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Hybrid LCA for sustainable transitions: principles, applications, and prospects

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ABSTRACT

Hybrid life cycle assessment (LCA) offers an integrated approach, combining process-based and input-output data. As such, it strives for a more comprehensive and precise evaluation of alternative technologies and products, supporting sustainability transitions. A review of 114 studies from 2016 to 2022 reveals that hybrid LCA applications are most commonly focused on energy systems (24 %), with a strong emphasis on assessing climate change impacts. Hybrid LCA is crucial for addressing the data gaps prevalent in environmental evaluations of renewable energy technologies. Methodological innovations, such as combining hybrid LCA with multi-objective optimization, show promise in pinpointing ideal locations and designs for energy plants, such as biorefineries. However, a concerning observation is that many studies employed oversimplified or inadequately documented hybridization procedures, raising questions about their robustness. The review also identifies several remaining challenges in hybrid LCA, including the linearity assumptions, omission of capital goods, price data uncertainties, and inconsistencies in environmental flow data. A significant advancement lies in creating standardized datasets, especially for construction materials. Such datasets could enable large-scale evaluations of embodied impacts across projects, facilitating the selection of construction materials based on comprehensive material trade-offs and supporting net-zero carbon construction. Furthermore, to enhance hybrid LCA in future research, this study presents a streamlined classification of the various methods, clarifying their intended purpose and computational structure.

Nomenclature

Abbreviations	
EC	Embodied carbon
EE	Embodied energy
EEIOA	Environmentally-extended input-output analysis
EPiC	Environmental Performance in Construction
EOL	End-of-life
GHG	Greenhouse gas
HLCA	Hybrid life cycle assessment
IEE	Initial embodied energy
IHL	Integrated hybrid life cycle assessment
IO	Input-output
IO-LCA	Input-output life cycle assessment
IOT	Input-output table
LCA	Life cycle assessment
LCEE	Life cycle embodied energy
LCI	Life cycle inventory
MA	Matrix augmentation
MOO	Multi-objective optimization
OE	Operational energy
PLCA	Process-based life cycle assessment
PP	Polypropylene
PXC	Path exchange
SPA	Structural path analysis
THL	Tiered hybrid life cycle assessment
Symbols	
$\mathbf{A_p}$	Technology matrix in PLCA
$\mathbf{A_{io}}$	Technology matrix in IO
$\mathbf{A_h}$	Technology matrix in hybrid LCA
$\mathbf{B_p}$	Environmental extensions matrix in PLCA
$\mathbf{B_{io}}$	Environmental extensions matrix in IO
$\mathbf{B_h}$	Environmental extensions matrix in hybrid LCA
$\mathbf{C^d}$	Downstream cut-off matrix
$\mathbf{C^u}$	Upstream cut-off matrix

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(*continued*)

$\mathbf{f_p}$	Functional unit in PLCA
$\mathbf{f_{io}}$	Functional unit in IO
$\mathbf{f_h}$	Functional unit in hybrid LCA
$\mathbf{I}$	Identity matrix
i, j	Rows and columns in matrix notation
$\mathbf{q_p}$	Total environmental implications in PLCA
$\mathbf{q_{io}}$	Total environmental implications in IO
$\mathbf{q_h}$	Total environmental implications in hybrid LCA

1. Introduction

Process-based life cycle assessment (PLCA) and environmentally-extended input-output analysis (EEIOA) are two widely recognized methods for systematically assessing the environmental impacts of products, technologies, sectors, countries, and activities [1–3]. PLCA has been extensively employed to assess the environmental impacts of product alternatives throughout their life cycles, such as comparing emerging sodium-ion batteries to existing lithium-based technologies [4]. It has also been applied at various scales, from process to enterprise and organizational levels [2,5]. Owing to its widespread application, PLCA is now highly standardized, encompassing a range of ISO standards [6,7]. EEIOA is also used at the product level, which is known as input-output LCA (IO-LCA) [8,9]. However, EEIOA is generally better suited for quantifying and analyzing environmental impacts at macro scales, such as sectoral, national, and global levels [10]. Notably, EEIOA highlights emissions from the previously perceived "emission-less service" sector, by uncovering the substantial emissions embodied in services' upstream supply chains, emphasizing its relevance for climate change mitigation [11].

Although both methods are frequently used, each has its advantages and limitations. PLCA is considered to provide more precise assessments because it is based on processes, such as steelmaking or manufacturing of cathodes, and uses product-, technology-, or organization-specific data to represent inputs into the various life cycle stages of the subject under study. This is referred to as foreground data. When specific data cannot be obtained, background data from available PLCA databases are used, such as for product end-of-life (EOL) [12,13]. The better data precision, however, necessitates a subjective system boundary selection [14,15]. This is because, although many processes can be considered within the complexities of a globalized economy, a PLCA inevitably neglects some processes. These omissions may occur consciously or unknowingly due to constraints such as budget, labor, data availability, and knowledge [16,17]. Consequently, this leads to truncation errors, resulting in an underestimation of environmental flows and impacts by 20–50 % [17,18], particularly in accounting for Scope 3 emissions [17].

Conversely, IO-LCA is typically based on economic input-output tables (IOTs) that describe all sectoral transactions within an economy or across economies in a given year [19]. When combined with sectoral environmental flows (e.g., CO_2 emissions) measured during the same year, the IOTs enable the tracing of the environmental implications associated with all economic transactions along supply chains. Therefore, IO-LCA is known to be comprehensive, i.e., it captures all impacts associated with the production activity of any economic sector, upstream or downstream of the sector's supply chain [20]. However, in IOTs, each sector is an aggregate of heterogeneous goods and services owing to the nature of macroeconomic statistics. For example, in the United States' 405-sector IOT, one of the most detailed IOTs available, "Turbine and turbine generator set units manufacturing" includes all types of turbines (except aircraft) and complete turbine generator set units, such as steam, hydraulic, gas, and wind turbines. IO-LCA's comprehensiveness thus comes at the cost of an aggregation error, limiting its precision for assessing the environmental impacts of specific products or technologies, such as renewable energy technologies [10]. Lastly, based on economic transactions among sectors, existing IOTs and hence IO-LCAs lack a description of consumer and post-use phases (i.e., product EOL), which are often included in PLCA studies.

Hybrid life cycle assessment (HLCA) has its roots in energy analysis methods first explored by researchers in the 1970s [21]. By integrating the strengths of PLCA and IO-LCA while mitigating their limitations, HLCA aims to improve the accuracy and precision compared to using only PLCA or IO-LCA [21]. Several studies have since reviewed the HLCA methodology [9,22,23]. Islam et al. [22] presented the first review of HLCA calculation techniques and highlighted their advantages and limitations for application purposes. Crawford et al. [23], in the first systematic review of 97 studies published between 2010 and 2015, categorized HLCA methods into four classes: tiered hybrid, integrated hybrid, path exchange hybrid, and matrix augmentation.

Despite these efforts, two recent developments underscore the need for a more up-to-date comprehensive review of HLCA. The first concerns notable methodological advancements in HLCA. Innovations such as the automation of HLCA processes and the compilation of hybrid datasets have the potential to substantially expand HLCA's accessibility to a broader audience beyond traditional users [23–27]. Moreover, efforts that address HLCA's persistent limitations, such as correcting double-counting errors and resolving uncertainties stemming from variable price data [28–30], are pivotal for improving the credibility and robustness of HLCA as an environmental accounting tool supporting policies and regulations. The second development relates to the increasing prominence of sustainability-focused regulatory and policy frameworks. Some examples include the EU's corporate sustainability reporting directive (CSRD) [31], the carbon border adjustment mechanism (CBAM) [32], and the global emphasis on Scope 3 emissions under the Greenhouse Gas (GHG) Protocol [33–35]. While these frameworks are not exclusively LCA-based, they often rely on LCA-derived concepts, tools, and data to achieve their objectives. This reliance highlights the need for robust and standardized methods to account for supply chain and life cycle impacts, making recent HLCA research advancements highly relevant.

This study offers a timely and critical review of the state of the art in HLCA research, focusing on standardizing its mathematical foundations and synthesizing HLCA-derived insights to inform technology, policy, and regulation for sustainability transitions. The review encompasses 114 publications that utilize or develop HLCA methods, published between 2016 and 2022. Beyond highlighting recent methodological advancements, it also introduces an updated taxonomy to categorize and standardize the various HLCA methods for future use. Furthermore, by thoroughly examining the mathematical principles of PLCA and IO-LCA, as well as the hybridization processes, this review hopes to facilitate broader adoption of HLCA, particularly among engineers involved in product design and development. Finally, through a comprehensive analysis of the HLCA literature, this review highlights the novel findings and identifies current focus areas and neglected aspects, including gaps in product and environmental impact coverage and remaining methodological limitations.

This review aims to strengthen HLCA's role as a critical tool in advancing sustainable practices across industries and supporting informed decision-making aligned with global sustainability goals. To the best of our knowledge, this is the first HLCA review to systematically assess the impact categories covered and the robustness of HLCA studies. It provides guidance for future research to implement HLCA more effectively, emphasizing the importance of validated computational procedures and broader inclusion of environmental impacts while shedding light on pathways to address remaining methodological limitations.

2. Systematic review method

This study employs the PRISMA approach [36] to systematically collect and analyze the literature, as shown in Fig. 1. The Web of Science and Scopus databases were used to identify an initial group of English-language publications for review. Publications were located by

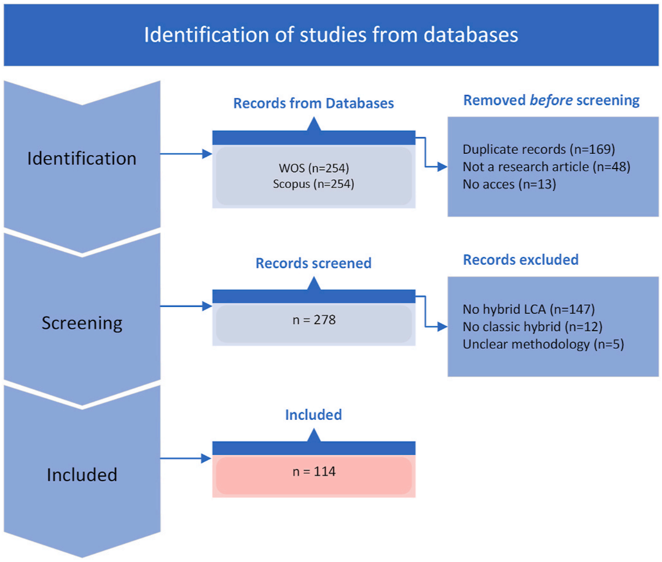


Fig. 1. Literature search and filtering process based on the PRISMA approach.

searching the title, abstract, and keywords using the following search terms: "hybrid LCA" OR "hybrid LCI" AND "input-output"; "hybrid LCA" AND "integrated" OR "path exchange"; "IO-LCA" OR "IOA-LCA" OR "EIO-LCA"; "hybrid life cycle assessment" AND "database"; "tiered hybrid LCA"; "input-output-based hybrid"; "process-based hybrid"; and "hybrid LCA". A temporal boundary of eight years, from 2016 to 2022, was selected to focus on the most recent HLCA methodological developments and applications, as studies from 2010 to 2015 have already been reviewed [23].

After removing duplicate records, inaccessible publications, review articles, letters to the editor, and books, the first-round search yielded 278 publications. These 278 publications were then further screened, excluding those that did not perform a hybrid LCA (e.g., combining exergy analysis and PLCA instead of integrating IO-LCA and PLCA) and those with unclear methodologies. In total, 114 suitable publications were advanced to the final review stage.

Each study's HLCA method, application, impact category coverage, and robustness were analyzed. The method, application, and impact categories are analyzed through a manual text search, while the robustness was assessed through the consideration of HLCA's key limitations, using the text analysis tool Atlas.ti. Based on the authors' expertise and previous HLCA reviews, this study focused on HLCA's four key limitations: uncertainty due to variable price data needed to convert IO and PLCA data to comparable units, double-counting issues, the exclusion of capital goods, and unrealistic linearity assumption. The search terms used in Atlas.ti included: "double counting"; "linear" AND "IOA" OR "IO" OR "input-output" OR "Life cycle assessment" OR "LCA"; "price" AND "variability" OR "uncertainty"; "cost" AND "uncertainty"; "capital goods"; and "capital inputs." Quotes generated by Atlas.ti were then manually analyzed to determine whether the study considered these key HLCA limitations. The literature analysis also provided insights into novel HLCA methodological developments and the potential for HLCA to support new policies and regulations.

All 114 papers were analyzed for this review, although not all are discussed or cited in the main text. It is possible that some relevant literature is unintentionally excluded. The review did not include conference proceedings or "grey literature", such as non-peer-reviewed reports from governments, companies, and non-governmental organizations, working papers, media coverage, and other web-based resources. Nevertheless, given the breadth of work in the field and the variety of reviewed studies, the bibliography can be regarded as representative of the state of the art in HLCA research.

3. The principle of hybridization – a math explanation

Before extensively reviewing HLCA methods, it is essential to define HLCA more accurately by discussing its principles, including the fundamental differences in the computational structures of IO-LCA and PLCA, as well as the purpose and steps of hybridization.

3.1. PLCA vs. IO-LCA

To understand HLCA methods, it is essential to first understand the different computational structures of IO-LCA and PLCA in assessing the environmental implications ($\mathbf{q}$) associated with the subject of interest, as shown in Eqs. (1) and (2), respectively.

$$\mathbf{q_p} = \mathbf{B_p A_p^{-1} f_p} \tag{1}$$

$$\mathbf{q_{io}} = \mathbf{B_{io}}(\mathbf{I} - \mathbf{A_{io}})^{-1}\mathbf{f_{io}} \tag{2}$$

Both methods use a matrix that contains environmental flows ($\mathbf{B}$), such as GHG emissions related to a process (in PLCA) or a sector's production (in IO-LCA), to calculate the environmental implications ($\mathbf{q}$) associated with the subject of interest on a functional unit basis ($\mathbf{f}$). These flows can be expressed in physical terms (possible in both PLCA and IO-LCA) or monetary terms (typically in IO-LCA). The technology matrix ($\mathbf{A}$) describes the production inputs and outputs and is essential in both PLCA and IO-LCA; however, it is structured differently. The critical yet less understood differences between PLCA and IO-LCA are illustrated in Fig. 2.

$\mathbf{A_p}$ in PLCA records processes in columns, where negative values indicate process inputs and positive values indicate the resulting output (e.g., 10 kWh of electricity in Fig. 2). All values in $\mathbf{A_p}$ are in physical units. In IO-LCA, the structuring of $\mathbf{A_{io}}$ differs, resulting in a distinct computational structure, as shown in Eq. (2) [19]. Each column in $\mathbf{A_{io}}$ describes the production recipe (i.e., inputs) required to produce one unit of output for any given sector (e.g., 0.13 million USD of manufacturing products is needed to produce 1 million USD of agricultural output in Fig. 2). $\mathbf{A_{io}}$ is square and symmetric, with diagonal values representing the sector's self-inputs. In contrast, $\mathbf{A_p}$ is not necessarily square, although Eq. (1) assumes it is, and hence its diagonal values have no specific interpretation. Furthermore, while $\mathbf{A_{io}}$ is derived from IOTs compiled and published by national statistical offices, $\mathbf{A_p}$ is compiled by PLCA practitioners, making it less comprehensive in covering all production processes related to the subject of interest.

3.2. Hybridization

To combine the precision of PLCA with the comprehensiveness of IO-LCA, HLCA methods use IOTs to estimate inputs that would otherwise be neglected in PLCA [37]. A clear distinction between the various ways of estimating inputs is lacking but essential for choosing the proper HLCA method, given the research purposes and data availability. The three types of missing inputs in PLCA that are addressed through hybridization using IOTs are shown in Fig. 3.

Neglected inputs in PLCA can be distinguished into cut-offs and unknown inputs. Cut-offs are inputs that are known but lack available production data. HLCA uses IO data to estimate two distinct types of cut-offs. For Type 1, the input quantity is known, but data on the supplying process is unavailable (e.g., as illustrated in Fig. 3, producing 1 kg of batteries requires 0.1 kg of polypropylene (PP), with no data on PP production). For Type 2, both the input quantity and process data are unavailable (e.g., the solvents required for battery production in Fig. 3). Unknown inputs are inputs the PLCA practitioner is unaware of due to the limited system boundary of PLCA studies. These often include critical but less conventional inputs, such as research and development or service inputs. The unknown inputs of a PLCA process can be estimated using the production recipe of an aggregated IO sector covering the

	Production of			
PLCA	Battery	Cathode	Electricity	etc
Anode (kg)	-0.4	0	0	...
Cathode (kg)	-0.33	1	0	...
Plastic (kg)	-0.1	0	0	...
Electricity (kWh)	-0.11	-0.002	10	...
Battery (kg)	1	0	0	...
LMO (kg)	0	-0.62	0	...
Heat (MJ)	-0.07	-0.65	-36	...
etc	...	...	...	...

IO-LCA ($/$)	Agriculture	Mining	Manufacturing	Services
Agriculture	0.20	0.20	0.20	0.20
Mining	0.001	0.001	0.001	0.001
Manufacturing	0.13	0.13	0.13	0.13
Services	0.09	0.09	0.09	0.09

Fig. 2. The technology matrix (A) describes production inputs and outputs. It is essential for both PLCA and IO-LCA, albeit based on different data types and structures. The example shows that $\mathbf{A_p}$ in PLCA records processes in columns, with inputs as negative values and outputs as positive values in physical units. In contrast, $\mathbf{A_{io}}$ in IO-LCA is symmetric, with columns describing production recipes (inputs) per unitary output, most commonly in monetary terms.

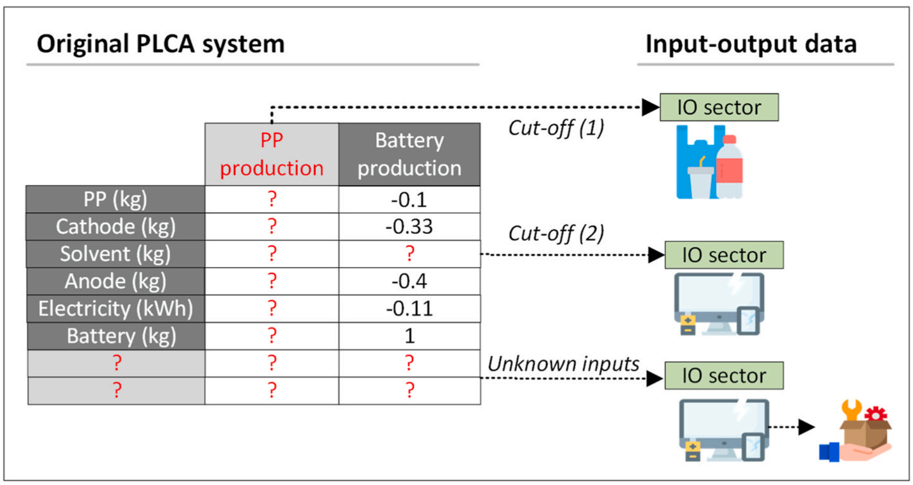


Fig. 3. Three types of missing input estimation in HLCA are illustrated using a PLCA process of battery manufacturing. For Type 1 cut-offs, the known missing inputs (e.g., “PP production”) are estimated using IO data describing sector production recipes (e.g., “Manufacture of basic plastics”) that resemble the inputs’ production process. For Type 2 cut-offs and Unknown inputs, the missing inputs are estimated using data from aggregated IO sectors that cover the subject under study (e.g., “Manufacture of electrical equipment”).

specific process (e.g., “Manufacture of electrical equipment” covers “Battery production” in Fig. 3).

The hybridization process that integrates IO-LCA and PLCA data hinges on addressing the structural differences between the two methods. First, the PLCA processes and missing inputs must be matched to aggregated IO sectors that cover these processes or produce the missing inputs (e.g., “Manufacturing of Basic Plastics” in Fig. 3). Price estimates are typically necessary to convert the data to compatible units. Additionally, the enriched data has to be manipulated to fit either the PLCA $\mathbf{A_p}$ or the IO-LCA $(\mathbf{I} - \mathbf{A_{io}})$ structure. Estimating unknown inputs, in particular, can introduce double-counting issues [37]. When all inputs from the corresponding IO production function are added during hybridization, some of these inputs may already be captured by the original PLCA process. This leads to excessive inputs that must be removed using double-counting correction methods [37].

Differences in temporal boundaries also affect hybridization. While PLCA models environmental impacts over a product’s entire life cycle, IO-LCA covers impacts for only a single year due to the annual nature of IOT data. This distinction can lead to substantial differences in IO-LCA and PLCA assessment results, especially regarding toxicity impacts [30,38]. For example, Agez et al. found that IO-LCA estimates for metal emissions account for only 33 % of the total ecotoxicity impacts compared to 99 % in PLCA, using the same impact method [30]. This means that IO-LCA’s lower impacts can partially be attributed to missing elementary flows and the annual characteristic of the IOT data, which often excludes longer-term emissions [30,38].

3.3. An updated HLCA taxonomy

The diverse purposes and scales of hybridization have led to a variety of HLCA methods, previously classified by Crawford et al. [23] as tiered hybrid LCA (THL), integrated hybrid LCA (IHL), the path exchange (PXC) method, and matrix augmentation (MA). THL aims to increase accuracy compared to PLCA by using PLCA data for the most important upstream processes, while the remaining inputs are covered by IO data. The PXC method improves precision compared to IO-LCA by disaggregating $\mathbf{A_{io}}$ and replacing specific data points with PLCA data. MA enhances the precision of IO-LCA by disaggregating IO sectors or creating new sectors using PLCA data. IHL methodologically integrates the IO and PLCA $\mathbf{A}$ matrices to model a specific product or system with improved accuracy and precision.

However, a review of the 114 studies revealed that many do not consistently define the computational structure underlying the HLCA methods used in their methodology. This lack of clarity contributes to the wrongful application of the methods, uncertainty in results, and limited adoption of HLCA. To address the confusion surrounding HLCA methods, this study proposes an enhanced classification scheme based on the computational structure of HLCA methods, distinguishing between data hybridization and computational hybridization. Differentiating between these two forms of hybridization is important because their analyses differ in comprehensiveness, transparency, and robustness. Unlike previous classifications by Crawford et al. [23] and Nakamura [39], this review further distinguishes between classic and systematic THL, given their different computational structures and applications.

Data hybridization methods use additional data in a way that matches the computational structure of the original IO-LCA or PLCA. For example, in data hybridization, the impact of 0.1 kg of PP is estimated by adding IO data to the original PLCA. By contrast, computational hybridization methods use a harmonized computational framework that integrates the computational structures of IO-LCA and PLCA. In this case, the IOT is appended to estimate the impact of the missing 0.1 kg of PP without directly merging PLCA and IO data; instead, the computation is hybridized using Eqs. (4) and (5) (see Section 4.2).

Based on this classification, Table 1 provides an overview of each HLCA method, covering its computational structure, hybridization purpose, advantages, limitations, and unique applications that are uncommon for most other HLCA methods. It also addresses each method's potential for dataset hybridization and automation, reliance on price data for hybridization, policy relevance, and usage frequency in the reviewed studies. Additionally, Table 1 lists foundational literature that established each method prior to this review period and highlights key citations from the reviewed studies that notably contributed to further methodological advancements. All elements in Table 1 are further discussed in Section 4.

4. HLCA computational structures: computational and data hybridization

Computational hybridization methods (IHL and systematic THL) are less commonly applied than data hybridization methods (PXC, MA, classic THL) as shown in Fig. 4. Furthermore, there has been no notable increase in the adoption of HLCA methods over time.

4.1. Data hybridization methods

Data hybridization methods adhere to the structure of the original analysis (e.g., IO-LCA) and use additional data (e.g., PLCA) to improve this analysis. These methods take various forms, defined here as the path exchange method (PXC), matrix augmentation (MA), and classic tiered HLCA (classic THL). Variations in classic tiered approaches are also discussed below.

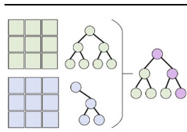
4.1.1. Path exchange method

The PXC method is infrequently used (9 %), possibly due to its time-intensive nature and complexity. It requires expert-level IO and PLCA data manipulation and analysis. As a data hybridization method, PXC implements hybridization based on structural path analysis (SPA), a

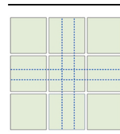
Table 1

Comparison of key characteristics of HLCA methods. Green visuals represent IO data and blue visuals represent PLCA data. A small portion of studies combine methods (5 %) or are theoretical in nature (2 %).

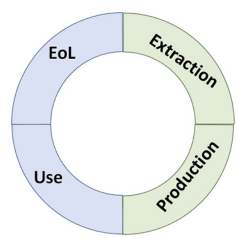
PXC



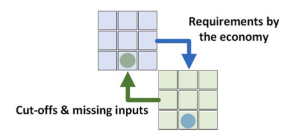
MA



Classic THL



Systematic THL / IHL



	PXC	MA	Classic THL	Systematic THL	IHL
Type	Data hybridization	Data hybridization	Data hybridization	Computational hybridiation	Computational hybridization
Computational Structure	IO-LCA	IO-LCA	PLCA	Integrated	Integrated
Purpose for hybridization	Increased precision	Increased precision	Increased accuracy	Specific cut-offs and unknown inputs	Increased accuracy and precision
Advantages	• Consistency & transparency • Avoids double-counting • Replaces most significant nodes • Any type of process data	• Little PLCA knowledge required • Small data dependency • Any process data	Fast and easy to comprehend	• Consistency & transparency • $\mathbf{A}_{io}$ and $\mathbf{A}_p$ remain intact	• Transparency • $\mathbf{A}_{io}$ and $\mathbf{A}_p$ remain intact
Limitations	• Complex and large time and computing needs • Assumes that IO and PLCA are representations of the same supply chain	• Neglects EOL • Scaled to original sale structure	No consistent computational structure: • Major double-counting risks • Unsuitable for comparison	• Requires double-counting correction • Only hybridizes **A** • Background truncation	• Complex and time costly • More complex double-counting correction • Only hybridizes **A** • Background truncation
Unique applications	• Construction of hybrid environmental flow coefficients • Estimation of truncation errors	Material consumption	NA	Estimation of truncation errors	Introduction of novel product/technology in the economy
Dataset hybridization possibilities	No	No	No	Yes	No
Automation possibilities	Yes	No	No	Yes	No
Price dependency	Low to medium	Low	Low	Medium to large	Large
policy application	Product benchmarking	Fast screening of impacts	None	Product benchmarking	Scenarios
Usage in studies	9 %	22 %	35 %	18 %	10 %
Core literature (original idea, before 2016)	[40,41]	[16]	[21,42]	[43,44]	[44,45]
Core literature (developments since 2016)	[26,46]	[47–49]	[50–52]	[27,30,37,53]	[29,54]

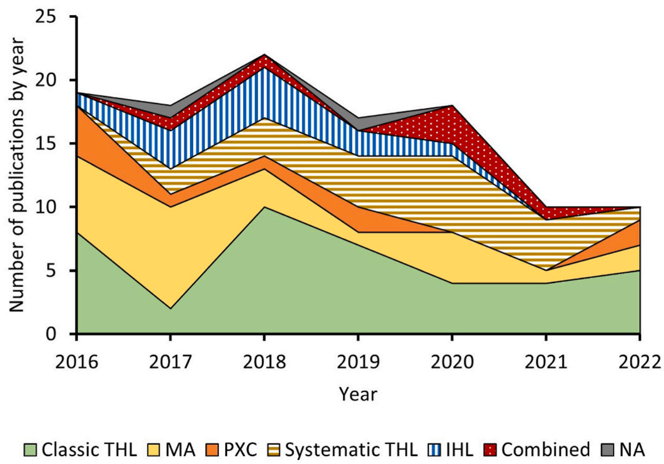


Fig. 4. The use of HLCA methods over time. The acronyms refer to classic tiered HLCA, matrix augmentation, the path exchange method, systematic tiered HLCA, and integrated HLCA. Some studies combine multiple HLCA methods. Theoretical papers did not always specify a particular method (labeled as not applicable, NA).

typical IO analysis technique. SPA is applied to both PLCA and IO data, forcing $\mathbf{A_p}$ into the matrix format of $\mathbf{A_{io}}$ (symmetric matrix and implicit output of 1) [55].

SPA disaggregates the data into individual paths and nodes, enabling the replacement of sectoral environmental intensities ($\mathbf{B_i}$) or technology coefficients ($\mathbf{A_{ij}}$) in IO with product-specific PLCA data or any other process data [41]. In this way, the entire supply chain of an IO sector is modified to represent a specific product or process. The strengths of the PXC method lie in its complete system boundary and replacement of only the most important nodes by reliable process data [46]. The IO nodes that are not replaced by PLCA data, i.e., the IO remainder, are converted to physical units using the price of the product under study [46]. The reliance on price data is relatively low, as it is only needed for the specific product under study.

Developments include the automation of various elements of the PXC method using object-oriented programming [46]. The streamlined approach saves time by partially automating the matching of IO sectors and PLCA processes, which enables the construction of embodied coefficients datasets, such as the EPiC dataset on Australian construction materials. Regarding computational limitations, Guan et al. [56] used sensitivity analysis to find elasticity coefficients, which, combined with a threshold, identify key linkages in the IOT. Although the selection of the threshold is subjective, it effectively reduces the computational workload significantly compared to SPA, making it more useful for large-scale applications. The semi-automated PXC method ensures consistency by using the same datasets and assumptions in the hybridization software for all products to be hybridized. This consistency offers opportunities to apply the method for benchmarking and comparing products and materials (e.g., based on hybrid coefficient datasets) [26].

4.1.2. Matrix augmentation

MA focuses on disaggregating or adding IO sectors using PLCA data, as shown in Table 1 [16]. It is tailored for specific industries or products, making it particularly useful for case studies [25]. MA's large adoption in 22 % of the reviewed studies can be attributable to its suitability for case studies, relatively low data dependency, and limited required knowledge of PLCA. Disaggregating IO sectors allows for the assessment of specific products within a broad IO sector, such as specific construction materials within the aggregated construction sector [57–59]. Adding new IO sectors is useful for assessing novel products and technologies, such as biofuels [60–63]. MA studies generally exclude EOL due to the IOT's focus on economic activities. However, Salemdeeb et al. [48,49] applied MA to assess the environmental impacts of food waste management and prevention by modeling waste treatment infrastructure as intermediate inputs in the IOT and including EOL in life cycle costs [62–65].

Most studies scale the output of the new or disaggregated IO sector to the structure of the original sector [60,61,63–65], which limits the benefits of MA [66]. Ghosh & Bakshi [47] conducted a SPA on the augmented IOTs to determine the importance of activities, which, combined with uncertainty data, facilitated the construction of an acceptable hybrid life cycle inventory (LCI). Diverging from the original MA method, several studies directly used energy data in physical units to circumvent the unreliable energy price data in constructing the augmented table [57,58,67]. Since MA is usually applied to only one or a few sectors, it is relatively quick and straightforward, making it suitable for fast project screening. However, as augmentation and disaggregation are limited to selected sectors, aggregation errors are only partially addressed, leaving upstream aggregation errors unresolved.

4.1.3. Classic THL

A tiered analysis serves various purposes, such as estimating missing materials, capital goods, and financial services, and can be implemented through different approaches [23]. Tiered studies are differentiated into classic and systematic THL due to differences in computational structures and applications.

Classic THL studies allocate elements of the studied system to either PLCA or IO data in multiple ways, combining LCI results from these separate calculations [39]. Around 18 % of the reviewed studies use PLCA data for use, disposal, and large contribution processes, while using IO data for the remaining upstream life cycle stages, such as material extraction. Similarly, 9 % of the studies use PLCA data for Scope 1 and Scope 2 emissions and IO data for Scope 3 emissions. Three studies allocate the functional unit based on the organization's monetary expenses, assigning all operational expenses and investments to Scope 3 emissions (Type 2 cut-off) [50,68,69]. Approximately 8 % of studies use a third approach that uses IO data to estimate more specific activities, which can be both types of cut-offs and unknown missing inputs, such as services.

Data hybridization using classic THL is quick and relatively straightforward since the IO and PLCA data are added in a case-by-case manner [23,70]. This straightforward approach can explain classic THL's frequent usage in 35 % of the reviewed studies, but it is also a source of potential errors, such as double-counting [70]. Most reviewed classic THL studies lack a clear computational structure, offering little detail on the allocation of functional unit elements to IO data. Additionally, they often do not address double-counting issues (79 %) or dependency on price data. Moreover, since the structure is based on PLCA, practitioners must select the relevant processes, which means some processes will still be excluded and truncation errors remain [23]. The lack of clear computational structure and insufficient consideration of double-counting issues in the reviewed classic THL studies undermines the robustness of these studies [23]. The limitations also undermine classic THL's suitability for product promotion or policy recommendations.

4.2. Computational hybridization methods

Computational hybridization methods, such as IHL and systematic THL, hybridize the computation rather than the data. By preserving the original data, these methods ensure high transparency.

4.2.1. Integrated hybrid LCA

Only 10 % of the studies use IHL, which connects the PLCA and IO-LCA technology matrices in a mathematically consistent way using cut-off matrices [44]. The upstream cut-off matrix ($\mathbf{C^u}$) estimates cut-offs and unknown inputs in the PLCA system using the background IOT.

The downstream cut-off matrix ($\mathbf{C^d}$) enhances the background IOT by adding the specific functional flow represented in the PLCA foreground system. The computational structure of IHL takes different forms across the reviewed studies. This review follows Heijungs et al. [71], unifying under $\mathbf{A_h^{-1}}$ as shown in Eq. (3). This approach eliminates the additional steps needed to modify the PLCA technology matrix to fit the stringent IO-LCA's ($\mathbf{I}-\mathbf{A}$) structure, with its symmetric $\mathbf{A}$ matrix and implicit output of 1 [72,73]:

$$\mathbf{q_h} = \mathbf{B_h}\mathbf{A_h^{-1}}\mathbf{f_h} \tag{3}$$

in which:

$$\mathbf{B_h} = \begin{pmatrix} \mathbf{B_p} & \mathbf{B_{io}} \end{pmatrix}, \mathbf{A_h} = \begin{bmatrix} \mathbf{A_p} & \mathbf{-C^d} \\ \mathbf{-C^u} & \mathbf{I\text{-}A_{io}} \end{bmatrix}^{-1}, \text{and } \mathbf{f_h} = \begin{pmatrix} \mathbf{f_p} \\ 0 \end{pmatrix} \tag{4}$$

IHL distinguishes itself from other HLCA methods due to its unique applications and usefulness in modeling scenarios [74–76] and optimization studies [77–79]. This is enabled by the downstream cut-off matrix, which links the effects of introducing a new product or technology to the economy [75,80]. However, since PLCA datasets are incomplete, background truncation errors persist when using IHL (and systematic THL) [81]. A major disadvantage of IHL is the data- and time-intensive process required to construct the cut-off matrices [44]. For instance, data is needed for all cut-offs and unknown inputs to connect the monetary $\mathbf{A_{io}}$ data to the PLCA system, which operates in physical units. Furthermore, the total sales of the functional unit in the economy for a given year are necessary to construct $\mathbf{C^d}$, but this information is often unavailable. To address the uncertainty caused by price variability, Teh et al. [82] developed a mixed-unit IHL, that utilizes physical production and consumption flows derived from material flow analysis (MFA) studies.

4.2.2. Systematic THL

The computational structure of systematic THL is derived from the IHL method. However, the downstream cut-off matrix $\mathbf{C^d}$ is set to zero due to its high data requirements and likely small influence on results when considering a specific system [43], such as beef processing [83]. In the reviewed literature, studies refer to Eq. (5) as either tiered or integrated HLCA without a clear consensus. This study classifies Eq. (5) as systematic tiered instead of IHL because of the hybridization purpose. IHL aims to integrate the precision of $\mathbf{A_{io}}$ and the accuracy of $\mathbf{A_p}$. In contrast, Eq. (5) focuses solely on improving PLCA accuracy by estimating cut-offs or unknown inputs, aligning with the objectives of classic THL but with a more systematic computational approach. Systematic THL was applied in 4 % of the reviewed studies to estimate cut-offs and in 14 % of the studies to estimate unknown inputs.

$$\mathbf{q_h} = \begin{pmatrix} \mathbf{B_p} & \mathbf{B_{io}} \end{pmatrix} \begin{bmatrix} \mathbf{A_p} & \mathbf{0} \\ \mathbf{-C^u} & \mathbf{I\text{-}A_{io}} \end{bmatrix}^{-1} \begin{pmatrix} \mathbf{f_p} \\ 0 \end{pmatrix} \tag{5}$$

The consistent computational structure and standardized options for double-counting correction [37] make systematic THL more suitable for policy applications such as benchmarking and product promotion than classic THL. The simplification of systematic THL compared to IHL enables the hybridization of complete datasets, as it does not require modeling a specific functional unit to obtain the data for the downstream cut-off matrix. Systematic THL has been used to estimate truncation errors in PLCA databases and to assess the role of services and capital in footprint modeling [27,30,53]. However, systematic THL is relatively dependent on price data, which is needed for each process to be hybridized. Another limitation of systematic THL and IHL is that they only hybridize the technology matrix ($\mathbf{A}$) but do not hybridize the environmental extension matrix ($\mathbf{B}$). This can lead to inconsistencies when estimating cut-offs and missing inputs, which might lead to increased direct emission estimates, such as those from fuels [37].

Significant progress has been made in automating HLCA using the systematic THL method. One example is the development of the similar technologies attributes method for double-counting correction to estimate missing inputs in the PLCA dataset ecoinvent through object-oriented code (pylcaio) [27,37]. This double-counting correction method employs heuristics, instead of expert knowledge, making it more suitable for full dataset hybridization as opposed to case studies [27,37]. Also, systematic THL was used to reduce uncertainties in HLCA related to variable price data. For example, Jakobs et al. [84] regionalized the PLCA supply chains by using regionalized price data for the hybridization. Moreover, Agez et al. [30] explored non-functional flow-based hybridization. In this approach, the unknown missing input is estimated using the IO production function of another non-functional flow common to both the IO sector and the PLCA process being hybridized, for which more reliable price data is available [30].

5. HLCA applications by subject area and impact category

HLCA was predominantly applied to assess the environmental impacts of energy systems (24 %) and the built environment (20 %) as shown in Fig. 5a. Less frequent applications focused on food, transportation, waste, materials, infrastructure, services, and organizational and corporate footprints. While most HLCA applications remain focused on conventional PLCA subjects, 26 % of studies assessed emerging technologies essential for the energy transition, such as electric vehicles (EV), carbon capture, batteries, and renewable energy. The results of these studies reveal HLCA's crucial role in informing the transition towards a low-carbon society by tracing upstream environmental pressures in complex supply chains.

This study reviews the built environment and renewable energy systems more extensively below, as these sectors received the most attention in the examined literature and align with this study's focus on informing energy transitions.

5.1. Renewable energy technologies

Driven by the imperative to achieve net-zero carbon societies, there is a growing focus on renewable energy systems and an increasing need

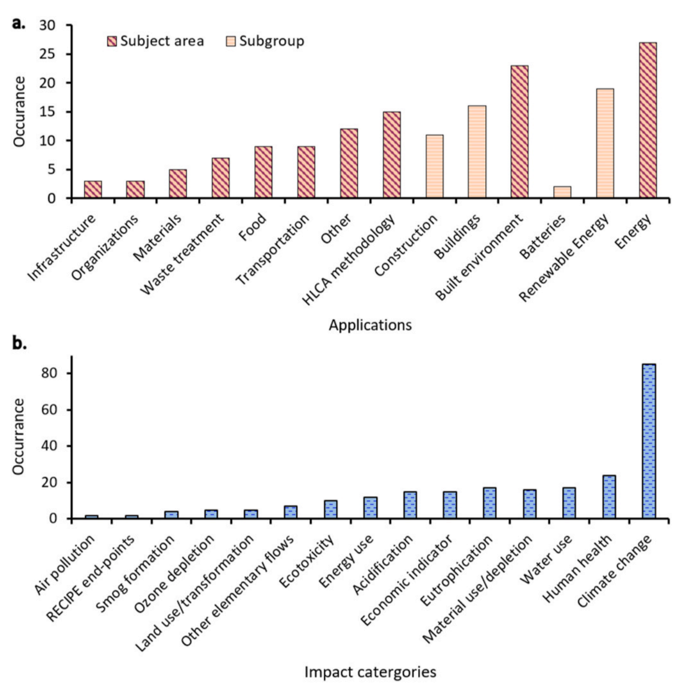


Fig. 5. Applications of HLCA studies between 2016 and 2022. (**a**) Occurrence of applications in HLCA publications (**b**) Coverage of impact categories in HLCA publications.

to holistically assess their environmental impacts [85]. From 2016 to 2022, HLCA was most frequently applied to energy systems (24 %), with a substantial focus on renewable energy technologies (17 %). HLCA is essential for assessing the environmental impacts of novel energy technologies, as data for these novel technologies are still lacking in PLCA databases [86–88].

5.1.1. Embodied carbon (EC)

In the widely-used ecoinvent dataset, GHG emissions of renewable energy PLCA processes are found to be among the most truncated (e.g., 26 % for electricity by solar photovoltaic), whereas fossil-fuel-based energy technologies show minimal truncation (e.g., 1 % for electricity from gas) [27]. Case studies have identified truncation errors of 11 % for corn-stover-based power generation in China [91] and 14 % for an onshore windfarm project in Colombia [89]. An Australian case study found truncation errors for renewable energy technologies ranging between 3 % and 33 %: geothermal (3 %), concentrated solar power (7 %), hydro reservoirs (8 %), solar photovoltaics (10 %), onshore wind (15 %), offshore wind (29 %), and hydro run-off (33 %) [65].

HLCA consistently reveals higher emissions from upstream electricity use in renewable energy technologies compared to PLCA, due to the extended system boundary of HLCA. For example, in Australia, electricity use of hydropower technologies accounted for 10–15 % of impacts in PLCA but 62 % in HLCA [65]. Moreover, Vélez-Henao & Font Vivanco [89] found that incorporating services through HLCA raised both direct (6 %) and indirect emissions (7 %) in a Colombian wind farm project.

5.1.2. Optimal decision-making

HLCA methods, such as MA, improve the precision of energy technology assessments by disaggregating IO energy sectors. For example, Wan et al. [90] analyzed the impacts of nine energy sub-sectors on water consumption, while the original IO database (WIOD) only included one aggregate energy sector. The IHL approach proves useful for studying the effects of introducing novel energy technologies on the local economy. For instance, Jongdeepaisal & Nasu [80] found that introducing a biomass power plant in Kochi prefecture not only had environmental benefits but also increased total economic output.

A new development in HLCA is the integration of flexible LCIs with multi-objective optimization (MOO), previously limited to PLCA [91]. Truncation errors in PLCA-based optimization can lead to suboptimal decisions. The reviewed studies show that combining HLCA with MOO better identifies trade-offs in evaluating new energy projects and technology alternatives [77,79]. For example, Yue et al. [92] used HLCA-based MOO to find that indirect emissions account for 58.4 % of the impacts in a bioethanol supply chain, which could have been partially missed with PLCA-based optimization. HLCA-based MOO also offers a framework for identifying optimal energy plant locations and designs, such as biorefineries [91], by evaluating trade-offs between economic and environmental targets enabled by integrating economic IO data.

5.2. The built environment

HLCA has been widely applied for environmental assessments of buildings (14 %) and construction projects (10 %), yielding promising results. The built environment is a major contributor to global CO_2 emissions (39 %) and energy use (36 %) [93], underscoring the importance of accurate environmental assessments in this sector. HLCA enables a thorough tracing of both upstream and downstream environmental pressures, crucial for addressing the considerable indirect emissions and energy use associated with construction and buildings. Incorporating PLCA data into HLCA enhances the accuracy of assessments for individual materials, buildings, and construction projects while maintaining the ability to trace indirect emissions. This dual capability provides valuable insights for optimizing resource efficiency and analyzing carbon footprints.

5.2.1. Embodied energy (EE)

The life cycle energy use of a building consists of operational and embodied energy, with embodied referring to all energy consumed or carbon emissions released by the goods, processes, and services associated with the building's construction, maintenance, and demolition [94]. As the number of energy-efficient buildings increases, operational energy (OE) efficiency gains are often achieved at the expense of higher EE [95–97]. Quantifying EE is more complex than OE due to the data gaps and inaccuracies in EE data within PLCA. HLCA is, therefore, increasingly used to address these challenges. It also proves valuable in identifying trade-offs between operating and embodied energy efficiency.

Table 2 illustrates the usefulness of HLCA in assessing the EE and EC of buildings and construction materials by comparing HLCA results against those derived solely from PLCA and IO-LCA. However, the variation in results depends on the HLCA method used, the scope, data availability, and quality of the studies, making it inappropriate to extrapolate the results beyond their specific contexts.

The EE of buildings generally increases when conducting an HLCA versus a PLCA due to the extended system boundary. Venkatraj and Dixit [98] assessed the EE of two education buildings and their possible assemblies using IO-LCA and energy intensities. They found changes in EE ranging from +17 % to +140 % and −6% to +79 % compared to PLCA. Disaggregating the relevant IO sector "education and vocational structures" resulted in even larger increases compared to PLCA (+212 % to +305 % and +68 % to +125 %) [98]. However, due to aggregation errors in IO data, using HLCA versus IO-LCA can lead to either an increase or decrease in EE of specific building materials, with variations ranging from −59 % to 181 % [57]. This could result in an underestimation of the embodied energy of materials such as aluminum, cement, copper, and lime when using the aggregated IO environmental coefficients for construction materials [57,58]. Therefore, sensitivity and uncertainty analyses are crucial to better understand the variability of HLCA results due to disaggregation.

5.2.2. Embodied carbon

Similarly, the total emissions (direct and indirect) associated with construction materials and buildings generally increase when using HLCA. In the case of an urban precinct, the largest increase in emissions when using HLCA versus PLCA results occurs in the embodied emissions, which rose by 22 % (including construction, maintenance, and EOL treatment), compared to a 17 % increase in transportation and an 11 % increase in operational emissions [99]. HLCA proves valuable in the preliminary material selection for construction projects, as it overcomes the variability in the completeness of construction materials' data in PLCA datasets, which range from 2 % to 99 % [26]. It can be abundant for materials such as plaster and concrete products (average of 54 %), while highly incomplete for products such as copper wire (11 %) [26]. Teh et al. [59] confirm this large variation in results when using HLCA compared to PLCA results for specific types of concrete and cement.

HLCA also enables the identification of large contributing sectors to the indirect emissions of construction, which is difficult with PLCA. For example, Yu et al. [100] showed that the manufacturing and 'electricity, gas, water, and waste services' industries contribute to over 80 % of the construction industries' EC. This facilitates the identification of how policies and measures in other sectors can contribute to reducing the overall GHG emissions of the construction industry. Lastly, the sensitivity analyses by Zhang et al. [101] showed that using IO-LCA for calculating the EC of individual buildings induces substantial aggregation errors and uncertainty. This stresses the importance of system boundary selection, which, if oversimplified, can underestimate total emissions (by up to 13.6 % in Zhang et al. [101]) and increases the uncertainty of the results.

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Table 2
Percentage changes in embodied energy (EE) and embodied carbon (EC) when using HLCA compared to PLCA and IO-LCA in studies focused on the built environment. Initial embodied energy (IEE) only includes construction. Life cycle embodied energy includes IEE, maintenance, and demolition. The superscripts explain if the scope excludes transportation and construction (a), maintenance (b), or operational emission (c).

Application	Scope	HLCA vs. PLCA EE	HLCA vs IO-LCA EE
Buildings [56]	IEE	+110 %	+31 %
Education buildings [98]	LCEE		Building 1: +212 to +305 % Building 2: +68 % to +125 %
Prefabrication in buildings [102]	IEE	Project A: +13 %, Project B: +11.%	
Building systems [103]	IEE[a]	Intensities range from +82 % to +96 %	Intensities range from +69 to +81 %
Prefabricated materials [104]	LCEE[b]	Range from +28 % to +73%[a]	Range from +26 % to +105%[a]
Building materials [57]	Direct + indirect		Extremes: Vitrified clay pipes (−17 %), clay tiles (−40 %), adhesives (−59 %), cement (+69 %), lime (+90 %), aluminum (+181 %)
Building materials [58]	Direct + indirect		Extremes: Bricks and clay tiles, vitrified clay pipes (−24 %), adhesives (−61 %), copper (+31 %), cement (+64 %), aluminum: (+172 %)
		HLCA vs. PLCA EC	**HLCA vs. IO-LCA EC**
Aluminum window [105]	Direct + indirect	+23 %	+69 %
Residential Buildings [101]	Direct + indirect	Small system boundary (SB): Total: +1.8 % & +2.5 %. Scope 3: +89 % & +96 % Broad system boundary: Total: +1.4 % & +1.6 %, Scope 3: +117 % & +127 %	Small system boundary: Total: +5.4 % & +6.9 %, Scope 3: 1% & −3% Broad system boundary: Total: +5 % & +6 %, Scope 3: +13 % & +12 %
Building systems [103]	IEE[a]	Intensities range from +69 % to +103 %	Intensities range from +63 % to +90 %
Urban precincts [99]	Direct + indirect	In total +16 %	
Construction products [100]	Direct + indirect	On average: +20 %	
Cement & concrete [59]	Direct + indirect	Ordinary Portland cement (OPC): +29 %, Mpa OPC concrete: +11–50 %, 25 MPa blended cement based concrete: +11–50 %, 50 MPa geopolymer concrete (GPC): +48–103 %	
FA-based GPC [29]	Direct + indirect	+103 % and +114 % for mixed-unit HLCA	

5.3. *Impact category coverage*

Over half (53 %) of the reviewed studies focus on one impact category, limiting the identification of trade-offs between different environmental issues. More specifically, 39 % of the studies only considered GHG emissions, while impacts such as ozone depletion, smog formation, land use, and land transformation are seldom considered (Fig. 5b). Moreover, HLCA studies often do not characterize the results (73 %), which means they do not translate the results from environmental flows into environmental or human health impacts (e.g., translating GHG emissions into climate change impacts). Without characterization, it is difficult to evaluate the significance and scale of the results and, therefore, to properly identify the most sustainable product or technology alternative.

The main barrier to comprehensive impact assessment in HLCA is the misalignment of the elementary flow data between IO and PLCA. IOTs generally cover only the general pollutants such as CO_2, CH_4, and SO_2, with a narrow scope (e.g., only emissions to air). However, PLCA datasets often cover more environmental flows and generally have a larger scope (e.g., also emissions to water and soil) [30,38,106]. The emission intensities between PLCA and IO also vary, due to different underlying data sources [106]. Environmental flow data are often missing for ecotoxicity, ionizing radiation, and ozone depletion in IOTs (e.g., in EXIOBASE) [30], which can explain the limited use in the reviewed studies. An exception is the United States-specific IOT (USEEIO), which contains 1901 elementary flows and is constructed to match the common PLCA impact assessment method TRACI [107]. This enabled a broad assessment across 10 environmental impacts for applications such as corn production [108], beef processing [83], and truncation error estimation [30].

5.4. *Robustness and validity*

The robustness and validity of the reviewed studies were analyzed through their explicit consideration of four HLCA limitations and pitfalls. Uncertainty induced by double-counting and variable price data is frequently considered. However, Fig. 5a shows that limitations related to the exclusion of capital goods and the linear modeling approach of HLCA are often overlooked.

Double-counting. In hybridization, there is a risk of double-counting inputs and environmental impacts. Novel developments include the review study by Agez et al. [37] which provides a comprehensive overview of double-counting correction methods, applicable to systematic THL, MA, IHL, and the PXC method. Moreover, they developed a double-counting correction method based on heuristics, instead of expert knowledge, which enabled full dataset hybridization [27,37].

Classic THL studies most frequently overlook double-counting issues (Fig. 6b). This is particularly concerning, as the risk of double-counting is amplified by the method's unclear computational structure and ambiguous system boundary selection. As a result, the lack of explicit

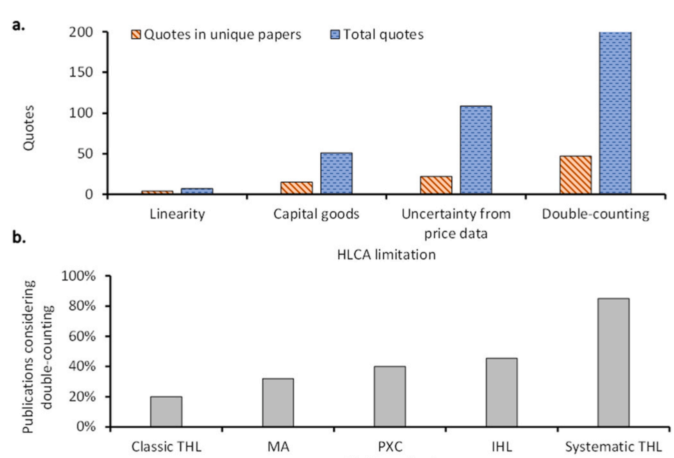

Fig. 6. Consideration of HLCA limitations in the reviewed publications. (**a**) Occurrence of a search term of four HLCA limitations in the 114 review papers. Orange bars (diagonal stripes) indicate the number of papers mentioning each limitation, while blue bars (horizontal stripes) show the total quotes of the search terms. (**b**) Percentage of studies considering double-counting. HLCA methods: classic tiered HLCA, matrix augmentation, integrated HLCA, the path exchange method, systematic tiered HLCA. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

double-counting correction reduces the robustness of classic THL studies. Double-counting is relatively straightforward to avoid in MA, which may explain why it is infrequently considered explicitly [58,67,102,109]. In the PXC method, the risks of double-counting are small since the IO-LCA system boundary stays intact. However, the identification of corresponding input-output and process nodes is a necessary step that helps avoid double-counting [26].

Uncertainty from variable price data. HLCA results are susceptible to price data due to its linear relationship in hybridization [26,83]. For example, Li et al. [83] found that the beef price accounted for 20 % of the variance in total impacts, with even higher variances in certain impacts, such as ozone depletion (95 %). Consequently, incorporating price variability into sensitivity and uncertainty analysis is essential in HLCA, yet it is often neglected. Additionally, the absence of distribution information for certain uncertainty sources, such as prices, necessitates the use of assumptions to create probability distributions [83,110].

Methodological developments using the systematic THL method have focused on limiting price uncertainty, by using regionalized PLCA data, non-functional flow-based hybridization, and mixed-unit HLCA [27,29,84]. Another promising development is the inclusion of price uncertainty ranges in the construction of hybrid coefficients databases [111], which enhances the transparency and reliability of these prefabricated datasets. More generally, Perkins & Suh [110] emphasize the importance of prioritizing supplier-specific data collection to improve the precision of HLCA results.

Capital goods. The exclusion of capital goods from IO production functions has traditionally been viewed as a limitation of hybridization [23,42]. However, PLCA processes also tend to underestimate contributions of capital goods systematically [81]. The novel integration of capital goods in IOTs has resulted in the use of endogenized IOTs in seven of the reviewed HLCA studies, such as in the EPiC database and the pylcaio software [26,30]. Font Vivanco [53] analyzed the influence of including services and capital goods on the environmental footprint, comparing PLCA, IO-LCA, and HLCA. The inclusion of capital goods resulted in a 25 % median relative change in the IO-LCA sectoral footprints [53]. However, the inclusion of capital goods in HLCA also resulted in increased rebound effects for all impacts except acidification [53]. Additionally, HLCA studies focused on building and construction materials increasingly consider capital energy use [57,58,67,98].

5.4.1. Linearity

Since both PLCA and IO-LCA are linear models, hybridization creates a linear model that does not include price effects and constraints, and as a result, does not accurately reflect the real economy which is characterized by nonlinear production functions [112]. Product promotion based on such linear extrapolation may result in under- or overestimation and only forms a rough estimate [113]. Therefore, using outcomes from nonlinear models in decision-making contexts can have significant implications. It is essential to consider the environmental impacts from product promotion, rather than focusing solely on the system or expanding system boundaries using HLCA. Yang & Heijungs [112] recommend incorporating additional models, such as systems dynamics, general equilibrium models, or agent-based models, into PLCA (and potentially HLCA) to better capture the environmental impacts resulting from product promotion.

6. Discussion

This review and the selection of studies relied primarily on two search engines, which may have excluded some relevant studies. Nevertheless, studies that focused on advancing HLCA methodology, which are central to this review, often utilized the HLCA classification proposed by Crawford et al. [23]. This suggests that it is unlikely these studies were missed using the defined search terms. Another potential source of error stems from the search terms used in the text analysis tool Atlas.ti to identify considerations of HLCA limitations. To minimize this, a variety of search terms, including synonyms, were used.

Table 3 summarizes the remaining data and methodological challenges in HLCA. The exclusion of capital goods in IO data has largely been addressed through the development of endogenized capital IOTs. However, addressing the linearity of HLCA remains a complex challenge, likely requiring the incorporation of alternative models, such as system dynamics. The risks of double-counting were considered in 41 % of the reviewed literature, yet reducing the uncertainty introduced by different double-counting correction methods remains a major methodological challenge.

Another major challenge is obtaining suitable price data for hybridization. Regionalized data is essential for reducing uncertainty induced by price variability and for aligning environmental flow data [28,30]. Major progress in MRIO database development, with nine global MRIOs, marks a key step in regionalization [114], while regionalized data in PLCA datasets remains limited [84,115]. Experimental approaches, such as mixed-unit HLCA [29] and non-functional flow-based hybridization [30], have been developed to address these issues but require further testing and refinement. Additionally, environmental flow data for ionizing radiation and ozone depletion is often missing in IOTs, and large inconsistencies exist in ecotoxicity impact categories across IO and PLCA data. Lastly, while PLCA datasets are useful for large-scale hybridization, they often heavily rely on proxies and outdated background data [116], which should be avoided whenever possible.

Moreover, HLCA methods show notable inconsistencies. To address this, this study proposes an updated HLCA taxonomy that distinguishes between data and computational hybridization, based on the computational structure. Most reviewed studies employed classic THL, which lacks a robust computational structure. While the PXC and IHL methods are promising, their use is limited. The PXC method requires substantial expertise, and its semi-automation software is not publicly available, restricting its larger-scale adoption. IHL is infrequently used due to high data dependency in constructing downstream cut-off matrices [43]. Lastly, there are many variations in systematic THL and IHL computations, which limits clarity and standardization.

Table 3
Summary of main data and methodological challenges and proposed solutions.

Data challenges	Proposed solutions
Quality price data	Supplier-specific data collection [110]
Limited environmental flows in IO datasets **Inconsistencies in environmental flow data between IO and PLCA**	• Harmonize environmental flows and impact assessment between IO and PLCA [30] • Regionalize IO characterization factors [30]
Outdated data and proxies in PLCA datasets	• More frequent updates of PLCA datasets • Supplier-specific data collection [110]
Methodological challenges	
Uncertainty from variable price data	• Use supplier-specific and regionalized PLCA data [28,110] • Futher research methods to surpass price data in hybridization [29,30]
Uncertainty from double-counting correction	Quantify the uncertainty from double-counting correction methods [28,84]
Accuracy issues in impact scores	Regionalize IO characterization factors [30]
Hybridizing environmental extensions in IHL and systematic THL	Use double-counting correction methods for hybridizing environmental extensions [37]
Standardizing HLCA methods	Unify under A_h^{-1} in systematic THL and IHL [71]
Linearity of HLCA	Incorporate scenarios, market mechanisms, and alternative models such as CGE [76,112,113]

7. Conclusion

This study not only reviewed the current state of the art in HLCA but also aimed to identify its role in supporting sustainable technologies, policy regulations, and transitions. In total, 114 studies were critically reviewed, focusing on the application, the HLCA method used, impact categories covered, and the consideration of limitations. The findings indicate that HLCA is most frequently applied in the environmental assessment of energy systems, construction, and buildings, while it is rarely applied in food, services, and corporate footprint studies. The majority of studies employ classic THL and focus heavily on climate change. Limitations associated with the linearity of HLCA, the exclusion of capital goods, and price uncertainty were infrequently addressed in the reviewed literature.

HLCA proved particularly useful in guiding sustainability transitions in the built environment and the energy sector by:

- Improving the assessment of novel technologies by integrating bottom-up PLCA data and estimating missing impacts using IO-LCA data.
- Providing a more equal basis for comparing different energy technologies and building materials by circumventing variance in PLCA datasets, as revealed in HLCA studies [86–88].
- Avoiding over- or underestimation of embodied impacts in specific building materials compared to IO-LCA, as demonstrated in Table 2 [57].
- Enabling the assessment of trade-offs in environmental, social, and economic indicators for specific technologies [62,81,114], as well as the identification of optimal outcomes using HLCA-based optimization [77,79].

Moreover, the study identified distinct roles for different HLCA methods in supporting climate policies. MA is well-suited for the rapid screening of projects and new technologies, while IHL is ideal for assessing the environmental and economic impacts of introducing novel technologies and policy scenarios. Systematic THL and PXC methods are the most promising for product benchmarking due to their consistency and automation options. The PXC method, in particular, supports the creation of prefabricated datasets of embodied material coefficients, enabling large-scale assessment of material trade-offs with a standardized system boundary across all materials. In contrast, the classic THL method may be unsuitable for policy and decision-making contexts due to its lack of a robust computational structure.

This review underscores HLCA's valuable role in future sustainability transitions beyond clean energy production and climate-neutral construction. However, future HLCA studies should broaden their focus and move beyond climate change to address burden shifting between impact categories. This study highlights the need to streamline the environmental flow data and impact assessment methods in PLCA and IO-LCA. Additionally, regionalized data in HLCA is preferred whenever possible, as it enables a broader coverage of more impact categories and reduces uncertainties introduced by variable price data [84]. Furthermore, future IHL and systematic THL studies should explore hybridizing the environmental extension matrices (**B**) to prevent inconsistencies.

The growing emphasis on automation, hybrid dataset compilation, and regulatory requirements such as the EU's CSRD and CBAM highlights the importance of addressing key challenges identified in this review. For instance, CSRD requires comprehensive and standardized reporting of company-level emissions, while CBAM necessitates precise sector-specific assessments of direct and indirect emissions, which demand robust integration of PLCA and IO-LCA data. Key issues such as inconsistencies in environmental flow data, reliance on outdated PLCA proxies, and unresolved double-counting correction uncertainties could hinder the ability of HLCA methods to meet these regulatory requirements. Additionally, as HLCA applications evolve, emerging approaches such as optimization-based HLCA and predictive computational models introduce new opportunities for trade-off analyses but also pose challenges, including variability due to price data and regional inconsistencies.

Enhancing the robustness and applicability of HLCA remains a key priority. Despite progress in the double-counting correction methodology, uncertainties associated with the selection of double-counting correction methods should be quantified in future research. Open-access HLCA software, particularly tools that automate hybridization, would be beneficial for wider adoption. Unifying the inversion under $\mathbf{A}_h$ in systematic THL and IHL would improve clarity and facilitate broader HLCA adoption. Finally, incorporating scenarios, advanced market mechanisms (e.g., rebound effects) [76], and alternative models (e.g., CGE) [113] could help more accurately anticipate the impacts of product promotion, thereby strengthening the robustness of results to better inform long-term planning and decision-making.

Credit author statement

Conceptualization: RHH, RW; Formal analysis: RHH; Methodology: RHH; Supervision: RW; Visualization: RHH; Roles/Writing – original draft: RHH; Writing – review & editing: RH, RW, AT

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in the copyediting process. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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