of time that are in the future compared to the time of the assessment. Retrospective studies assess past or current systems as they are, while scenario analyses typically rely on what-if simulations, which diverge from the past course of events. Furthermore, unlike scenario analyses, forecasts aim to predict elements of the assessed future.

For each of the three types of assessments, the studies are divided between two alternative categories regarding the data collection. The first category uses previously collected DLCI data. They are not necessarily related to the past but they are already fully available at the time of the assessment. In the second category, DLCI data are continuously collected and so they are not fully available at the beginning of the assessment. Since the focus is on case studies rather than meta-studies, the four literature reviews are not included in this classification.

Firstly, the majority of studies, 37 out of 63 publications, deal with retrospective assessments. These are either methodological publications [21–23] or focus on determining the dynamic environmental impacts of a system as it is [16,24,25]. The development of DLCI methodologies is crucial, and so is the dynamic assessment of systems which could lead to a bottom-up approach for a fully dynamic LCI database, rather than the top-down approach used by Pigne et al. [26]. These publications might not be at the center of attention for researchers aiming to develop DLCI models for Industry 4.0 applications, yet we consider them in the review to provide a fuller description of the literature.

Of these 37 publications, 10 deal with continuously collected DLCI data. The manufacturing field is represented by various publications regarding personalized furniture manufacturing [27], a generic shop floor [4,28], injection molding [29], grinding [30], and ceramic tile production [31]. The relative overrepresentation of manufacturing case studies in the continuously collected DLCI data category can be attributed to the focus that this sector has received in Industry 4.0 initiatives [6]. Consequently, we can assume that sensors used for relevant data collection are more widely adopted than in other sectors. Nonetheless, case studies in this category include power plants [32], a generic enterprise case study [20], and solar photovoltaic systems [33]. Of these 10, eight are conference proceedings and only two are journal articles [30,31]. Therefore, some of the publications keep the description of the models at a high level [20,29,33]. Others, even if they are more detailed, omit key information such as choices regarding allocation [4,31]. The only submitted supplementary data allow for the reproduction of results, but no code is available to reproduce the overall experiment for other case studies [30].

Table 2. The relationship between the type of the assessment (rows) and the data collection period in time (columns).

Type of Assessment	Previously Collected DLCI Data	Continuously Collected DLCI Data
Retrospective	[16–19,21–26,34–50]	[4,20,27–33,51]
Scenario analysis	[52–69]	[70–72]
Forecast		[73–77]

Secondly, 20 publications have as a goal the assessment of scenario analyses. Here, hypotheses are tested by changing key parameters in the model. Examples span from electric vehicles charging scenarios [52], cost-optimized lithium-ion battery management [56], and configuration changes in a manufacturing process [59], to future energy system optimization [62,65]. A particular case of scenario analysis limits the change among scenarios to the temporal differentiation parameter, leaving the product system parameters constant [67].

Only three publications use continuously collected DLCI data to perform scenario analysis [70–72]. Curiously, one of them is the oldest publication among those describing continuous data collection [70]. Here, MTConnect enables continuous data collection from the shop floor, which is then used as input to discrete event simulation models [70]. The aim is to project DLCI data and consequently environmental impacts, similarly to what Rodger et al. [64] envision without the continuous data collection. The second publication assesses four environmental indicators for the hourly electricity consumption in France [71]. These are then used to assess the environmental performance of demand-side management programs, finding that including a carbon price in the assessment might improve the performance [71]. The third publication of this group allows for both retrospective assessments for certification purposes and scenario analyses [72]. The user can therefore visualize LCA results across months of data, analyzing contributions toward the impact of a product within a timestep and over time as well as the impact of a selected driver across impact categories [72]. In the scenario analysis, the user can test the effectiveness of an action towards impact reduction goals over time and across impact categories [72].

Lastly, four papers use continuously collected DLCI data to make forecasts. They adopt machine learning to forecast the electricity technology mix [73] or the environmental impact of electricity consumption [74,76,77] of the following day. Even if these papers mainly aim to demonstrate the potential benefits of future applications using previously collected DLCI data, such applications would require continuously collected data. Indeed, the forecast window would shift and the machine learning models would be retrained to include new data on a daily basis.

A different classification of the goals found in the literature is detailed in Table 3. A more precise description of each goal is provided during the description and discussion of Table 3, later in this section. Even though some goals overlap with the findings of Table 2, they do so only partially. For example, goal 5 only partially overlaps with the continuously collected DLCI data category that we previously discussed. For each goal, we differentiate publications based on the chosen framework: attributional, consequential, or both attributional and consequential. Attributional LCA assesses the potential environmental impacts of a product or service system [78]. Consequential LCA assesses the potential environmental impacts due to a small change in demand for the studied products and system boundaries only include those activities that react to such change [79]. The number of papers referenced is not 63 as this classification is not exclusive, so publications can have more than one goal. Literature reviews are not included in this assessment, as they would cover most goals. Therefore, no publications were found to have more than two goals.

Table 3. The relationship between the goal classes (rows) and the choice of attributional or consequential modeling (columns).

Goal Classes (# of Papers)	Attributional	Consequential	Both
1. To assess the dynamic environmental impact (19)	[18,19,23,38,40–42,44,47,50,53–55,61,71]		[16,39,48,69]
2. To assess the dynamic environmental impact for optimization (15)	[30,32,59,64,73–76]	[24,43,49,56,77]	[57,69]
3. To compare static and dynamic assessments (15)	[22,25,26,35,45,46,51,62,67,68]	[34,65]	[21,36,57]
4. To assess the dynamic environmental impact of future scenarios (13)	[52,58,60,62–64,70,72–74,76]	[65,77]	
5. To explore the potential of sensors to automate the inventory analysis phase (12)	[4,20,27–33,51,70,72]		
6. To compare the dynamic environmental impact of different product systems (3)	[17,37,66]		

The more publications deal with a goal, the higher the goal is in the list. The difference in publication number between the first and the third goal is only four, depicting a fair distribution of goals within the literature. Goals 4 and 5 are less common, with only 13 and 12 publications, respectively, and even less so is goal 6, which is limited to three publications.

Goal 1 is the most generic of the classification, as it groups publications that are not aligned with the other, more specific goals. Due to the inclusion and exclusion criteria used in this systematic literature review, all publications use DLCI. Moreover, all publications in this goal use attributional modeling. Some studies aim at assessing the dynamic environmental impact of a product system such as integrated urban water systems [38], electric vehicles [18,53], residential buildings [54], power-to-X technologies [61], or solar photovoltaics [63]. Other publications put less focus on the case study and on the dynamic assessment results and more on the methodological approach that is developed. Examples span from a sensitivity analysis on the temporal resolution [55] to agent-based modeling of a biomass supply chain [41] to a computational tool for DLCI [23]. Further discussion on these methodological publications can be found in Section 3.2. Both attributional and consequential approaches are used with regard to goal 1 for the modeling of different electricity systems on an hourly basis, which are then applied to electric car charging in Portugal [39] and in the USA [16] as well as to space heating in buildings in France [48].

To be included in this goal 2 class, publications need to clearly describe how insights gained with DLCI could be used to pursue environmental impact reductions. Indeed, some publications state among their aims the definition of a sustainability-based optimization, but when the optimization is left as a proof of concept these works are excluded from goal 2 [4,27]. Within goal 2, nine publications use attributional modeling and seven use the consequential one, the most of any goal class. This is understandable, given the need to understand potential unforeseen consequences of decisions aimed at reducing environmental impacts. Still, some publications propose strategies, based on attributional modeling, to reduce environmental impacts based on hotspot identification [30], fuel purchasing and operational strategies [32], discrete-event simulation of manufacturing systems [59,64], decision support for material and process innovation [40], as well as shifting production towards hours that are forecast to have a less impacting electricity mix [73,74,76]. Considering consequential LCA publications, a trade-off between different optimization objectives, such as water consumption and the impact on climate change, is quantified in the case of an industrial wastewater treatment system [24]. Moreover, shifting electricity demand based on forecast marginal hourly electricity mixes is proposed for energy storage systems [56], cloud computing [43], data centers [49], demand-side management [69], and generic electricity consumption [77].

Two thirds of the publications in the goal 2 class deal with a single optimization objective: reduction in energy consumption [75] or reduction in climate change impacts [32,43,49,56,64,73,74,76,77]. By doing so, these publications ignore the risk of potential burden shifting, which happens when impacts are reduced in one impact category but increased in one or more others. Multi-objective optimizations deal with relevant flows and midpoint impact indicators such as monthly electricity use, electricity use per produced bearing unit, monthly climate change impacts, and climate change impacts per produced bearing unit in the case of Lofgren et al. [59]; climate change impacts and water consumption in O′Connor et al. [24]; and 11 midpoint impact categories from the Environmental Design of Industrial Products 97 (EDIP 97) [80] in Filleti et al. [30]. In the case of net-zero energy buildings, a multi-objective optimization focuses on two indicators: construction costs and impact on climate change [57]. The temporal demands for electricity and heating are optimized to reduce impacts on climate change. While the difference between optimums obtained with a static LCA and a dynamic attributional one is found to be minor, they become more relevant when dynamic consequential and attributional optimums are compared [57]. Finally, in the study by Walzberg et al. [69] the multi-objective optimization deals with four endpoint impact categories. However, the use of endpoint impact categories is not recommended for comparison tasks, implicit in optimization studies, because trade-offs and burden shifting within an endpoint impact category cannot be tracked [81].

A common objective in the literature is the comparison of the environmental impacts of a product system using static and dynamic LCIs, classified under goal 3. This is often used to justify the added complexity of a dynamic study against the traditional static LCA [46]. The need for such a demonstration is exacerbated by the fact that ISO standards do not cover dynamic assessments [1,2], which might increase the perceived arbitrariness of dynamic LCA results. Olindo et al. [45] argue for the need for DLCI to assess systems such as battery electric vehicles and electrolytic hydrogen, while highlighting the limitations of guarantee of origin and residual electricity mix [45]. DyPLCA is a tool to extend the temporal differentiation to the whole LCI, based on ecoinvent 3.2 [26]. This top-down approach can help to solve issues with DLCI, which is typically temporally differentiated in the sole foreground system. Based on the same original model, [23], Shimako et al. [67] perform a sensitivity analysis on parameters such as the temporal resolution of different impact categories [67]. Electricity systems are again at the center of the case studies in two publications that employ both modelings under goal 3 [21,36]. Here, the discussion verges on the how and why each modeling approach should be used, while at the same time dealing with the choice between a static and a dynamic study. In the Italian case, hourly marginal electricity mixes obtained with the consequential approach vary more than average hourly electricity mixes [21]. However, hourly marginal electricity mixes are suggested for applications regarding buildings with variable electricity demand [36] and demand-shifting applications in general [21]. Other methodological articles that are included in this publication will be further discussed in Section 3.2.

Publications classified under goal 4 deal with the assessment of the environmental impacts of future scenarios, relative to the time of the assessment. Depending on the goal and scope of the study, the assessment can continue for hours, days, or decades. It is important to mention that this is not strictly correlated to the time horizon that is chosen in the LCIA phase, which is less variable. Rather, it is related to the temporal scope, which is usually linked to the life cycle of the product [5]. However, the temporal scope is usually limited to the short-term for discrete event modeling of manufacturing systems [64,70], but it can span to the medium-term [72] and long-term for assessments that consider larger and slower changes. For example, in the case of the assessment of the penetration of electric vehicles in the Italian fleet, the temporal scope lasts until 2030 [65]. Therefore, the temporal scope should be carefully chosen depending on the the goal of the study and to minimize cut-offs due to this choice. Moreover, it is common for continuously collected DLCI data studies to see the temporal scope of the study shift with time [73,74,76].

Publications classified under goal 5 investigate the potential of IoT and sensorization to automate the DLCI data collection. Due to the extensive time and costs required for the traditional LCI phase, being able to automate the most relevant sections could bring significant benefits [4]. As noted in the previous classification regarding continuous DLCI data collection, manufacturing case studies are well represented [4,20,27–31,51,70,72]. It is worth mentioning how Barni et al. [27] suggest the development of a digital twin based on real-time data collection, which can support decision making and in particular drive sustainability-aware decisions [27]. Majanne et al. [32] apply DLCI modeling to the monitoring of the environmental impacts of monitored power plants [32]. A deeper dive into the methodologies of the publications under this goal can be found in Section 3.2.

The comparison of the dynamic environmental impacts of different product systems, which fulfill similar functions, is present in three articles only, as classified in class 6. Di Florio et al. [37] compare two cogeneration systems linked to thermal energy storages [37]. While daily and seasonal variability of the DLCI is presented and discussed, the comparison of environmental impacts between the systems is between seasonal averages. To test the robustness of the results, four Monte Carlo simulations, one for each season, are carried out [37]. Faria et al. [17] perform a comparative DLCA among gasoline, diesel, hybrid electric vehicles, and battery electric vehicles [17]. Comparisons of environmental impacts are made using yearly and monthly averages, without discussing the distribution of the environmental impacts within each year or month. Finally, Shahraeeni et al. [66] compare diesel and natural gas for light duty trucks using static results [66].

About 78% of the case study publications, 49 out of 63, use attributional LCA, seven choose the consequential approach, and seven publications adopt both of them. Notably, no publication uses consequential modeling under goals 5 and 6. This is understandable for goal 5, as in these publications the automation of the data collection is described but the focus is not on the decisions that new available data could enable. However, a consequential assessment of the use of one technology rather than another, as is investigated under goal 6 publications, would seem preferable to support a more robust choice among the alternatives.

3.2. Integration of Dynamic Life Cycle Inventory

In this section, we analyze the different strategies that are found in the literature to integrate a DLCI into LCA studies. To conduct this analysis, we use three of the data extraction forms described in Section 2.4, namely the modeling, the dynamic component in the LCI, and the temporal resolution. When considering the three data extraction forms concurrently, we are able to shed light on how previous studies have dealt with specific problems. Finally, we describe the methodologies that, for different reasons, could be relevant for practitioners working with DLCI.

The modeling is divided in three exclusive categories, namely white-box, gray-box, and black-box [82]. White-box models, such as most LCA studies, are fully explainable and interpretable, meaning that results are obtained through known functions of the inputs [82]. Therefore, the dynamic flows are synthesized and modeled into fixed equations with the aim of representing their temporal variability. As with every white-box model, the abstraction due to the use of fixed equations might lead to lack of precision in the results, especially when the model is not robustly validated. Black-box models such as machine learning are not explainable and interpretable, so it is not possible to reproduce step-by-step how the inputs are used to result in the outputs of the model [82]. Machine learning is increasingly popular for a multitude of tasks, due to the growing availability of data and computational power, and is touted as being able to support environmental issues in various ways [83]. Gray-box models are a combination of the theoretical structure of white-box models and of the data-driven approach of black-box models.

The dynamic component of the LCI, the second data extraction form used in this section, is relevant as it provides a more detailed picture than the overall case study. This focus helps to identify which processes or sub-systems vary with time, as most publications do not have a fully dynamic LCI. The third data extraction form is the temporal resolution used in the DLCI. Of particular interest is its link to the dynamic component for the LCI, as it can be a suggestion to practitioners on how to deal with a specific problem.

In Table 4, the modeling is the means by which the dynamic feature is integrated in the study. In 57 publications, or about 93% of the reviewed literature, after the exclusion of the four literature reviews, a white-box model is chosen. Cornago et al. [73] is the only study to deploy a gray-box modeling approach [73]. The objective function of the machine learning models, the black-box component, is the electricity production of each technology present in the local mix. The machine learning models are deep neural networks, which use as input the electricity production of each technology from the previous day. The forecasts are then linearly combined with their respective LCA impact in the white-box component, to obtain the hourly LCA impact of the electricity mix [73]. Black-box models found in the literature deal with the same forecasting problem, but choose a strategy called direct forecasting [73], as it does not require a subsequent linear combination. Indeed, the objective of the machine learning models in black-box studies is the hourly LCA impact of the electricity mix [74,76,77], as well as electricity consumption [74,76]. The inputs of the forecasting models are similar in nature to those by Cornago et al. [73]. However, machine learning models vary from a neural network that counts two layers of long short-term memory (LSTM) cells followed by a layer composed of a linear output neuron [74,76] to a support vector machine [77].

Electricity consumption, electricity technology mix, and the combination of the two represent the largest share for the dynamic component in the LCI within the selected literature, contributing 4, 13, and 22 studies, respectively. This can be traced to the relevance that electricity consumption has as a driver of LCA impacts, as well as the maturity of electricity meters and the variability of the environmental impacts of electricity mixes. Considering the current trend of electrification of various sectors of the economy, most notably in the automotive sector, the attention seems like a good bet.

Table 4. Modeling, dynamic component in the LCI, and temporal resolution in the literature.

Modeling	Dynamic Component in the LCI	Temporal Resolution	References
White-box	Electricity consumption	0.5 h	[56]
		1 min	[28]
		Not available	[64,75]
	Electricity technology mix	1 h	[19,21,34,43–45,48,57,61]
		Not available	[29,59]
	Electricity consumption and technology mix	0.5 h	[71]
		1 h	[16–18,25,36,37,39,42,47,49,50,52–54,58,63,65,68,69]
	Foreground system	1 s	[51]
		10 s	[32,70]
		1 h	[38,62]
		1 year, 1 month, 1 day depending on the impact category	[55]
		1 month	[31,72]
		Not available	[4,20,27,30,33,40]
	Product life cycle system	0.5 day up to 1 year	[67]
		1 year but the methodology can work with temporal resolutions of at least 1 s	[22]
		Not available	[23,26,46]
	Technology mix	1 day	[60]
	Water flow	1 h	[24]
	Biomass quality	1 month	[41]
	Dummy case study	1 month	[35]
	Vehicle fleet operation/municipal drive cycle	Not available	[66]
Gray-box	Electricity technology mix	1 h	[73]
Black-box	Electricity technology mix	1 h	[77]
	Electricity consumption and technology mix	1 h	[74,76]

However, a more holistic approach that extends the dynamic components in the LCI as much as possible should be preferred, and it should be made possible with a wider data collection. A choice adopted by 13 publications is to consider as the dynamic component all flows that are part of the foreground system, which are those that can be measured and controlled. This solution is adopted predominantly by manufacturing case studies, where a gate-to-gate perspective is common [30,70].

Even more comprehensive is to use a fully dynamic LCI, where the whole product life cycle system is dynamic. Three methodologies, all white-box models, are developed to manage the computation of fully dynamic LCI [22,23,35]. They are designed in a way that can be integrated with a dynamic LCIA.

Firstly, the enhanced structure path assessment (ESPA), which extends structural path analysis, is a widely known technique in input–output analysis [35]. It makes use of power series expansion to solve the dynamic inventory, and the matrix inversion is replaced with a product of convolution of the discrete distribution functions. A drawback of this approach is that it is not available online and is used in just one other publication [46].

Secondly, the approach that consists of a direct traversal of the supply chain graph [23] introduces a promising method for dynamic LCI that has been developed as a prototype web application, called DyPLCA [26]. It is based on a process flow network structure and makes use of a depth-first graph search algorithm to build the temporal model. However, this proof of concept is not coupled with an LCIA framework and it is not clear if the method can deal with datasets without temporal information, raising doubts over its integration potential with existing LCA databases. Regarding the treatment of the LCI as a graph, it is worth mentioning that this approach poses a key methodological challenge due to the cyclic nature of the supply chain graphs. Loops can be encountered, and a cut-off function must be applied to halt potentially infinite loops in supply chain traversal. This method is used in two other publications to assess the relevance of using DLCI and the assumption on the time horizon on environmental impacts results [67] and to describe the online tool that enables the use of the methodology [26], which is available to the public.

Finally, Cardellini et al. [22] employ a best-first search strategy to solve the dynamic inventory problem, creating the Temporalis tool [22]. Here, processes are nodes of the graph and flows are edges, which can be both static and dynamic. Furthermore, the temporal distributions of the product–process and biosphere–process interactions are taken into account, using convolution as used by [35]. This methodology therefore builds on top of the first two, while at the same time solving some shortcomings. Namely, this approach can deal with LCI and LCIA that are only partly dynamic, as is often the case, and can manage both relative and absolute time references. The temporal resolution can be as little as 1 s. A major advantage is that the Python code is fully available in a dedicated GitHub folder.

The ESPA, DyPLCA, and Temporalis are designed for DLCA using previously collected data. Other models, that we are about to describe, might be better suited to elaborate continuously collected data, since they were developed with this scope. We should stress, however, that, if a dynamic LCIA is needed, the three previously analyzed models and tools should be the starting point for future developments.

Before the development of models for continuously collected DLCI data is possible, practitioners should consider in which format data are generated from the different machines. A solution to make such formats uniform is the use of a common standardized interface protocol for data exchange and collection from the shop floor, such as MTConnect [4,30,51,70]. Subsequently, attention should be devoted to data management steps to ensure efficient data handling, storage, and analysis [4].

If the model needs to deliver real-time emission and environmental impacts results, continuous DLCI data collection might not be enough. Indeed, needed data might not be available [4] or measurements might be unreliable without a certain time lag [32]. Simulation methods should be employed to overcome these issues. For example, Majanne et al. [32] apply extended Kalman filters to estimate real-time fuel consumption used in a power plant [32].

Bengtsson et al. [70] develop a discrete-event simulation of a manufacturing system whose input is data gathered with MTConnect [70]. The goal is to project long-term environmental impacts based on production statistics. Therefore, the simulation conserves the modeling granularity obtained by the MTConnect data, both in terms of assessed dynamic processes and in terms of temporal resolution. The use of discrete-event simulation for DLCI is also advanced by Lofgren et al. [59] and, more recently, Rodger et al. [64], although these publications do not rely on continuously collected DLCI data [59,64]. To represent the manufacturing system, a unidirectional process flow chain, alternated by buffers, is proposed [64]. Buffers are used to model time lags, material availability, and process bottlenecks [64]. A similar approach is a modular DLCI model for real-time assessment of the dynamic environmental impacts of a manufacturing system [28]. A gate-to-gate approach is chosen and the granularity of the modules is a trade-off between the ease of modeling and the detail of the assessment. Potential issues regarding the allocation of environmental impacts are discussed and recommendations for how to deal with them are presented for cases such as waste, discarded products, standby times, setup and ramp-up times, transports, storage, energy systems, heating, ventilation, air conditioning, buildings, administration, and auxiliary systems [28].

To widen the consideration of DLCI beyond a manufacturing floor gate-to-gate approach, an interesting solution is proposed by Tao et al. [20] and Ferrari et al. [31]. Here, continuous DLCI data collection combines IoT infrastructure with enterprise resource planning (ERP) software. Thus, the ERP provides dynamic data for sections of the product system that would have otherwise been part of the static background system. However, the resulting data quality might not be as high as it is for primary data, due to difficulties in characterizing processes mapped through the ERP [31]. Rovelli et al. [72] do not have access to ERP data in their steel making case study and have to collect primary data from various sources [72]. The modular approach deals with collection and wrangling of data into an Excel spreadsheet, which is subsequently manipulated in Python to allow the integration of different functions such as label-specific sustainability reporting, contribution analysis, what-if scenarios, and data visualization tools [72].

Collet et al. [55] propose a methodology to assess which flows, part of the product system, are more relevant when introducing a partially dynamic LCI [55]. Through sensitivity analyses on environmental and economic flows, the dynamic parts of the LCI should be those that, with the added dynamic, translate to higher environmental impact variations. Moreover, a different temporal resolution is suggested depending on which impact category is the most affected [55]. The goal of this article seems promising for the smart use of a partially dynamic LCI. However, the methodology requires significant data collection or assumptions and it is not adopted by other publications.

Electricity-related studies either use one hour or half an hour as temporal resolution, due to the prevalence of this temporal resolution in electricity network operators' databases. Indeed, depending on the country, these temporal resolutions are used in day-ahead electricity markets. Day-ahead markets determine how much electricity should be produced in a certain hour by the power plants available in the market zone, as well as imports and exports with neighboring market zones. Therefore, they establish the hourly electricity technology mix trajectory for the following day.

When selecting the temporal resolution for a study with dynamic LCIA, practitioners should consider which impact category could be impacted the most. Indeed, Shimako et al. [67] demonstrate with a series of sensitivity analyses on the temporal resolution, one for each impact category, that different LCIA models have different sensitivities to the temporal resolution parameter [67]. While the climate change impact category does not seem to be influenced by temporal resolutions up to 1 year, the toxicity model shows a greater response, thus requiring a temporal resolution of 0.5 day [67].

3.3. Identification of Research Gaps

In this section, we summarize and discuss the research gaps highlighted by this systematic literature review, as listed in Table 5. Therefore, this section aims at guiding future research development for DLCI projects. For each research gap, we describe its meaning and we discuss its relevance. However, the order presented in Table 5 does not reflect a ranking of significance, but rather it follows the flow of the presentation of Sections 3.1 and 3.2.

The first two research gaps are the most directly linked to sustainability-linked strategies brought forward by Industry 4.0. Indeed, only 17 publications deal with continuous DLCI data collection and only 11 automate the data collection process through IoT or sensors in general (see Tables 2 and 3). This practice would have the potential to generate large amounts of data, which could be used to compile DLCI databases, to improve the representativeness of static LCI databases, and to design new strategies to decrease environmental impacts. More studies are needed to evaluate and compare proposed methods to define best practices. The literature is even more lacking when it comes to scenario analyses or forecast using continuously collected DLCI data. One of the pillars of Industry 4.0 is the CPS, which allows for the dynamic and autonomous coordination of machines and production systems, which share information [6]. To be able to include life cycle engineering strategies in the CPS goal, sensitivity analyses and forecasts are both needed to support the decision making.

The assessment and management of uncertainty are well-debated and common in the general field of LCA, as it is considered crucial to improve data quality, reliability, and credibility of LCA results [84]. However, the topic is rarely addressed in the DLCI literature, although an approach aiming to reduce uncertainties in the carbon footprint of solar photovoltaic systems is proposed [33]. The only instance of a Monte Carlo simulation of a case study in the literature performs the analysis at a seasonal level, through four static simulations [37]. While Monte Carlo simulations in DLCI might be computationally unfeasible, further research is needed to adapt known methodologies or to develop new ones.

Table 5. Research gaps identified in the literature and their relevance for the development and diffusion of DLCI studies.

Research Gap	Relevance
1. Lack of continuously collected DLCI data case studies	Continuous DLCI data collection should be the main enabler for DLCA, yet only a few studies are published
2. Lack of scenario analyses using continuously collected DLCI data	Environmental impact reduction strategies need to rely on "what-if" simulations
3. Lack of comparative DLCI studies	Comparative DLCI studies are methodologically not trivial, since comparing different environmental impact trajectories is more complex than comparing two static numbers
4. Uncertainty in DLCI studies	How to assess, communicate, and manage the uncertainty in DLCI studies?
5. Interpretation guidance of DLCI data	The time dimension adds complexity to the interpretation phase. How to interpret and effectively communicate results in the case of (partial) DLCI studies?
6. Identification of strategies to reduce environmental impacts based on DLCI data	How can DLCI data inform environmental impact reduction strategies?
7. Identification of sectors with the highest margin of LCA impact reduction due to strategies to reduce environmental impacts based on DLCI data	Many studies focus on electricity mix and consumption. Are there other sectors that would particularly benefit from a DLCI approach?
8. Challenging replicability due to lack of key modeling information or code	An increase in transparency is needed to speed up the sharing and evolution of methodologies, as well as to improve reproducibility

The interpretation phase is often considered overlooked and some of its steps are not commonly applied by LCA practitioners [85]. Moreover, the time dimension adds complexity to the interpretation phase, which results in different strategies to communicate results within the literature. Examples vary from a standard line plot [22], to histograms with distribution ranges [43] and to box plots [19]. An important variable in this choice is the presence of dynamic LCIA characterization factors. Moreover, depending on the goal of the study, on the temporal resolution, and on the time horizon, using static cradle-to-gate LCA coefficients might lead to incorrect variability of impacts over time. An example is in the assessment of the environmental impacts of the consumption of electricity on an hourly basis. To account for the overall impact, static cradle-to-gate LCA coefficients can correctly characterize each technology in the electricity mix. When considering impact variability for consumption load shifting from one hour to the next, however, only the operational impacts should be contemplated. Further research is needed to provide customized guidance on the interpretation phase of DLCI studies, as Laurent et al. [85] do for static LCA ones [85].

Static LCA strategies to reduce impacts typically revolve around hotspot analysis [86]. However, hotspot analysis can be adapted to DLCI studies to support the use of the increased dynamic data availability [87]. Any strategy should take into account potential burden shifting across impact categories, life cycle stages, and, when DLCI is used, through time.

The literature is particularly concentrated on strategies that take advantage of the variability of electricity mixes and consumption. However, a systematic effort should be dedicated to investigate which sectors could pursue environmental impacts reduction by using temporally differentiated data.

The last research gap might be one of the most challenging to address. This could be due to privacy or business concerns in sharing the large amounts of data produced within DLCI studies. Indeed, partial non-disclosure agreements are common for LCA practitioners even in static LCA, as industrial partners prefer to publish aggregated results. However, methodologies should be shared with as much detail as possible, to ensure replicability and transparency of the scientific process, as well as to verify sustainability claims.

4. Discussion

In this section, we put this study into context by comparing it to previous literature reviews dealing with dynamic LCA. Then, as far as the goal and scope, the implementation of the DLCI, and the identified research gaps are concerned, we discuss potential implications in both research and practice of the knowledge and perspective gained from this paper. Since four literature reviews on dynamic LCA have already been published [5,12–14], we strove to address a remaining research gap. We focus on how DLCI is implemented in the literature, particularly in publications that can directly or indirectly offer relevant knowledge for Industry 4.0 applications.

Building on issues of data quality requirements individuated by Beloin-Saint-Pierre et al. [5], such as age of data, technology coverage, source of data, and uncertainty description [5], we propose the first goal and scope classification in Table 2. Acknowledging these issues allows us to point out the need for continuously collected DLCI data to obtain technology-specific knowledge. By highlighting in our classification continuously collected DLCI data publications, readers can explore how the higher level of data quality can be used. Together with the second, more detailed classification of Table 3, Section 3.1 should help LCA practitioners aiming to develop DLCI projects to find projects that could be relevant due to goal and scope similarity. Su et al. [14] find that 70% of publications are retrospective assessments [14], a percentage close to the 59% verified in our study, although the focus of the studies differs. Sohn et al. [12] argue that attributional DLCA might be preferred to consequential DLCA in the case of complex systems, due to the lower data requirement [12]. While this issue could be circumvented by transparently applying a cut-off, the cut-off itself might reduce the comparability of results across studies [12]. We agree that managing the trade-off between model complexity and representativeness is not trivial. Nonetheless, the choice between attributional and consequential DLCA should account for data availability but it should ultimately depend on the goal of the study. Regarding the goal and scope phase, Lueddeckens et al. [13] discuss the time horizon, a parameter which can significantly influence DLCA results [13]. The length of the temporal horizon can change from study to study and it can be seen as a political decision dependent on the case study and on the considered impact categories [13]. However, the relevance of the temporal horizon is reduced when dynamic characterization is not considered, such as in DLCI. While DLCI can lead to underestimation of environmental impacts because of incomplete dynamic mapping of the LCI, DLCI does avoid the underestimation of environmental impacts due to discounting factors built in the dynamic characterization.

Section 3.2 aims at describing the existing methodologies employing DLCI, which components of the LCI are considered dynamic, and what temporal resolution is adopted in each study. Therefore, with Section 3.2 we support LCA practitioners aiming to develop DLCI projects looking for a more technical understanding. Partially dynamic LCA studies, such as DLCI, are considered useful but their outcomes should be carefully interpreted to avoid the introduction of biases due to missing dynamic data. We concur with

Sohn et al. [12] that, to manage this, the influence of dynamic elements of the inventory should be assessed in a sensitivity analysis. Lueddeckens et al. [13] limit the discussion on the LCI phase to the temporal resolution of the inventory, while the study by Beloin-Saint-Pierre et al. [5] is more detailed, especially in the description of the approaches and tools for DLCA. However, regarding the more limited DLCI approach we have described other promising approaches to develop Industry 4.0 applications. The modular nature of LCA is exploited in discrete-event simulation models [28,64,70], modular tools collecting real-time data through spreadsheets [72], or ERP [20,31]. We also highlight the potential of machine learning in forecasting DLCI [73] or dynamic environmental impacts [74,76,77].

Since this is a literature review, we did not address previously identified research gaps. However, we can discuss how these compare to the ones we found, as well as to our findings. Section 3.3 summarizes the research gaps that are found throughout this literature review. Therefore, Section 3.3 should be useful for researchers who are interested in understanding which are the future research needs we have identified. In a defined set of case studies involving buildings, Su et al. [14] identify as an existing problem the lack of rules by which dynamic components should be considered in the LCI [14]. This finding suits our assessment, even if we dealt with a wider set of case studies. We found that manufacturing case studies with wide availability of continuously collected data tend to consider the whole foreground system as dynamic. We agree with Su et al. [14] that the inclusion could be justified on the basis of cut-off criteria, both on the temporal variability of the inventory parameter and on the temporal variability of the environmental impacts. While the latter is the most interesting result, highly variable inventory parameters should be closely tracked as well, as they might be more relevant for different impact categories. Completing more DLCA studies and considering dynamism only when relevant to the resulting environmental impacts are also described as future priorities [5], considering a sensitivity analysis as a tool to assess this relevance [55] or different temporal differentiations depending on the impact category [67]. We concur with Sohn et al. [12] and Beloin-Saint-Pierre et al. [5] on the need for a common reporting standard and relative metadata to foster the diffusion and automation of the exchange of DLCI or DLCA data. This is echoed in our research gap 8, in our call to improve replicability.

5. Conclusions

This study regarded a subset of articles dealing with DLCA, namely those with a prevalent focus on DLCI. The systematic literature review analyzed and presented methods and applications for DLCI, with particular attention to Industry 4.0 applications such as continuous data collection through IoT. We provided two classifications for the goal and scope phase, as well as one for the integration of DLCI. The classifications on the goal and scope phase can support LCA practitioners in finding relevant studies that aim to achieve analogous goals when developing a new DLCI project. Similarly, the classification for the integration of DLCI can support the same process with regard to the relevant method for a certain application or in selecting needed characteristics. Here, we organize the presentation around parameters such as white-box modeling, gray-box modeling, black-box modeling, the dynamic component in the LCI, and the temporal resolution to guide the readers towards the most pertinent publications.

A limit of this systematic literature review might be in the literature selection phase, due to the lack of standardization of the nomenclature used in dynamic LCA studies, in spite of previous efforts [5]. The use of standardized keywords could have ensured a more comprehensive literature selection, but the lack of efficiency in this process meant that thousands of titles had to be screened just to select 67 publications.

DLCA and Industry 4.0 are still not widely adopted, so research gaps are as important as current literature knowledge in order to guide future research. Therefore, we have highlighted eight research gaps that, when successfully addressed, could benefit the diffusion and development of sound DLCI studies with Industry 4.0 applications. Although the automation of data collection for DLCI studies seems promising to improve data representativeness and to enable the continuous update of DLCI, such practice is still limited. Within these studies, only three use the continuously updated added knowledge of DLCI for scenario analyses [70–72], which are fundamental to test the effectiveness of environmental impact reduction strategies, possibly before they are put in place. Further research should be dedicated to how to best achieve this. Moreover, more comparative DLCI studies are needed to establish a best practice on how to compare different product systems dedicated to similar functions. This might require the use of more advanced statistical metrics and statistical tests to reflect results that need to be evaluated as trajectories and not as static averages. The lack of specific guidance for DLCI studies on the interpretation phase and on how to assess, communicate, and manage data and result uncertainty are two other research gaps that need to be addressed. Most of the applications in this direction revolve around manufacturing case studies, electricity technology mix, and consumption. Due to the trend of electrification of different sectors of the economy, electricity is supposed to increase its already relevant role as a driver of environmental impacts. However, further research should investigate in which sectors insights gathered from DLCI could be used to lessen environmental impacts. Similarly, strategies to reduce environmental impacts by using DLCI data other than electricity consumption shifting should be investigated [73,74,76,77]. Finally, the last research gap revolves around the challenge of study replicability, an issue that is affecting the whole LCA field, as well as many other scientific fields. The credibility of data sources, methodologies, and sustainability claims requires transparency, ease of sharing, cybersecurity, and trust among the involved actors and along all steps of the scientific process.

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Abbreviations

The following abbreviations are used in this manuscript:

LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
DLCA	Dynamic Life Cycle Assessment
DLCI	Dynamic Life Cycle Inventory
CPS	Cyber-Physical System
DPI	Dynamic Process Inventory
DSys	Dynamic Systems Inventory
ESPA	Enhanced Structure Path Assessment
ERP	Enterprise Resource Planning
IoT	Internet-of-Things

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