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BIM-based life cycle assessment: A systematic review on automation and decision-making during design

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ABSTRACT

Life Cycle Assessment (LCA) is essential to achieve a Net-Zero Carbon Built Environment and inform effective mitigation strategies for environmental impacts throughout a building's life cycle. However, collecting Life Cycle Inventory (LCI) data and the Life Cycle Impact Assessment (LCIA) processes are complex and time-consuming. BIM-LCA integration enables automated quantity-take-off, supporting faster evaluation of different design options and decision-making. Consequently, research on BIM-LCA has grown significantly since 2013. However, previous literature reviews on BIM-LCA do not cover developments from the past three years, nor do they assess how BIM-LCA supports decision-making or how decision-making methods can enhance its adoption and use, particularly among non-LCA experts.

A systematic literature review was conducted following the PRISMA protocol to address this gap. A total of 115 research articles (2019–2024) were analysed according to design phases, BIM object LOD, LCA application, data exchange and extraction methods, automation degree, and decision-making features, covering Multi-Criteria Decision Analysis, Multi-Objective Optimisation, and Sensitivity/Uncertainty analyses.

The findings highlight advancements in LCI automation. However, several challenges remain, including manual BIM-LCA data mapping during LCIA and limited research on: BIM-LCA for renovation projects, dynamic data exchange for OpenBIM, standardised LOD for different LCA applications, and local databases for budget-based targets. Furthermore, few studies integrate LCA with economic and social indicators, and decision-making methods are mainly absent from BIM-LCA tools.

This study outlines research directions to address these limitations and improve BIM-LCA automation and decision-making. Future efforts will focus on gathering insights from industry stakeholders to establish priorities for user-centred BIM-LCA development.

1. Introduction

The architecture, engineering, and construction (AEC) industry is responsible for approximately 40 % of global greenhouse gas (GHG) emissions, 50 % of all material consumption [1], and more than one-third of all waste generation [2]. Moreover, the AEC sector is regarded as one of the least digitised industries. It relies heavily on traditional practices and invests little in research and development, which are all strong factors behind its slow productivity growth.

Enhancing competitiveness and digitalisation, minimising GHG emissions, reducing dependence on virgin resources, and tackling construction and demolition waste (CDW) are top priorities for European policy [3]. Initiatives such as the Digital Europe Programme, the Circular Economy Action Plan, and the Renovation Wave promote decarbonisation, innovation, and digital data management throughout the building lifecycle, and integrate instruments and solutions to mitigate these issues [4].

Life Cycle Assessment (LCA) is a recognised method for evaluating the environmental impacts associated with raw material acquisition, production methods, user behaviour and disposal or recycling. It covers the entire life cycle of a product, as defined in ISO 14040 and 14044 standards [5]. Unlike other industrial processes, which typically involve a limited number of standardised elements with short lifespans, buildings incorporate a wide variety of products with long lifespans and unique characteristics. Furthermore, building construction occurs in uncontrolled environments, under the influence of external factors and multiple stakeholder decisions. As a result, performing a conventional LCA in buildings can be complex and time-consuming. Practitioners face

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many challenges in collecting Life Cycle Inventory (LCI) data, conducting Life Cycle Impact Assessments (LCIA), and interpreting results [6]. As such, dedicated international and European standards by ISO/TC 59/SC 17 [7–9] and CEN/TC 350 [10–12] have been proposed to guide Building LCA.

Building Information Modelling (BIM) combines geometric and semantic data regarding a built asset, effectively communicating and maintaining spatial relationships, geographic information, material specifications, and project timelines throughout the building lifecycle [13,14]. This integration is beneficial for collecting LCI information, as it automatically retrieves relevant data, reducing both time and labour. As Building LCA becomes increasingly automated, it becomes quicker and easier to generate results for all design alternatives, thus supporting decision-making.

Owing to these advantages, research on BIM-based LCA has grown significantly over the past decade, more precisely since 2013 [15]. However, these rapid advancements challenge researchers and practitioners as they try to fully understand the progress, which may result in the underutilisation of the benefits associated with BIM and LCA integration. Conducting a systematic literature review is therefore essential to consolidate recent knowledge and promote its effective adoption.

Several literature reviews have categorised different BIM-LCA integration approaches, highlighting the challenges, advantages, and limitations associated with each. For instance, Soust-Verdaguer et al. [16] focused on how BIM can simplify data input and optimise the output of BIM-based LCA tools. Other authors [17,18] classified BIM-LCA according to the data exchange processes: 1) export BoQ into Excel, 2) export BoQ into a dedicated LCA tool, 3) use LCA add-ons for BIM software, 4) use visual programming languages (VPL), 5) use the IFC format for data transfer, and 6) include LCA data in BIM objects, using a library of BIM objects and materials with LCA data integrated as parameters. Safari et al. [19] classified them into conventional (i.e., unidirectional data flow), static (i.e., using Globally Unique Identifiers (GUIDs) assigned to each object within the IFC schema), and dynamic (i.e., BIM add-ons and dynamo scripts), and Obrecht et al. [20] based their analysis on the automation degree (i.e., manual, semi-automated and automated).

Furthermore, Mora et al. [21] highlighted the lack of integrated LCA databases in BIM-based tools, discussing interoperability and automation challenges. Teng et al. [22], Lu et al. [23] and Seyis [24] identified key barriers, such as inadequate BIM modelling, limited interoperability, lack of standardised LCA procedures and LCA data on building materials [24]. Tam et al. [15] analysed the interactive processes between BIM and LCA according to the ISO 14040, concluding that software integration at the LCI stage is poor.

Zheng et al. [25] assessed four typical BIM-LCA approaches, highlighting the trade-offs between accuracy and efficiency, whereas Tam et al. [18] proposed a method to select the optimal BIM-LCA integration approach for each design phase. Expanding the scope, Llatas et al. [26] and Berges-Alvarez et al. [27] explored the integration of BIM and Life Cycle Sustainability Assessment (LCSA), emphasising the need for data harmonisation across LCA, Life Cycle Costing (LCC), and Social LCA. Additionally, Tan et al. [28] examined strategies to enhance the use of Multi-Criteria Decision Analysis (MCDA) and BIM in areas such as LCA, retrofitting, supplier selection, and constructability.

Although many literature reviews have addressed the topic of BIM-based LCA, they were all conducted prior to 2022. Only a few recent contributions, such as Huang et al. [29] and Chen et al. [30], included developments from the last three years. Huang et al. [29] performed a systematic literature review on BIM-based LCA to assess embodied carbon in early design, highlighting the need for development of standardised methods that allow a continuous LCA through design. Similarly, Chen et al. [30], summarised the characteristics of commonly used BIM software and energy performance tools, focusing on their capabilities and limitations.

Taken together, previous reviews have predominantly focused on categorising BIM-LCA integration and identifying their benefits and challenges. However, limited attention is given to how BIM-LCA aids decision-making, enhances building performance, or integrates with other economic and environmental assessments. Specifically, there is a need to address the following research questions: **RQ1 -** What obstacles hinder decision-making in BIM-based LCA? **RQ2 -** What solutions have been developed to address these challenges? **RQ3 -** What challenges remain overlooked, and how can they be addressed?

Additionally, further exploration is needed on how emerging technologies, such as Machine Learning (ML), Multi-Objective Optimisation (MOO), and Multi-Criteria Decision Analysis (MCDA), solve interoperability challenges, automate manual LCI and LCIA processes, predict environmental impacts at early design, and find optimal design solutions.

To address these research questions and fill the identified gap, a systematic literature review (SLR) on BIM-based LCA from the past five years was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. 115 relevant articles were selected for the content analysis, which was based on seven key criteria: (a) building design phase, (b) Level of Development (LOD) of BIM objects, (c) LCA application, (d) data exchange, (e) data extraction, (f) automation degree, and (g) decision-making capabilities. Through this approach, the study examines the current state of BIM-based LCA, consolidates recent advancements, and identifies future research directions needed to achieve fully automated processes capable of supporting data-driven design decisions.

The paper structure is as follows. After this introduction, Section 2 outlines the SLR methodology; Section 3 presents the results based on the recent literature using the aforementioned criteria; Section 4 discusses the identified BIM-LCA challenges, current developments, and future research directions; and finally, Section 5 presents the conclusions.

2. Materials and methods

The PRISMA 2020 protocol [31] provides a structured methodology for screening, assessing eligibility, and synthesising the SLR results. The Covidence web tool [32] was used to manage all references throughout the screening and eligibility process, supporting duplicate removal, blinded screening by multiple reviewers and conflict resolution in alignment with PRISMA guidelines.

The keyword search focused on three main topics: (1) BIM, (2) LCA, and (3) Building Design, targeting article titles, abstracts, and keywords in two journal databases, Scopus and Web of Science (WoS). Table 1

Table 1
Query keywords used in Scopus and WoS databases.

Main Category (‘AND’ Boolean Operator)	Sub-Keywords (‘OR’ Boolean Operator)	Limitations (‘AND’ Boolean Operator)
Life Cycle Assessment	*"life cycle assessment" OR "Life-Cycle Assessment" OR " Life Cycle Sustainability Assessment" OR "life cycle environment* assessment" OR " life cycle analysis" OR "life cycle *environment* analysis" OR "lifecycle assessment" OR " lifecycle analysis" OR LCA OR GWP OR " global warming potential " OR " carbon footprint " OR " embodied carbon "*	Timeline 01/01/2019 to 30/11/2024 Articles/Journals English language
Building Information Model	*"building information model* " OR "BIM"*	
Case Application	"building design" OR "design stage*" OR "building material*" OR "construction material*" OR "new construction" OR "renovation" OR "refurbishment" OR "existing building" OR "retrofit"	

outlines the main topics and corresponding keywords used in the research query. The results cover the period from 2019 to November 2024.

Only original articles from peer-reviewed journals were included in the review; review articles, grey literature, editorials, conference papers, and articles not written in English were excluded from the selection. The decision to exclude conference proceedings was based on three practical considerations: (1) Methodological consistency and depth: many conference papers lacked sufficient detail for robust content analysis, particularly in areas such as automation, data integration, and decision-support; (2) Avoiding duplication: a preliminary screening revealed that over one-third of the conference papers retrieved using the Table 1 research query were later published as journal articles with expanded content and were therefore already included in the SLR. Others reused BIM-LCA methods to assess different case studies with no further innovation in automation or decision-making (see supplementary materials 2, Appendix A: List of Conference Papers not included in the SLR); (3) Manageability: including conference proceedings would artificially increase the number of records, without adding substantial methodological diversity or insight.

A total of 359 articles were identified through database search, and 13 were found through citation searching, resulting in 241 articles after removing duplicates. The duplicates were determined automatically by the Covidence web tool. During the screening phase, 57 articles were excluded based on title and abstract review, and eight were excluded because the full text could not be accessed. In the eligibility phase, from the 176 analysed articles, 61 were excluded based on the inclusion and exclusion criteria detailed in Table 2. Ultimately, 115 articles met the inclusion criteria and were retained for detailed content analysis (Supplementary material 1, Appendix B: Full List of Articles Included in the SLR and Classification). The full selection process is illustrated in Fig. 1.

The content of the 115 articles was analysed based on seven key categories that characterise BIM-LCA methods, as identified in previous literature reviews [16,17,20,25], and shown in Fig. 2. These categories are related to different phases of BIM-based LCA and align with the ISO 14040 and ISO 14044 LCA framework. According to these standards, LCA consists of four key phases. The first phase, Goal and Scope Definition, establishes the purpose of the study, the reference study period, the functional unit, and the system boundaries. The second phase, LCI, involves data collection and quantifying all inputs and outputs across a product's life cycle. The third phase, LCIA, translates inventory data into environmental impact indicators, including classification, where emissions are assigned to impact categories, and characterisation, where raw data is converted into impact indicators using equivalent factors, following methodologies such as ILCD, EF 3.0, CML, ReCiPe, and TRACI.

Table 2
Exclusion and Inclusion criteria for eligibility during full-text review.

Inclusion Criteria	Exclusion Criteria
BIM-based LCA methods or tools are identified.	BIM-based LCA methods or tools are not identified
BIM-based LCA is performed during the design phase. (Studies that considered both design and operational phases were also considered).	BIM-based LCA is performed during the operational phase.
BIM-based LCA is used to evaluate a case study.	BIM-based LCA is not used to evaluate a case study
The LCA is performed on buildings.	The LCA is performed on infrastructure projects, e.g., bridges, roads, and tunnels.
Embodied impacts are considered.	Only operational impacts are considered.
ML, MCDA, or MOO are applied to aid decision-making.	–
Other indicators such as Life Cycle Cost, Design for Disassembly and Adaptability are considered.	–

The fourth phase, Interpretation, involves analysing results to identify key environmental impacts and areas for improvement.

In the context of BIM-based Building LCA, products, waste, and processes involved in the building's life cycle are extracted from BIM models during the LCI phase. In the LCIA phase, characterised LCIA data for individual products is mapped to BIM objects and summed up to assess the building's environmental impact.

The **Design Phase (CAT1), BIM Object Level of Development (LOD) (CAT2)** and **LCA Application (CAT3)** are related to the Goal and Scope Definition phase, as they determine at which design phase the LCA will be performed, what is the purpose of the LCA, and the level of information needed in the BIM model. **Data extraction (CAT4)** and **Data exchange (CAT5)** correspond to the LCI phase, which defines how data is collected, structured, and transferred. The **Automation Degree (CAT6)** is associated with LCI and LCIA, as it assesses the data exchange and mapping automation between these combined tools. Finally, **Decision-Making (CAT7)** is linked to the Interpretation phase, which involves analysing results and integrating insights into decision-making. Other aspects of BIM-based LCA are also analysed, such as the databases and system boundaries used, case study characteristics, and additional environmental, economic, and social indicators beyond LCA. The results are recorded in spreadsheets (See supplementary materials 1- Appendix B: List of Articles Included in the SLR and Classification), and the categories are summarised in Fig. 2 and described in the following sections.

2.1. Design phase (CAT1)

BIM-based LCA methods can be distinguished according to the building **Design Phase (CAT 1)** [33]. The first, *early design*, focuses on early design assessments, in which parametric optimisation is typically applied with simplified LCA methodologies [34–38]; during this phase, project decisions are the most impactful and least expensive to alter [6]. The second, *detailed design,* includes methods tailored for when comprehensive building and material data is available. The third, "*construction design*", refers to "as-built" BIM models with all building information. The fourth, *continuous LCA*, involves using techniques that enable continuous monitoring of LCA results throughout the design process. This includes the ability to track project history and progressively align LCA inputs and outputs as more detailed and accurate data become available at each design phase.

2.2. BIM object LOD (CAT2)

The design phase is directly related to **the Level of Development, or LOD (CAT2)**, of BIM objects, which is described by the American Institute of Architecture as *"the minimum dimensional, spatial, quantitative, qualitative, and other data included in a Model Element"* and is divided into five levels, ranging from 100 to 500 [39]. Although the term LOD has been replaced by LOIN (Level of Information Needed) in ISO 19650–1 [40] and ISO 7817–1[41], the two approaches differ. While LOD establishes predefined levels (e.g., 100, 200, 300), LOIN focuses on what information is required, when it is needed, and for what purpose, without relying on fixed levels. As most of the articles in this SLR still refer to LOD, it has been adopted as the reference term.

LOD 100 defines the preliminary layout, rough size, and object geometry. In LOD 200, preliminary dimensions and materials are established. In LOD 300, key materials and components are specified, including sizes, shapes, locations, wall layers, and structural elements. In LOD 400, material specifications, detailed shapes, and reinforcement in structural elements are defined with sufficient detail for fabrication. Finally, LOD 500 establishes as-built product and material specifications. Each LOD may be further specified using intermediate levels between the main thresholds (e.g., LOD 350).

As a general rule, LOD progresses to meet the information requirements of each design phase [42]. The LOD should be aligned with the goal and scope of the LCA, as well as with the design stage, and

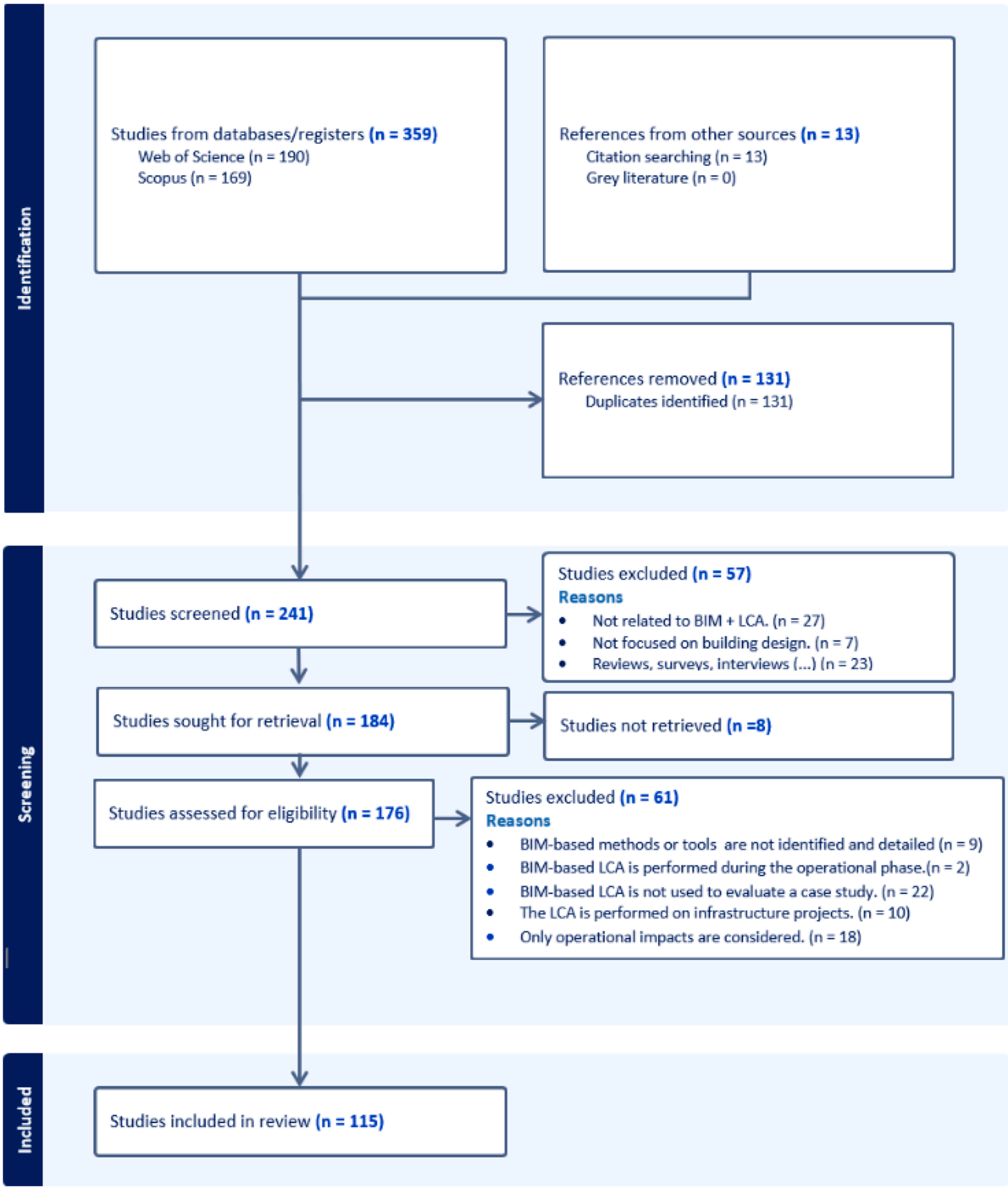

Fig. 1. Prisma diagram.

well-defined in the BIM Execution Plan (BEP). For instance, a lower LOD may be sufficient for comparing early-stage design options, whereas a higher LOD is required when conducting LCA for compliance with green building certification schemes such as BREEAM or LEED.

Santos et al. [43] have suggested that LOD 300–350 is the reference point for accurate, detailed, and complete LCA calculations. By contrast, LOD 200 is generally used for screening or simplified assessments, often supported by external databases containing typical pre-defined construction solutions for building elements [44,45]. At this stage, practitioners frequently rely on estimated material quantities and generic LCA data, which introduces high levels of uncertainty and reduces the precision of the results. This relationship between LOD and data quality is critical for decision-making, as it directly influences the level of confidence in comparing design alternatives [46].

In this SLR, the articles were classified as follows: if LOD is not explicitly stated, it is classified as *"not specified"*. Articles addressing continuous LCA across design phases often reported a range of LOD (e.g., 100–300). In other cases, a LOD range (e.g., 200–300) may also indicate that BIM models (architectural, structural, MEP) are not developed uniformly across all disciplines. For example, structural components may reach a LOD of 300 at an early stage, while other elements, such as walls or roofs, may remain at lower LOD.

2.3. LCA application (CAT3)

The EeBGuide Handbook [16,26] established three types of **LCA application (CAT3)** depending on the goal and scope of the assessment, the practitioner's experience, the data availability, and the building project's state of development: *Screening LCA, Simplified LCA*, and *Complete LCA*. The *Screening LCA* involves simplified data input and is less precise, focusing on fewer impact categories and life cycle modules. While a *Simplified LCA* requires greater expertise from the LCA practitioner, it is less comprehensive than a *Complete LCA*, which considers all life cycle modules and impact categories, commonly performed with

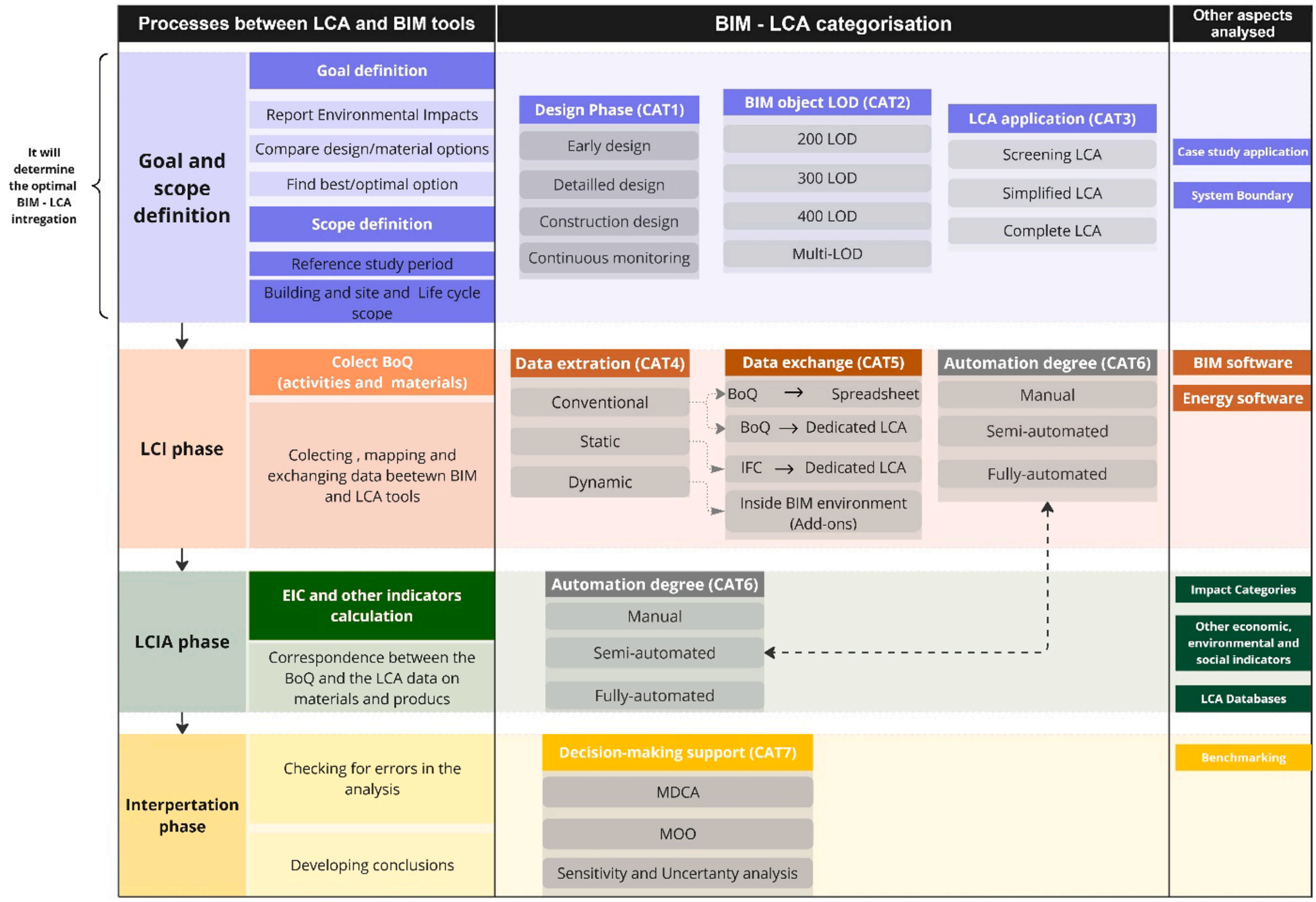

Fig. 2. The Categories that define BIM-LCA integration and their relation to the four phases of the ISO 14040 series were used to analyse the selected articles.

Table 3
The relationship between LCA application categories, the type of LCA data, life cycle stages and impact categories.

LCA application (CAT3)	LCA data	Life cycle Stages (EN 15,978)	LCA impact categories
Screening LCA	Generic LCA data	**A1–3** (Product Stage) **B6** (Operational energy use) **B7** (Operational water use)	One or two indicators, e.g., • Global Warming Potential (GWP) • Energy use (MJ)
Simplified LCA	Generic or average LCA data	**A1–3** (Product Stage) **B6** (Operational energy use) **B7** (Operational water use) **C3–4** (Waste processing, Disposal of Waste)	Reduced indicator set, e.g., • GWP • Abiotic Depletion Potential (ADP) • Acidification potential (AP)
Completed LCA	Specific LCA data EPDs	**A-D** Cradle to Cradle	Complete set, (e.g., EN 15978 + EN 15804+A2) • GWP • Ozone depletion (ODP) • Photochemical ozone creation (POCP) • AP • Eutrophication (EP) • Resource use • Water Scarcity (…)

LCA software such as Simapro and GaBi [16]. Table 3 represents the type of LCA data, life cycle stages and impact categories used in each LCA application. Fig. 3 illustrates the relationship between the **Design Phase (CAT1), BIM objects' LOD (CAT2)** and **LCA Application (CAT3).**

2.4. Data extraction (CAT4)

Data extraction (CAT4) broadly defines how data is extracted from the BIM models and outlines the data flow between BIM and LCA tools. Safari et al. [19] identified three types of data extraction between the BIM model and the LCA tools: conventional, static, and dynamic. In the *Conventional Approach*, after the quantity take-offs (QtO) from BIM models, the Bill of Quantities (BoQ) is stored in an information container, which is then automatically or manually inserted into LCA software.

In the *Static Approach*, the BIM model is exported as an Industry Foundation Classes (IFC) file and imported into LCA software, potentially benefiting from Information Delivery Specifications (IDS) and the Globalids. IDS ensures that IFC files meet predefined data requirements, improving data consistency and simplifying model updates. IFC Globalids are Globally Unique Identifiers (GUIDs) assigned to each object within the IFC schema, and can be used to track and link building elements across different tools. When Globalids are preserved between IFC versions, the LCA software can retain existing links between geometric

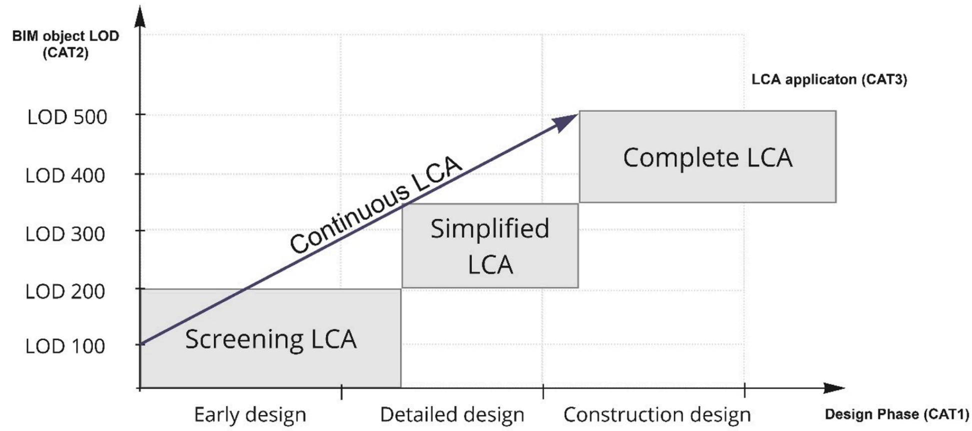

Fig. 3. The relationship between the design phase (CAT1), BIM objects' LOD (CAT2) and LCA application (CAT 3).

and environmental data, avoiding the need to re-establish them during BIM model updates [47]. Alternatively, this interoperability can also be achieved through structured naming conventions—for example, by linking construction classification codes (CCS) or descriptions to corresponding entries in LCA databases.

In contrast, the *Dynamic Approach* aims to establish a bidirectional data flow. When the BIM model is changed, LCA results are automatically updated, supporting an iterative design process and enabling real-time feedback within the BIM environment.

2.5. *Data exchange (CAT5)*

Data exchange (CAT5) defines the specific format and methods during data exchange between these combined tools. Previous studies [16–18] have identified six types of data exchange processes: 1) export BoQ into Excel, 2) export BoQ into a dedicated LCA tool, 3) use LCA add-ons for BIM software, 4) use visual programming languages (VPL), 5) use the IFC format of BIM models for data transfer, and 6) include LCA data in BIM objects, using a library of BIM objects and materials that

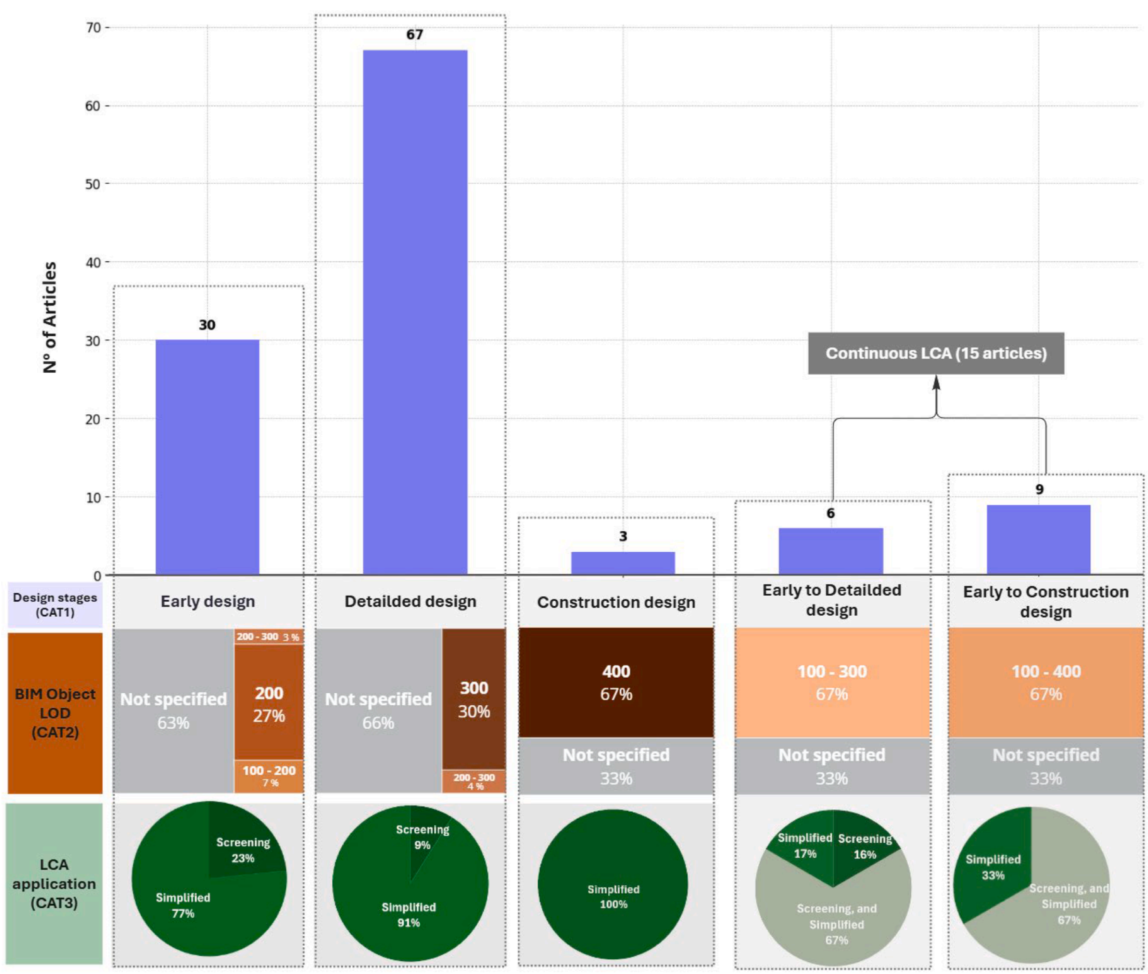

Fig. 4. Breakdown of the 115 articles by design phase (CAT1), LOD of the BIM object (CAT2) and LCA application (CAT3).

already have LCA data integrated within their parameters.

2.6. Automation degree (CAT6)

Automation degree (CAT6) in BIM-LCA integration is classified based on the level of manual intervention required. Two key aspects define automation in this context: (1) During LCI – Automating extraction and data exchange between the BIM model and the LCA tool; (2) During LCIA – Automatically mapping building elements and materials to environmental impacts in the LCA databases. Works that achieved full automation in both LCI and LCIA were classified as *Fully Automated*. Those where at least one phase was automated were categorised as Semi-Automated, while studies relying entirely on manual processes were classified as manual.

2.7. Decision-Making support (CAT7)

Decision Support (CAT7) methods aid in evaluating trade-offs, optimising performance, and reducing uncertainty in building sustainability assessments. It considers using Multi-Criteria Decision Analysis (MCDA), Multi-Objective Optimization (MOO), hybrid MCDA-MOO approaches, and Sensitivity/Uncertainty Analysis to enhance decision-making in BIM-LCA integration. For a more detailed discussion about each decision support method, please refer to Section 3.7.

3. Content analysis

3.1. Design phase (CAT1), BIM object LOD (CAT2) and LCA application (CAT3)

Among the 115 articles analysed, most conducted an LCA for a specific design phase (Fig. 4). Approximately 26 % (30 articles) addressed the early design, 58 % (67 articles) the detailed design, and 3 % (3 articles) the construction design. Meanwhile, 13 % (15 articles) proposed methods to perform a LCA continuously throughout the design process.

Fig. 4 illustrates the expected correlation between the design phase (CAT1), BIM object LOD (CAT2), and LCA application (CAT3). In early design, LOD 200 was the most used (27 %), followed by LOD 100–200 (7 %) and LOD 100–300 (3 %). However, 63 % of the articles did not disclose the LOD. This may be attributed to poor reporting practices, varying levels of awareness among researchers regarding the relevance of LOD in BIM-based LCA workflows, and the lack of standardised LOD/LOIN according to different LCA applications. Regarding the LCA application, 77 % of the studies conducted a Simplified LCA, while 23 % performed a Screening LCA during early design.

During the detailed design, LOD 300 was the most used (30 %), followed by LOD 200–300 (4 %), whereas 66 % of the articles did not specify LOD. In this phase, 91 % performed a *Simplified LCA*, while 9 % applied a *Screening LCA*. Additionally, LOD 400 is typically used during the construction design, where 100 % of the articles performed a *Simplified LCA*.

None of the 115 papers performed a *Complete LCA,* which reflects the difficulty of these analyses, particularly regarding data availability for life cycle stages such as transportation, deconstruction, and end-of-life. Furthermore, it suggests that, in most cases, the effort required for a *Complete LCA* is deemed unnecessary, as a *Simplified LCA* is considered sufficient to support the hypotheses tested in the articles.

The methods developed for *continuous LCA* throughout the design process use a multi-level LOD approach, specifically LOD 100–300 and 100–400, depending on the design phases included; 33 % did not specify the LOD. This approach is more effective than using multiple BIM-based LCA tools. First, data can be lost between software, leading to the need to repeat the LCI and LCIA processes. Second, early analyses involve high uncertainty with practitioners making non-standardized, iterative assumptions that vary by user and software, complicating result comparisons and decision-making.

The early design uncertainty is evident in the contrasting conclusions of the following studies. Hollberg et al. [48] traced the embodied GWP throughout the design of an office building in Switzerland, concluding that the embodied GWP measured during the early design can be twice as high as that measured during the detailed design due to changes in the quantity and types of materials used. Meanwhile, Nawrocka et al. [46] did the same comparison in a Danish context, finding that LOD 200 models resulted in 14.7% lower GWP than LOD 400 models. These differences in how LOD influences GWP results are conditioned by regional context, typical construction systems, and databases used — KBOB in the Swiss case and Ökobaudat in the Danish case.

Both studies suggested a single LCA tool throughout the design process to improve consistency and align early LCA results with as-built buildings. Additionally, using predefined components, surface area-based calculations instead of volumetric models, and ML trained on past projects could enhance accuracy.

In this sense, Ansah et al. [49] and Lee et al. [50] used predefined Families and Types (F&T) and BIM templates for prefabricated components. Cavalliere et al. [51] aligned types of LCA data to the BIM object LOD as follows. For LOD 100**,** average LCA values, along with minimum and maximum GWP values, are used for building systems (e.g., envelope, structure); for LOD 200, average LCA values, along with minimum and maximum GWP values, are used for construction assemblies (e.g., walls, columns); on LOD 300**,** specific LCA data (i.e., EPDs) is used for construction assemblies; for LOD 400 specific LCA data is used for materials. Similarly, Mohamed et al. [52] used average LCA data from the ICE database for LOD 200 and EPDs for LOD 300. Palumbo et al. [53] suggested that instead of relying on generic LCA data during LOD 100 to 200, EPD should be used with a Safety Factor (SF) and Range Factors (minimum, maximum, average, and median values). The SF is the percentage deviation between impact indicators' minimum and maximum values within a type of product, for example, within contiguous compressive strength classes of a concrete structure.

On the other hand, Parece et al. [54] proposed different QTO methods that align LCA data with the BIM object's LOD. For early design / LOD 200, a catalogue of building assemblies with material quantities and average GWP values is stored externally. A construction classification system (CCS) code establishes a link between BIM element quantities and materials in the database. The CCS is used to develop a hierarchic LCA database, where groups or building functions are composed of systems and systems of materials. Arvizu-Piña et al. [55] proposed the same approach for exterior walls; the different materials options are retrieved from a Mexican database containing typical construction systems. Li et al. [33] used the CCS codes of building components to link them to predefined groups of materials in an external database.

Forth et al. [56] and Schneider-Marin et al. [57] proposed enriching the model with a knowledge database containing all the necessary information, such as the technical and environmental data required for the LCA during early design. Each material is linked to functional layers, with an environmental impact assigned from the Ökobaudat database [58]. Experts then combine these materials to create generic building components, specifying thickness ranges for the different layers. The same approach was used by Rezaei et al. [59]; first, materials were assessed for environmental impacts from the Ecoinvent database [60], then construction assemblies were defined and linked to BIM objects.

Soust-Verdaguer [61] proposed a correspondence between IfcBuildingElement classes and materials in the BCCA "Andalusian Construction Cost Base" data structure for cost estimation to calculate the material quantities of each element. They concluded that this method could estimate 89 % of the material volume from QtO and 60 % of the overall impacts during early design. On the other hand, Hansen et al. [62] concluded that using predefined components in early design can underestimate the total impact by an average of 12 % compared to detailed design results.

All the approaches mentioned above were developed as research-based tools and were validated through application to one or more case studies. To date, no BIM-LCA commercial software tool known to the authors implements any of these methods.

3.2. Data extraction (CAT4) and data exchange (CAT5)

The conventional approach is the most used type of data extraction (CAT4), representing 42 % of the reviewed articles, followed by the dynamic (39 %) and static approaches (15 %) (Fig. 5). In 4 % of the articles, the type of data extraction and exchange could not be identified.

Both the conventional and static approaches are vulnerable to data loss, inconsistency, and lack of interoperability, as they require the transfer of the BoQ between tools in varying formats [19]. These limitations become particularly prominent when information is entered manually or when the semantic structure and naming conventions are not standardised or aligned across software platforms. Semantic inconsistencies in BIM objects or IFC entities—such as variations in object classification, property sets, or naming conventions—can lead to the misinterpretation or omission of critical data during import/export operations [63].

To address these challenges, it is essential to define the BIM Uses (e.g., LCA application), and corresponding information requirements and LOD in the BEP, before BIM model development begins. When using IFC for data exchange, the adoption of Information Delivery Manuals (IDM) and Model View Definitions (MVD) is recommended, as they ensure the correct structuring of data according to the intended BIM Use without loss of important attributes such as materials or classification codes. Additionally, IDS can be used to validate exported IFC files. As an example, Santos et al. [63] developed an IDM and an MVD to ensure that IFC files include the specific data requirements and structure needed for LCA integration.

Moreover, the limitations of conventional and static approaches extend beyond interoperability issues; they also fail to capture the iterative and time-sensitive nature of the design process, unlike the dynamic approach.

The most common Data Exchange (CAT 5) is Type 2, which involves exporting the BoQ to a dedicated LCA tool and is predominantly used during the detailed design, as shown in Fig. 5. Type 2 is typically used to combine BIM-LCA with other indicators and compare design solutions, as shown in Fig. 6. This contrasts with earlier literature reviews (2012–2020) [15,20], which identified Type 1—exporting the BoQ to Excel—as the predominant approach for BIM-LCA integration. This shift suggests efforts to use more automated processes, as Type 1 generally requires more manual work. However, some studies still rely on this method [64,65]. Recent adaptations of Type 1 have evolved into methods that resemble the use of IFC GlobalIds in the static approach. For instance, Carvalho et al. [66] and Soust-Verdaguer et al. [67] used spreadsheets in which data were linked to the BIM model through naming conventions, allowing materials and components to be modified within BIM and automatically update results in the spreadsheets. Power BI is also used to enhance the visualisation of results.

The second most used method is Type 3 (Add-ons), frequently employed during the early and detailed design. Regarding continuous LCA throughout the design, Type 4 (VPL scripts) and Type 3 (BIM add-ons) are the most commonly adopted, as they support iterative workflows and facilitate the tracking of design changes and project history.

The preference for types 2 and 3 may be attributed to the user-friendly interface of commercial LCA tools, such as OneClick LCA and Tally. Several authors [68–73] used OneClick LCA to assess the GWP and other impact categories. For instance, Felicioni et al. [72] compared the environmental impacts of reinforced concrete structures and cross-laminated timber using DesignStudio and OneClick LCA. Shibata et al. [74] combined Elmhurst Design SAP 10.2 for energy simulation with OneClick LCA for LCA and LCC to evaluate electric heating retrofit options. However, several challenges were reported using OneClick LCA including double counting in overlapping elements such as walls and slabs, depending on the available QtO methods. The "Grouping elements

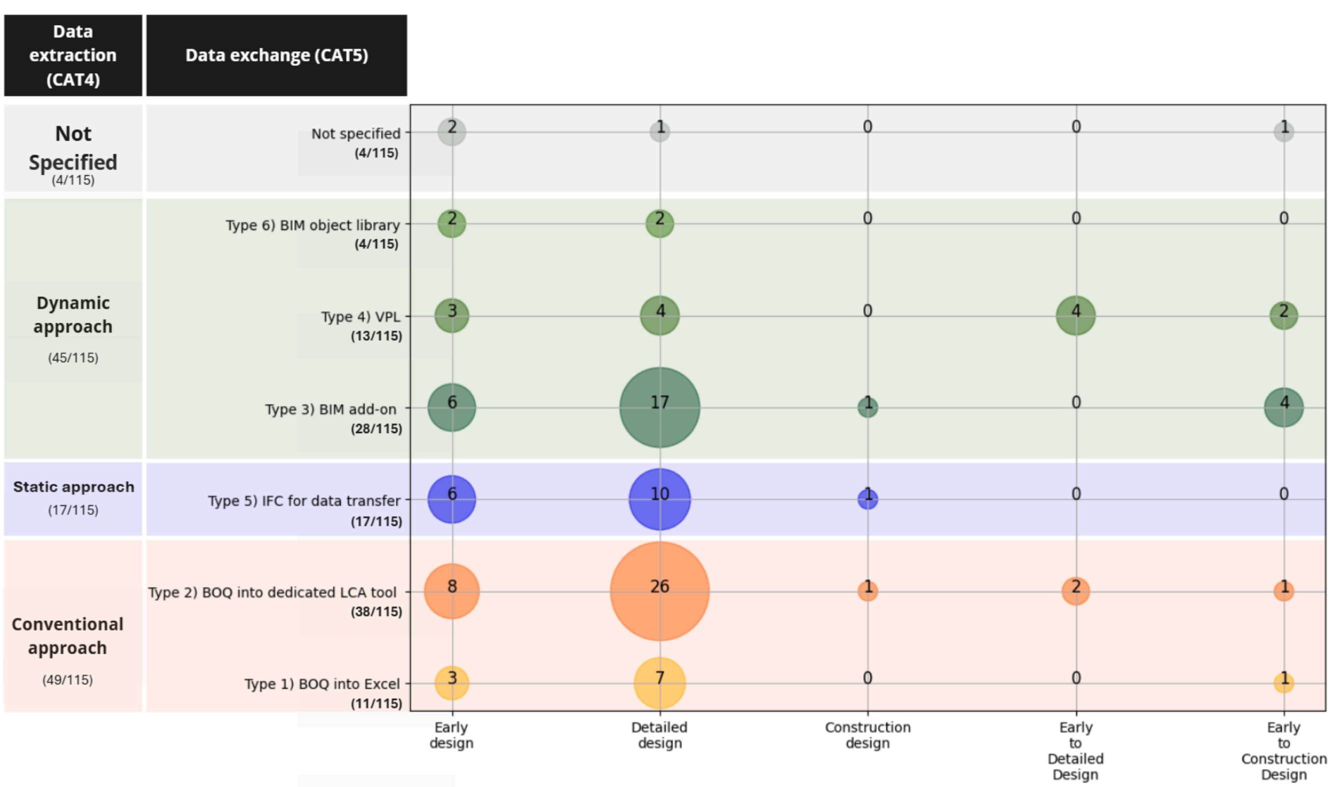

Fig. 5. Bubble matrix expressing the relation of the design phase (CAT1) and data extraction (CAT4) and data exchange (CAT5).

Fig. 6. Bubble matrix expressing the relation between the goals of the articles and data extraction (CAT4) and data exchange (CAT5) used.

as a whole" method is limited to predefined components within the OneClick LCA database, while the "Breaking down family types into materials" disconnects family and type associations, potentially leading to double counting when materials are incorrectly assigned to components [75].

Similar issues were reported with Autodesk Revit's Tally add-on [76–78]. Authors reported that material identification and specification in Tally are laborious and time-consuming, compounded by the limited availability of LCA data. The restricted number of materials in Tally often leads to assumptions about choosing similar materials.

It is also important to note that OneClick LCA and Tally, as most commercial tools, rely on different LCA databases and modelling assumptions, which lead to divergent results even when applied to the same project. For instance, Dalla Mora et al. [79] compared the results of a masonry residential building assessed using both tools and found an average deviation of 22 % across impact categories.

Besides OneClick LCA, other dedicated LCA tools, such as Athena Impact Estimator [80], SimaPro [81,82] and Open LCA [83] were used.

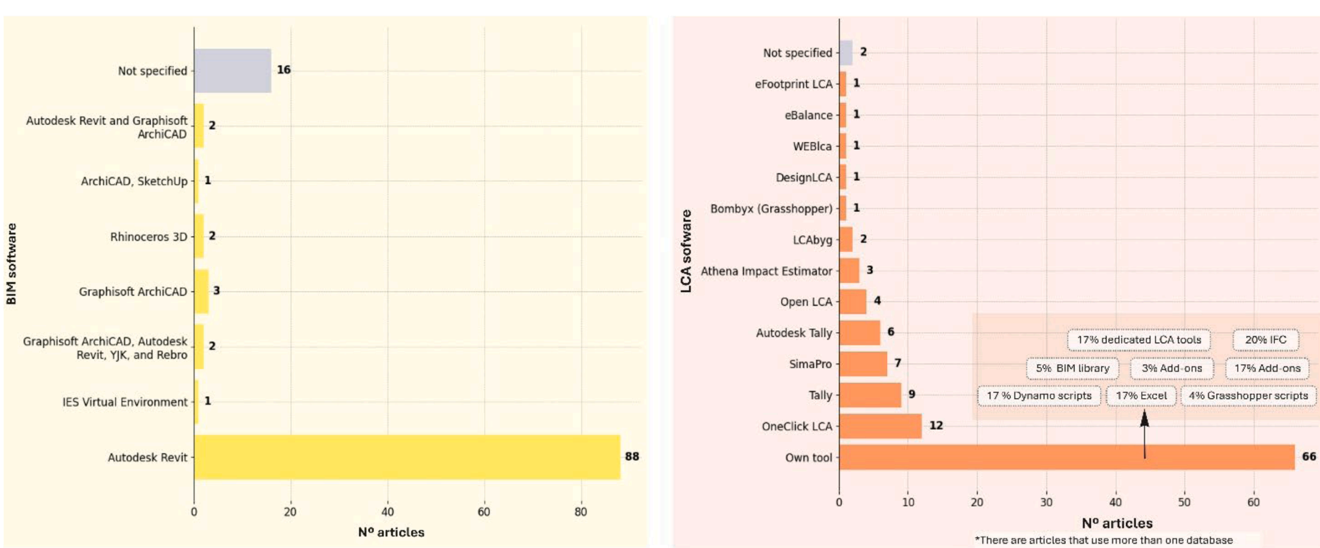

Fig. 7. Breakdown of the 115 articles by BIM software and LCA software.

In these cases, BoQ and annual energy consumption data, calculated using Autodesk Green Building Studio or DesignBuilder, were manually inserted into the LCA software.

On the other hand, many authors have focused on developing their own LCA tools. The most common types are Type 3 (Add-ons), Type 2 (Dedicated LCA tools), and Type 4 (VPL scripts), as shown in Fig. 7. For instance, Bowles et al. [84] developed the Hawkins\Brown Tool, an Autodesk Revit add-on that calculates material volumes and generates instant GWP visualisations alongside a web-based tool for improved data management, similar to OneClick LCA. Nehasilová et al. [85] developed ArchiCAD and Revit add-ons integrated with a web-based interface to manage LCA data and a cost-estimating database from the Czech Republic. Alwan et al. [86] developed a Python-based tool that calculates embodied carbon, suggests low-carbon material replacements, and compares outcomes against RIBA 2030 Climate Challenge targets. Sobhkhiz et al. [87] integrated semantic web technologies with BIM and LCA to enhance data management and interoperability, converting design, material, and supplier information into RDF format and developing ontologies for structured data integration. Jalaei et al. [88] proposed a BIM-based procurement system integrating EPD data in order to verify low-carbon compliance targets.

Type 5 (IFC for data transfer) is the third most common method, widely used in detailed and early design phases, but less prevalent in continuous LCA. Deng et al. [89] developed an IFC-based LCA tool that enables ArchiCAD, YJK, Revit, and Rebro models from different building disciplines to perform LCA calculations using a collision detection algorithm, ensuring accurate deduction of overlapping quantities. Serrano-Baena et al. [90] proposed an IFC-based LCA for material comparisons, linking IFC files to FIEBDC-BC3 databases [91] containing technical and environmental data. Forth et al. [92] combined the IFC format with the BIM Collaboration Format (BCF) and a knowledge database, previously discussed in Section 3.1, to develop a decision-support tool for non-LCA experts. The tool provides direct visual feedback through colour-coded IFC model viewers and heat maps, allowing users to identify environmental hotspots, compare design variants, and assess uncertainties during early design stages.

In terms of scalability, these studies rely on region-specific LCA databases (e.g., FIEBDC-BC3 for Spain, Ökobaudat for Germany) and are limited to embodied carbon, excluding operational emissions.

Type 4 (VPL scripts) are commonly used for parametric modelling and rapid assessment of material options (see Fig. 6). For instance, Hunt et al. [93] proposed an Autodesk Dynamo tool to assess the embodied GWP of structural models during early design, while Carvalho et al. [40] created a Dynamo script for LCA and LCC, simulating 18 design scenarios with different wall, roof, and floor combinations. Alvarez et al. [27] integrated Power BI into a Dynamo-based workflow capable of calculating GWP and economic costs for various design options. Giaveno et al. [34] and Ansah et al. [49] developed Dynamo scripts to assess multiple LCA impact categories using EPD and generic LCA data linked via Excel. Beyond Dynamo, Alwan et al. [36] used Grasshopper and DesignBuilder to assess different material options, while Károlyfi et al. [35] simulated 48 alternative steel frame warehouse designs based on Eurocode standards.

Type 6, i.e., using a green BIM library with LCA data in objects and materials parameters, is the least utilised method (3 %, 4 articles). Its limited adoption is mainly due to the scarcity of BIM objects containing LCA data and the lack of standardisation in data structuring, which could be resolved with product data templates. Santos et al. [43,94] and Lee et al. [50] embedded EPD data within BIM objects, enabling instant economic and environmental impact calculations within the BIM environment. Llatas et al. [95] and Soust-Verdaguer et al. [44] expanded this approach by creating BIM object libraries enriched with LCA, LCC, and S-LCA data, alongside a dynamic script to add this data into BIM objects, later extracted into a semantically enriched IFC.

According to Zeng et al. [25], Type 4 (VPL scripts) is most effective for early design, while Type 3 (BIM add-ons) is the most suited for detailed and construction design, taking into account the information requirements, time and complexity, automation, and required user expertise. However, stakeholder collaboration within the BIM environment is overlooked. Different BIM software are typically used across various building specialities, making add-ons and VPL scripts inefficient when applied to different federated models. For instance, Autodesk Tally is exclusive to Autodesk Revit, while DesignLCA is designed for ArchiCAD [96]. In this scenario, using tools that allow open formats is essential to comparing aggregated results during the design process.

3.3. Automation degree (CAT6)

As shown in Fig. 8, only 2 % of the analysed articles implemented a fully automated LCA workflow, while 88 % adopted a semi-automated approach, and another 7 % relied on manual processes. Regarding LCI, all 115 studies performed a QTO from the model. The manual input of BoQ into LCA tools has become less common (only 7 %), marking a shift from findings in previous research (2012–2020) [20]. However, this manual process is still necessary when using advanced LCA tools such as SimaPro and Athena Impact Estimator, as BIM models often do not meet their specific data requirements, and the data is not structured in a compatible format for automatic exchange. A potential solution to this interoperability challenge is the approach proposed by Xu et al. [97], which developed a data transfer tool between the IFC file and SimaPro.

During LCIA, mapping LCA data to BIM objects remains time-consuming and ambiguous, with 77 % of studies still relying on manual processes. No significant advancements have been made in automation and standardisation since previous literature reviews (2019–2021) [15].

Type 5 (IFC for data transfer) offers a potential solution by permanently linking LCA data to building geometry through Global Ids. In contrast, Type 6 (BIM libraries enriched with LCA and BIM data) embeds pre-linked environmental data within BIM objects. However, both approaches still require an initial manual mapping process for each BIM object.

Standardised data structures and naming conventions have been used to streamline this process, as shown in Fig. 8. For example, One-Click LCA matches the Family and Type (F&T) and the material description to the LCA database, but the F&T has to be written coherently, in English and according to the guidelines provided on the website [75]. It also saves user preferences, i.e., the link between an LCA value and an F&T is stored.

Ansah et al. [49] and Awan et al. [36] previously mapped BIM model F&T and material descriptions to LCA databases in a spreadsheet. Soust-Verdaguer et al. [67] developed a BIM template focused on materials and pre-defined elements, organized by tags and codes. Ge et al. [98] created an Autodesk add-on to automatically assign LCA data to prefabricated building components using a naming convention. Alvarez et al. [27] linked BIM objects with LCA and LCC databases using assembly codes, while Parece et al. [54] used the SECCLasS CCS derived from Uniclass, and Li et al. [33], the Standard for BIM Classification (GB/T 51269–2017). Additionally, Cang et al. [99] developed their own code structure and Naneva et al. [100] applied the eBKP-H cost-planning codes to connect BIM objects with LCA data.

Using a CCS or similar structured data approach enables machine-readable and transparent data exchange between BIM and LCA tools thereby creating the foundation for Machine Learning (ML) techniques to automate this process. Forth et al. [56] demonstrated this by applying Natural Language Processing (NLP) to automatically match IFC elements with a knowledge database containing technical and environmental information. IFC elements are classified with the German cost group schema, and cosine similarity is used to match vectorized textual descriptions. This allows classification at different levels—element, material category, and material option.

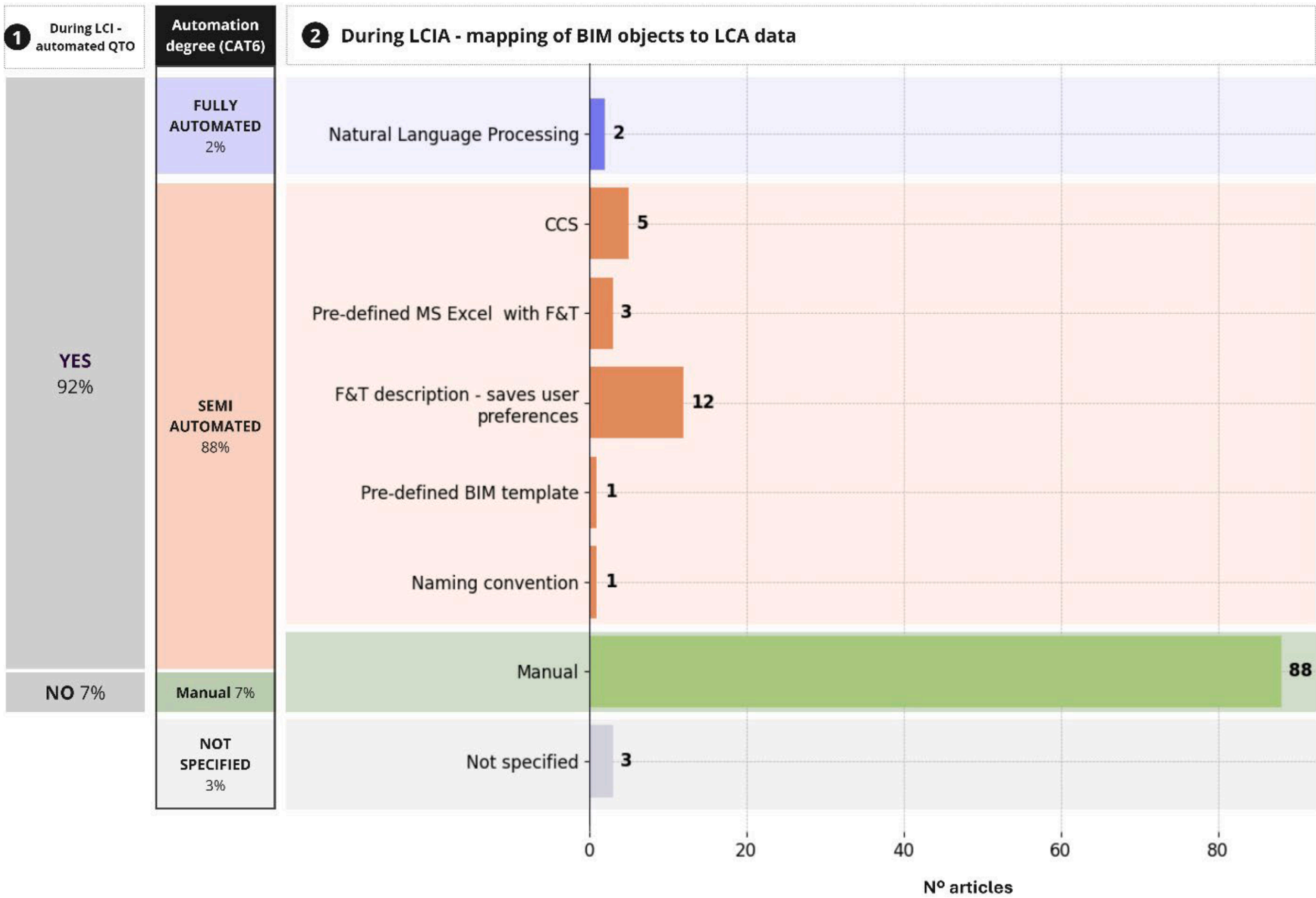

Fig. 8. Breakdown of the 115 articles by Automation Degree (CAT6), 1) during LCI and 2) during LCIA.

3.4. Databases and system boundary

During the LCI and LCIA stages, construction materials, products, and processes are typically assigned environmental data sourced from either generic LCI databases or EPD-based databases containing LCIA results for specific building products. As shown in Fig. 9, the most widely used database is Ecoinvent (21 %, 25 articles) [83], a generic LCI database. This is followed by GaBi and Ökobaudat (13 %, 15 articles), which include both generic and manufacturer-specific EPDs. The ICE (Inventory of Carbon and Energy) database is also frequently used (13 %, 15 articles) and provides average EPD data developed for the UK.

A persistent challenge in Building LCA is the limited availability of representative, context-specific environmental data for construction materials. Current practices often depend on generic LCI databases that fail to capture the regional variability and product specificity present in third-party verified EPDs. Studies have shown that reliance on generic

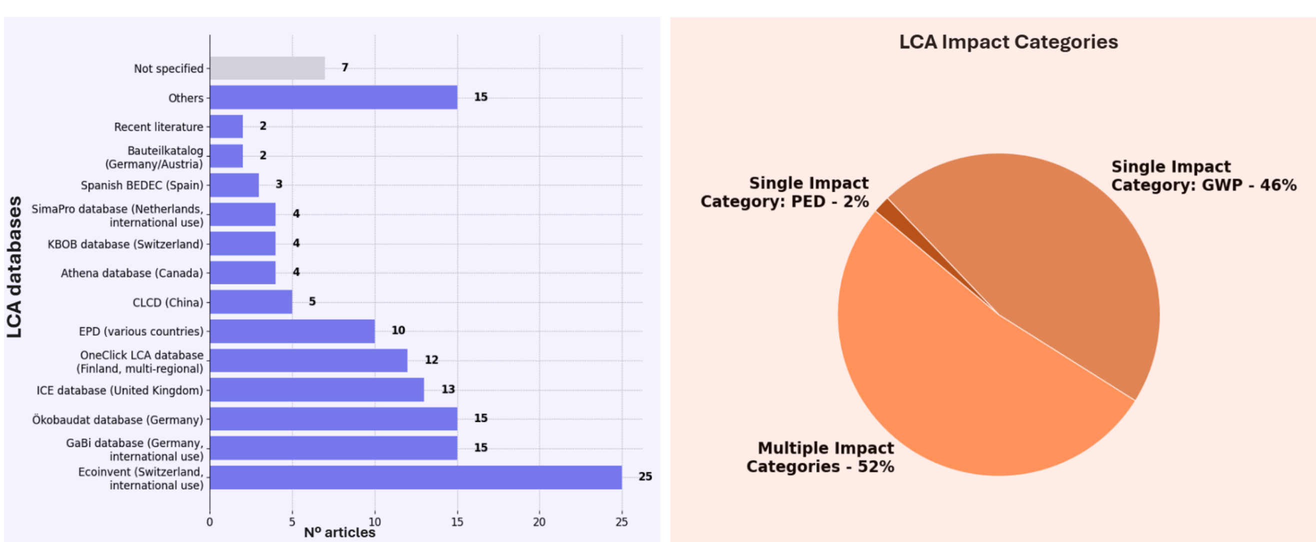

Fig. 9. Breakdown of the 115 articles by LCA database and LCA Impact Categories.

databases leads to deviations exceeding ±50 % across several environmental impact categories when compared to results based on EPDs [101].

According to ConstructionLCA's *Guide to EPDs* [*102*], over 13,000 verified EPDs in compliance with EN 15804 were available at the beginning of 2024. However, these EPDs predominantly cover finishing products, such as cladding, flooring, and insulation materials [103]. Moreover, only a fraction of these EPDs are currently available in machine-readable formats, such as XML or JSON-LD [104,105], which are essential for automation and integration in BIM-LCA workflows.

Although the use of EPDs in BIM-LCA studies has increased since the publication of the ISO 21930 and EN 15804 [15], their availability and digital interoperability remain limited [15]. Recent European regulatory developments are expected to increase the EPD publication. The 2024 revision of the Construction Products Regulation (CPR) introduces a mandatory requirement for the disclosure of Global Warming Potential (GWP) for all construction products by 2026, and the revised Energy Performance of Buildings Directive (EPBD) establishes the mandatory whole-life cycle GWP assessments for new buildings, starting in 2028 [106].

According to the EN 15978 standard, the building life cycle is divided into five main stages: product (A1–A3), construction (A4–A5), use (B1–B5), and end-of-life (C1–C4), plus an additional stage (D) for benefits beyond the system boundary. As shown in Fig. 10, most articles focused on the production phase (A1–A3) (94 %), followed by waste processing and disposal (C3–C4) (60 %), transportation (A4) (51%), and replacement (B4) (46 %). Only 38 % considered operational energy use (B6), while use phase (B1), refurbishment (B5), operational water use (B7), and benefits occurring outside the system boundary (D) were rarely included. This is mainly due to data availability issues and high uncertainty in scenario assumptions, making these phases harder to assess. As a result, these phases may be omitted due to the infeasibility of obtaining reliable inventories.

Regarding impact categories, 48 % only considered one impact category, predominantly GWP, while 52 % considered multiple impact categories. These results are consistent with the previous research (2019–2021) [15,19]. The most commonly used LCIA methods include ReCiPe 2016, CML-IA (in accordance with EN 15804+A1), TRACI 2.1, EF 3.0/ PEF (in accordance with EN 15804+A2), and GWP factors based on IPCC guidelines. Additionally, Cheng et al. [107] proposed a custom LCIA method.

Due to variations in impact categories, characterisation factors, and units of measurement, results obtained using different LCIA methods are often not directly comparable [108]. For instance, CML-IA and TRACI 2.1 differ significantly in the definition and selection of impact categories. CML-IA includes categories such as acidification potential (expressed in kg SO_2 eq) and eutrophication potential (kg PO_4^{3-} eq), while TRACI 2.1 covers smog formation potential (kg O_3 eq) and human health criteria pollutants (kg $PM_{2.5}$ eq).

Another essential distinction between LCIA methods is the level of aggregation they offer. Some methods include only midpoint indicators, which quantify impacts at a point midway along the cause-effect chain

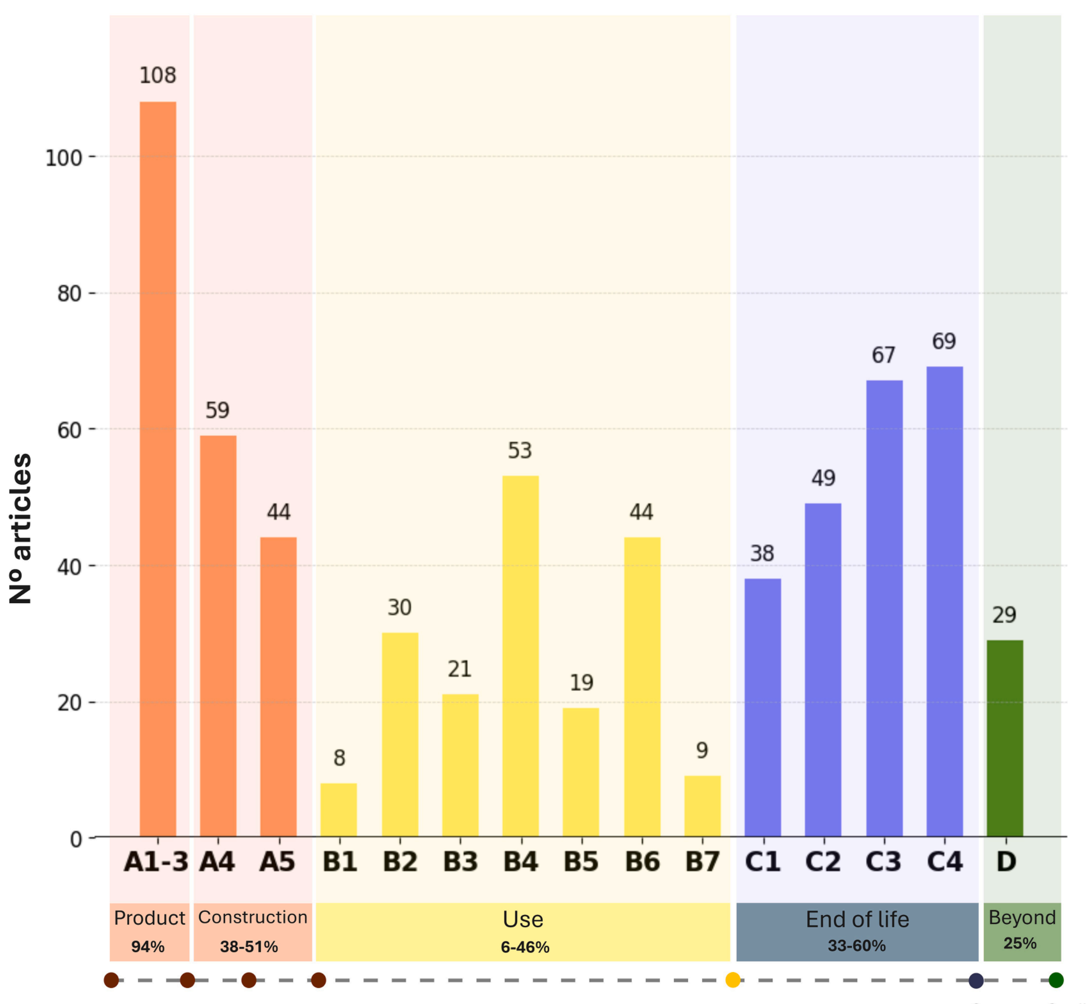

Fig. 10. Breakdown of the 115 articles by building life cycle modules according to EN 15978.

(e.g., GWP). In contrast, others include endpoint indicators, which express damage to target areas such as human health, ecosystem quality, or resource availability. Methods like ReCiPe 2016 provide both midpoint and endpoint indicators and allow the aggregation of single scores (i.e., translate multiple impact categories into a single value for decision-making). In contrast, methods like CML-IA and TRACI 2.1 provide only detailed midpoint-level results.

According to Meex et al. [41] and Kägi et al. [78], BIM-LCA users, particularly those without expertise in LCA, prefer a single aggregated environmental impact score at the building level, as considering multiple impact categories often makes decision-making more complex and less intuitive.

3.5. Case study application

As shown in Fig. 11, the most common case studies are multi- and single-family residential, office, and educational buildings, primarily located in Europe, Asia, and South America. Among these, 83 % are new construction, while only 14 % are renovation projects.

Despite growing interest in BIM-LCA integration for renovation and refurbishment, many tools still struggle to fully incorporate the technical complexities of such projects, leading to interoperability problems and time-consuming manual processes. In contrast to new construction, which focuses mainly on new materials and components, renovation projects must also consider existing structures, their conservation state and interventions. In addition, these processes involve the removal, reuse and recycling of materials, as well as the production of waste and the introduction of new materials, all of which must be adequately addressed in BIM-based LCA tools [109].

Some studies have explored BIM-LCA applications in renovation projects. For instance, Forastiere et al. [69] analysed the economic and environmental impact of passive, active, and renewable energy retrofit strategies. Feng et al. [110] assessed embodied and operational impacts across six different renovation and reconstruction scenarios for single-family homes. Besana et al. [70] used OneClick LCA to evaluate the embodied carbon of retrofit strategies, noting that to account for reused materials, each material had to be manually identified as reused in the web tool. Dauletbek et al. [111] compared an existing building with renovation scenarios designed to meet Passive House and low-energy building standards in China, highlighting that LCA databases lack sufficient data on material recycling and that interoperability issues remain a significant challenge. Soust-Verdaguer et al. [112] argued that the level of automation in BIM-LCA applications for renovation and retrofit projects remains low, and that available tools should better account for both existing and new building elements.

To address interoperability challenges, Fenz et al. [113] developed a web-based tool that processes IFC files of existing buildings to generate multiple renovation scenarios. The tool automatically modifies IFC files for each scenario, allowing for energy, LCA, and LCC analyses. First, it identifies relevant building elements associated with each renovation measure. For example, external façade insulation corresponds to IfcWall, IfcWallElementedCase, and IfcWallStandardCase. The tool then groups elements, accordingly, enabling users to select entire component groups or individual elements for renovation. Users can also specify which layers of the existing building need to be removed or replaced, after which the tool generates different material combinations for each renovation measure. Furthermore, Kim et al. [114] employed point cloud data obtained from 3D laser scanning to generate BIM models that accurately represent the as-built conditions. Subsequently, these models were enriched with LCA data to facilitate more precise and detailed LCA.

Despite advances in research-based tools that integrate CDW quantification and material recovery scenarios, such functionalities are not available in commercial software such as OneClick LCA and Tally, leading practitioners to rely on time-consuming manual processes.

These tools cannot differentiate between existing and new elements or account for the functional condition of existing components, both of which are essential considerations in LCA. Additionally, they do not allow the definition of deconstruction strategies and simulation of multiple scenarios for component reuse and waste treatment.

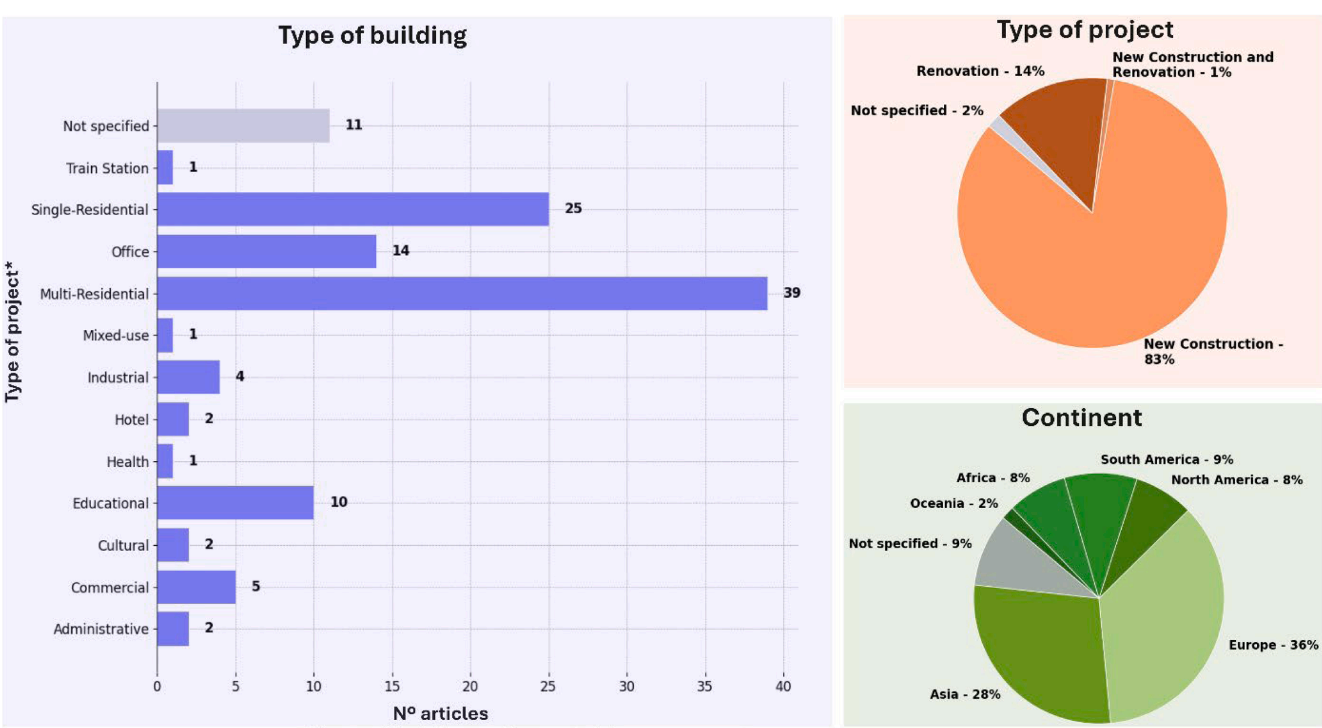

Fig. 11. Breakdown of the 115 articles by type of building, project and continent.

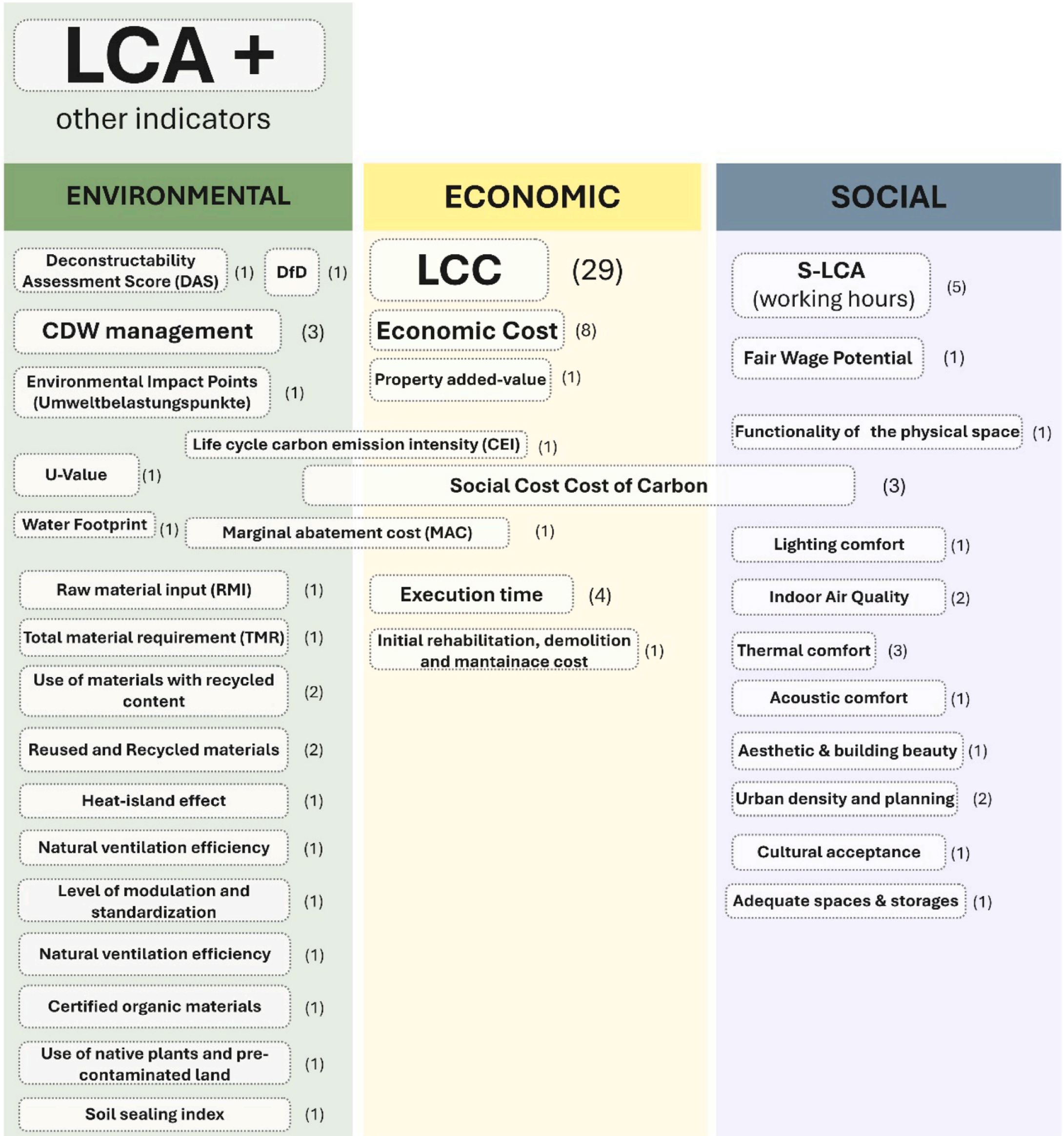

Fig. 12. Different indicators considered by the 115 articles divided into environmental, economic and social aspects.

3.6. *LCA and other indicators*

3.6.1. *Environmental, economic and social indicators*

A total of 51 articles have expanded traditional LCA by incorporating additional environmental, economic, and social indicators to enhance sustainability assessments and decision-making (Fig. 6 and Fig. 12). For instance, Latas et al. [95], Soust-Verdaguer et al. [44] and Soust-Verdaguer et al. [61] introduced the Sustainable Product Declarations, which are similar to EPDs, but with the addition of LCC and S-LCA data. S-LCA is measured using the metric *"medium risk-hours equivalent units"*. This metric quantifies the number of working hours associated with a medium level of social risk for a given impact category—such as labour rights, health and safety, or fair wages [115]. They used a bottom-line library, which integrates data from the Spanish BEDEC database, Ecoinvent, and the BCCA (*Base de Costes de la Construcción de Andalucía*). Similarly, Boje et al. [116] calculated LCA and LCC, including waste disposal costs and carbon emission taxes, and S-LCA to estimate working hours from an as-built model of an office building.

On the other hand, Sameer et al. [117] quantified Raw Material Input (RMI), Total Material Requirement (TMR), GWP, and water footprint using the AWARE (Available Water Remaining) method . Carvalho et al. [118] assess SBTool PT-H criteria, a Portuguese green building certification, covering LCA, LCC, energy analysis, waste management, accessibility, and thermal comfort.

Other authors have focused on CDW management and deconstruction strategies. Quiñones et al. [119] created an Autodesk Revit add-on that automates the assessment of recycling vs. disposal options for CDW, enabling designers to quantify the environmental benefits of recycling without requiring extensive LCA expertise. Su et al. [120] integrated BIM, Geographic Information Systems (GIS), and LCA to estimate and analyse building CDW during the design. Kim et al. [121] developed a BIM-based tool using node-edge graphs to analyse the relationships between building components, assigning a *Deconstructability Assessment Score* (DAS). The tool also integrates LCA and LCC to evaluate environmental impacts and costs across the building's life cycle, concluding that DfD strategies can reduce GEE emissions by up to 40 %. Guerriero et al. [122] introduced a digital platform that generates an as-built BIM model from point-cloud scans, exporting it in IFC format. The platform then builds material inventories and assigns end-of-life scenarios for each material using the Circular Footprint Formula (CFF). Similarly, Gan et al. [123] proposed an AI-enhanced approach using weakly supervised learning to automate BIM model generation from point clouds and calculate GWP. Sun et al. [124] assessed the GWP and reuse potential of mass timber construction and concrete buildings.

From an economic perspective, Zhang et al. [125] used the Carbon Emission Intensity (CEI), a metric that quantifies carbon emissions per unit cost, expressed as the ratio between GWP (CO_2e) and LCC. CEI is used to assess the environmental impact relative to the cost throughout the building life cycle. Lu et al. [126] developed an OpenBIM tool for calculating Marginal Abatement Cost (MAC), which is the cost of reducing one additional ton of CO_2e. It evaluates the cost-effectiveness of carbon reduction measures.

Other authors measured the Social Cost of Carbon (SCC), a metric within LCC that quantifies the cost to society of climate change-related damage caused by one additional ton of CO_2e. It is based on the Marginal Damage Cost (MDC) [127]. For instance, Heydari et al. [128] calculated material costs, energy savings, and SCC using the Net Present Value (NPV) method. Rostamiasl V et al. [129] performed an LCC considering land acquisition, construction, design, SCC, operational costs, and resale value. Lu et al. [130] developed an Open-BIM tool to assess SCC at the building design, incorporating both static and dynamic SCC models. The static SCC represents the immediate economic impact of carbon emissions, while the dynamic SCC accounts for future climate scenarios, discount rates, and projected climate targets.

3.6.2. Dynamic LCA

A well-known limitation of traditional static LCA, recognised since its introduction and discussed in the literature [131,132], is its inability to account for temporal variations in factors such as the energy mix, climate conditions, and user behaviour. This often leads to significant misestimations of environmental impacts, particularly in the context of buildings, given their long service life and the strong influence of occupancy patterns.

Dynamic LCA is a methodology capable of addressing these challenges by incorporating time-dependent variables that reflect temporal, social, technological, and economic changes [131]. For example, temperature increases driven by climate change can result in a rise of cooling energy demands while reducing heating needs, and the growing share of renewable energy and hydropower in the electricity mix can significantly reduce a building's carbon footprint over time.

However, its application in the built environment remains limited, particularly in the study of complex variables such as cultural behaviours and technological evolution. Only three articles explicitly considered dynamic LCA scenarios. For instance, Yang et al. [133] assessed 17 dynamic and static scenarios, considering temporal factors such as outdoor and indoor temperatures, the heat transfer coefficient of glass curtain walls, elevator energy recovery efficiency, electric grid mix, recycling rates, and material replacement cycles. Their findings indicate that static scenarios can overestimate carbon emissions by up to 66.7 %. Similarly, Jalaei et al. [134] performed static and dynamic LCA scenarios linked to climate projections and electric grid mix evolution, based on the RCP 8.5 projections for 2020 to 2079, alongside expected electricity grid emissions reduction. Similarly, Newberry et al. [135] extended this research by analysing electric grid mix scenarios to predict changes in carbon intensity over time, including an optimistic scenario that decreases from 102.93 kg CO_2e/kWh in 2022 to nearly zero by 2080, a pessimistic scenario with a slower rate, and a net-zero scenario.

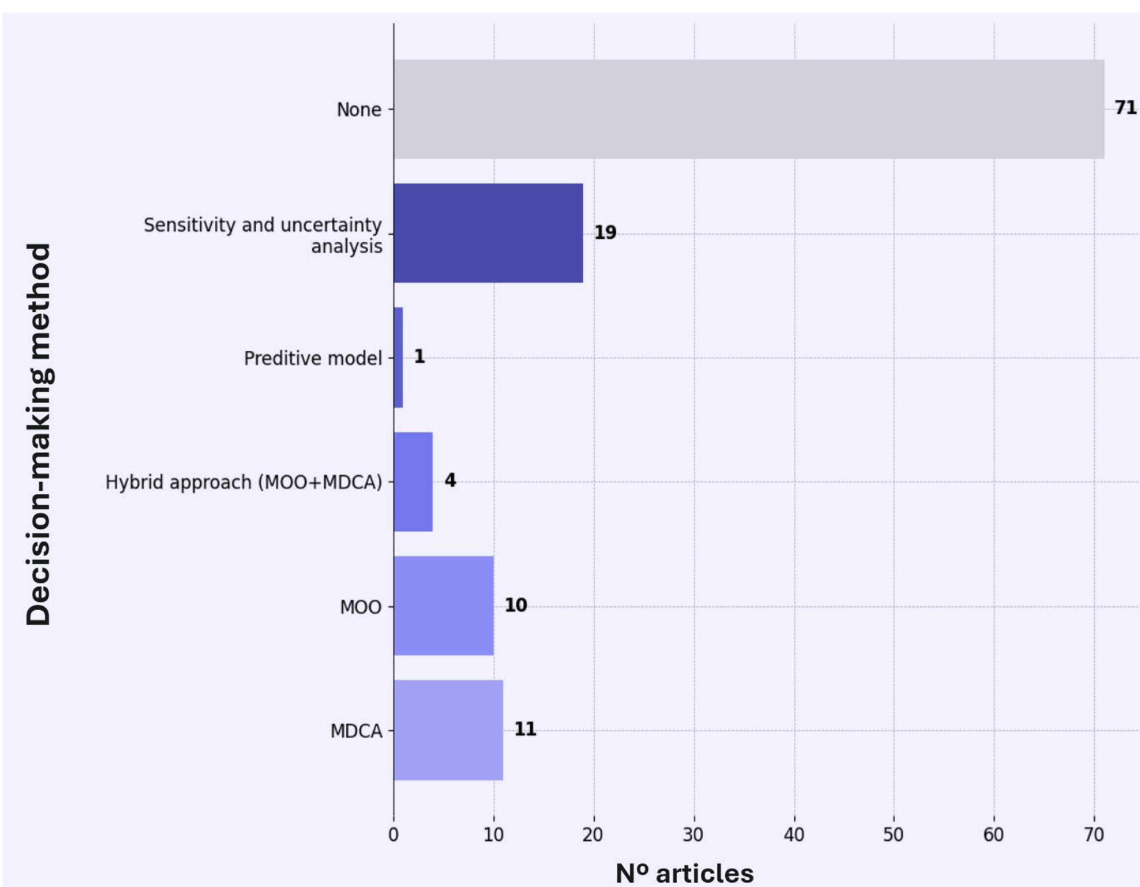

Fig. 13. Breakdown of the 115 articles by decision-making method.

3.7. Decision-Making support (CAT7)

Decisions made during a project significantly affect performance throughout the building life cycle. In section 3.6.1, it was shown that several studies extend beyond environmental assessment and LCA by also incorporating economic and social indicators. While this broader scope allows for a more comprehensive evaluation of sustainability, it also increases the complexity of the decision-making process. As project objectives become more multidimensional—often involving conflicting criteria in the short and medium term—the need to balance these diverse priorities becomes more demanding.

Different decision-making methods can be beneficial in navigating these multifaceted and often contradictory scenarios. As shown in Fig. 13, 38 % of the articles analysed in this SLR employed some form of decision-support method—such as Multi-Criteria Decision Analysis (MCDA), Multi-Objective Optimisation (MOO), hybrid approaches (MCDA + MOO), predictive models, or Uncertainty and Sensitivity analyses—to identify the most suitable design option. Table 4 summarises typical decision-support methods and design variable generation strategies, aligning them with decision objectives, project phases, data requirements, computational demand, and stakeholder involvement. Furthermore, Table 5 details the 24 studies that explicitly applied MCDA, MOO, or hybrid approaches, including the tools used, the case study, independent and dependent variables (i.e., design variables and criteria) considered.

MCDA is used to prioritise decision alternatives by aggregating qualitative and quantitative criteria into a single evaluative score [166]. The process involves defining alternatives (independent variables), identifying relevant evaluation criteria (dependent variables), and assigning relative importance to each criterion through expert input, stakeholder consultation, or project-specific priorities [28]. MCDA is especially useful during the early design, where decisions are most impactful, but data availability is often limited. It has low computational demand and, when combined with parametric design workflows, allows for rapid assessment of multiple alternatives (Table 4).

Although MCDA offers clear benefits - such as structuring trade-offs and supporting preference-based decisions - its integration into BIM-LCA remains limited, with only 11 out of 115 studies (9 %) adopting this approach (Fig. 13, Table 5).

Among the applications of MCDA in BIM-based LCA, Taher A. et al. [136] proposed a framework that integrates BIM, LCA, energy analysis, and an MCDA method designated as Analytic Hierarchy Process (AHP) to select the best design alternative while considering cost, time, aesthetics, material availability, energy efficiency, and impact categories from LCA. The weighting of the criteria is determined using a pairwise comparison matrix, where experts rate the importance of each criterion relative to others on a scale from 1 to 9. Similarly, Abdelaal et al. [137] applied AHP to evaluate concrete structures by balancing embodied carbon, energy, and economic costs. Additionally, Namaki et al. [138] evaluated three construction systems for a single-family house, considering different LCA impact categories.

Other researchers employed the Fuzzy AHP (FAHP) method, which refines traditional AHP by incorporating fuzzy logic to address uncertainties and subjective judgments in decision-making. Filho et al. [140] used FAHP to determine the best construction, painting, and roofing materials for low-income housing, considering different LCA impact categories, costs, and social factors and Figueiredo et al. [141] used it to determine different materials for ceilings, doors, floors, walls

Table 4
Types of decision-making methods matched to analysis objectives, design phases, data requirements, computational demand, and stakeholder involvement.

Decision Objective	Description	Typical Methods / Tools	Suited Design phases	Data Type Required	Computational Demand	Stakeholder Input	References
Prioritisation	Rank predefined alternatives based on preferences	**MCDA:** AHP, TOPSIS, WSA, MIVES, Delphi (…)	All phases; particularly useful in early design for concept evaluation	Qualitative + Quantitative	Low to Medium	Yes	[136–146]
Optimisation	Find best trade-offs between conflicting objectives	**MOO:** NSGA-II, HypE, GAMS, BIP (…)	All phases, but early design carries high uncertainty, so decisions should be made with caution	Quantitative only; qualitative data must be converted to numerical scales	Medium to High	No	[128,147–155]
Optimisation + Prioritisation	Generate Pareto-optimal solutions, then rank based on preferences	**Hybrid:** NSGA-II + TOPSIS, MOO + AHP, MOO + WSA	All phases; useful when both performance and stakeholder input matter	Idem, with preference weights	Medium to High	Optional	[37,156–158]
Performance benchmarking -Predictive model	Identify reference performance ranges (e.g., max-min GWP for each building element) and variable impact across alternatives	Random Forest, Regression trees, Support Vector Regression (…)	All	Training data (e.g., from parametric simulation)	Medium to High (training);	No	[159]
Design variables generation – parametric*	Generate many variants by varying design parameters	Grasshopper, Dynamo, Design of Experiments	Early Design (concept exploration)	Geometric parameters	Low to Medium	No	[128,37,155,152]
Design variables generation – ML/metamodels	Use ML models to approximate the behaviour of design variables (instead of running all simulations)	LSSVM, ANN	All	Training data (e.g., from parametric simulation)	Medium to High (training); Low (application)	No	[156]
Sensitivity analysis	Understand which variables most influence outcomes	One-at-a-time (OAT), Sobol, regression-based methods	All; especially early design and model validation	Quantitative (model input and output)	Low to Medium	No	[73,77,107,124,128,129,134,143,144,146,154,157,158,160–165]
Uncertainty analysis	Assess how variation in inputs affects reliability of results	Monte Carlo, fuzzy logic, @RISK	All; critical for early design and scenario testing	Quantitative	Medium to High	No	

* Only articles that combine parametric modelling with a decision-making method.

Table 5
Summary of the 26 articles that carried out an MCDA, MOO or a Predictive model, detailing the tools used, case study, the independent and dependent variables, and design stage.

Decision support	Article	Decision support method	Tools	Case study	Independent Variables	Dependent Variables	Design phase
Multi-criteria analysis (Prioritisation)	[136]	AHP	SimaPro + Own tool C# for AHP (research-stage)	Health Building	Different types of roof slabs for a hospital project	Cost, Time, Aesthetics, Availability of material, Energy Efficiency, Environmental Impact and LEED rating analysis	Detailed design
	[137]	AHP	One-Click LCA and HBERT for LCA + Not specified for AHP	Industrial Structural design	Type of structure (different types of concrete structures)	Embodied GWP, Embodied energy, Cost	Detailed design
	[138]	AHP	One-Click LCA + Excel	Single-Residential Building	Different materials for structure, isolation and windows	GWP, OD, AP, EP, DNRE, Social Cost of Carbon	Detailed design
	[139]	AHP	Autodesk Tally + Not specified for AHP	Single-Residential Building	Different materials for structure and walls	GWP, Cost, Thermal Comfort, Cultural Acceptance, Schedule	Detailed design
	[140]	FAHP	Autodesk Tally + Not specified for FAHP	Single-Residential Building	Structure, Painting, Roofing materials	Cost, LCA impact categories, Community Investment	Detailed design
	[141]	FAHP	Own tool (add-on) for LCA + *R* Project for Statistical Computing (open source)	Multi-Residential Building	Different materials for ceilings, doors, floors, walls and windows	GWP, AP, EP, LCC and Fair Wage Potential	Detailed design
	[142]	AHP-TOPSIS method	Autodesk Tally + Not specified for AHP-TOPSIS	Educational Building	Different Demolition Waste scenarios with different CDW recycling rates	GWP, Energy consumption, Total cost, Landfill Cost saving	Detailed design
	[143]	Modelo Integrado de Valor para una Evaluación Sostenible (MIVES) and Delphi	Own tool (add-on) for LCA and MIVES/ Delphi (research-stage)	Multi-residential building renovation	Different interior rehabilitation scenarios	Initial rehabilitation cost, Maintenance cost, Demolition cost, Property added-value, Rehabilitation process time, Embodied Energy (EE), Embodied Water (EW), Construction Waste (CW), Operational Energy (OE), Demolition Waste (DW), Functionality of the physical space, Adequate spaces & storages, Thermal comfort, Indoor air quality, Lighting comfort, Acoustic comfort, Aesthetic & building beauty	Detailed design
	[144]	TOPSIS method	Own tool (add-on) for LCA and TOPSIS (research-stage)	Multi-Residential Building	Different materials for Structure, Roofing, External walls, Windows, Doors, Internal walls, Ceiling, Flooring	Embodied GWP; Economic cost; S-LCA (working hours)	Detailed design
	[145]	The criteria and their importance are defined Active House Protocol.	Active House Protocol (commercial)	Single-Residential building	Design options (Prefabricated timber frame and X-LAM (cross-laminated timber) technology	LCA impact categories, Thermal comfort	Early design
	[146]	Choosing by advantages (CBA)	SimaPro + Not specified for CBA	Education building renovation	Different low-cost seismic rehabilitation techniques	Execution costs Execution time Level of modulation Level of standardization Level of industrialization GWP, FPMF, Damage to human health (HH)	Detailed design
Multi-objective optimization (Optimisation)	[147]	NSGA–II algorithm	Own tool + DesignBuilder for LCA and NSGA–II (research-stage)	Educational Building Renovation	Building Envelop Roof, External Wall (EW), Window frame (W), Façade Type (FT), Glazing template (G), Window to Wall (WWR), Building Systems HVAC template-(HVAC), Mechanical Ventilation rate (MVR), Cooling Operation Schedule (COS), Heating Operation Schedule (HOS), Airtightness (A), Lighting template (Li), External Window Open (WO)	GWP, LCC	Detailed design

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Table 5 (*continued*)

Decision support	Article	Decision support method	Tools	Case study	Independent Variables	Dependent Variables	Design phase
	[128]	NSGA–II algorithm	Own tool (Dynamo) for LCA + JEPlus + EA for NSGA–II (commercial)	Administrative Building	Wall insulation thickness, Floor insulation thickness, Windows height, Floor concrete thickness, Wall gypsum thickness	Cooling and heating energy consumption	Early and Detailed design
	[148]	Mathematical optimisation model - GAMS (General Algebraic Modelling System)	Autodesk Tally + Not specified for GAMS	Multi-Residential Building Renovation	Walls, Windows, Lighting system, Heating system, Cooling system, Roof, Appliances, Solar Panels, Wind turbines	Annual energy consumption, LCC	Detailed design
	[149]	NSGA–II algorithm	Athena Impact Estimator + Honeybee and Ladybug + Script using Pymoo (Python library)	Multi-Residential Building	Envelope Materials	GWP, Operational energy, Embodied Energy	Detailed design
	[150]	NSGA–II algorithm	Not specified	Conceptual structural design	Site dimensions, Material types, Floor system, Foundation type, Lateral stability frame, Loads, Ground conditions	Cost, Embodied GWP, Maximized Free space	Early design
	[151]	HypE genetic algorithm (octopus add-on for grasshopper)	Own tool (Grasshopper)+ Octopus add-on (Grasshopper)	Multi-Residential Building	External shell components (wall, ceiling, and window), urban grid power system and renewable energy generation system.	Embodied energy, renewable energy, and embodied cost	Detailed design
	[152]	HypE genetic algorithm	Athena Impact Estimator + Octopus add-on (Grasshopper)	Multi-residential building	Material selection, thicknesses for External walls, Floors and roofs, window types	Life-Cycle Energy (LCE), LCC	Detailed design
	[153]	Binary Integer Programming (BIP) model	Autodesk Tally + CPLEX for BIP (commercial)	Building envelope	Exterior Walls, Floors, Ceilings, Windows, Doors	Life Cycle Energy Cost, Life Cycle Electricity Use, Life Cycle Fuel Use, Ease of Instalment	Detailed design
	[154]	Multiple Linear Regression Analysis	IBM SPSS statistics tool, @RISK (commercial)	Single-Residential Building Renovation	Building façade, Windows to wall ratio (WWR), Insulation material and thickness	Annual energy consumption	Detailed design
	[155]	Grid search algorithm (hyperparameter optimisation)	Own tool C# for LCA and grid search	Multi-Residential Building Exterior Walls	Different materials and thicknesses for each layer of the wall	R-value and LCA	Early design
Hybrid approach MOO+MCDA (Optimisation + Prioritisation)	[156]	LSSVM (meta-model) + NSGA-II +TOPSIS	Autodesk Tally + Green Building Studio + MATLAB	Multi-Residential Building	**Early Design phase:** Floor height, Building orientation, Window-to-wall ratio (WWR), Number of floors **Detailed Design phase:** Type of thermal insulating material for external walls, Type of external wall structure, Type of thermal insulating material for internal walls, Type of internal wall structure, Type of thermal insulating material for floors, Type of window frame and glazing **Construction Design phase:** Finishing material for external walls; Finishing material for internal walls; Type of flooring; Type of roof tiles	Embodied GWP Operational GWP	All
	[157]	NSGA–II and TOPSIS	Python Script using Pymoo library	Building Façades	Building façade material options and thickness	GWP, life cycle cost (LCC), and thermal transmittance (U-value)	Early design
	[158]	Multi-objective optimisation (Not specified) and a the weighted sum approach (WSA)	Autodesk Tally + Not specified for MOO	Single Residential Building	Walls, floors, roofs	LCC, Primary Energy Demand (PED), GWP, and Ozone Depletion Potential (ODP)	Detailed design
	[37]	NSGA–II + SBM-I model (DEA)	Bombyx + Honeybee / Ladybug for LCA + Wallacei X add-add-	Single-Residential Building	External walls, internal walls, floors, roofs, and windows	Embodied and operational GWP and surface energy flow	Detailed design

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Table 5 (*continued*)

Decision support	Article	Decision support method	Tools	Case study	Independent Variables	Dependent Variables	Design phase
			on (Grasshopper) NSGA–II				
Performance benchmarking	[159]	Random forest algorithm	Autodesk Tally + Python script using the Scikit-learn library	Multi-Residential	Façades, partitions, rooftops, side walls	Acidification Potential (AP), Eutrophication Potential (EP), GWP, Smog Formation Potential (SFP), PED, Non-Renewable Energy Demand (NRED), Renewable Energy Demand (RED), Mass	Detailed design

and windows considering LCA impact categories and Fair Wage Potential.

Other authors used hybrid MCDA methods—for instance, Han et al. [142] coupled the AHP and the TOPSIS. AHP was used to assign weights to different sustainability indicators (GWP, energy consumption, total cost, and landfill cost savings) based on their relative importance and TOPSIS to prioritise the solutions and identify the best demolition waste scenario based on its geometric distance from the ideal one. Zolfaghari et al. [143] combined the Integrated Value Model for Sustainable Evaluations (MIVES) with the Delphi method. MIVES structured the assessment of economic, environmental, and social criteria through a hierarchical decision tree and value functions, while Delphi was used to determine expert consensus on weightings. Soust-Verdaguer et al. [144] used the TOPSIS method to evaluate the economic cost, embodied GWP, and working hours of different material options for structural components, building envelopes, partition walls, and finishes. Their study used the Saaty scale for weight attribution. It included a Sensitivity analysis to examine how variations in the weighting of environmental, economic, and social dimensions influenced the results. Meanwhile, Vázquez-Rowe et al. [146] employed a Choosing by Advantages (CBA) method to identify the best seismic retrofit techniques for a primary school, considering LCA impact categories, technical feasibility, and economic costs, with Sensitivity analysis testing different methodological assumptions.

Another decision-making method is Multi-objective optimisation (MOO), used to address problems involving multiple conflicting goals and identify optimal solutions. In this SLR, 12 % (14 articles) use MOO or a Hybrid approach (MOO+MCDA) within the context of BIM-LCA (Fig. 13, Table 4).

Unlike MCDA, which deals with problems that lack explicit objective functions and instead prioritises/ranks a set of design alternatives based on weighted criteria, MOO requires all objectives to be formulated mathematically. It is used to find one or more solutions that satisfy all defined constraints while minimizing (or maximising) objective functions [155]. When improving one objective inevitably compromises another, MOO generates a Pareto front of non-dominated solutions. These are all optimal solutions in the sense that none is better than the others across all objectives; each represents a different trade-off between competing criteria (i.e., objective functions)[155,147].

MOO methods vary based on variable types and the linearity of objective functions. Common approaches include Evolutionary Algorithms (EAs) such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). The most widely used GA is the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), introduced by Deb et al. in 2002 [167].

For instance, Heydari et al. [128] applied NSGA-II using the JEPlus + EA tool for energy optimization, minimizing heating and cooling energy demand. Sharif et al. [147] used an NSGA–II to find optimal renovation scenarios considering budget constraints, energy consumption, LCC, and different LCA impact categories. Similarly, Motaleibi et al. [148] identified optimal retrofit strategies, such as the insulation of building envelope material components and mechanical and electrical equipment considering LCC and LCA. Atashbar et al. [149] used NSGA-II to find the optimal exterior wall cladding materials for residential buildings considering operational and embodied carbon and energy, and Kanyilmaz et al. [150], to optimize conceptual structural design, balancing structural performance, cost, and embodied carbon.

Abbassi et al. [151] used HypE genetic algorithm and the Octopus add-on for Grasshopper to analyse the trade-off between embodied and operational energy. Similarly, Sandberg et al. [152] considering LCC and Life Cycle Energy (LCE).

Beyond EAs, other mathematical optimization techniques have been applied. Najjar et al. [153] used Binary Integer Programming (BIP) to identify optimal residential building envelope materials, minimizing fuel and electricity costs while maximizing installation efficiency. Tushar et al. [154] performed a Multiple Linear Regression Analysis using the IBM SPSS statistics tool to predict energy consumption based on different insulation materials and window-to-wall ratios. Furthermore, Hassan et al. [155] implemented grid search hyperparameter optimization, a brute-force technique that systematically tests different combinations of model configuration settings (hyperparameters) to find the best-performing one. This was used to determine optimal material combinations for exterior walls, balancing thermal resistance (R-value) and LCA impact categories.

Other studies have integrated a hybrid approach combining MOO with MCDA. All points along the Pareto front generated by MOO are mathematically valid and non-dominated, meaning none is inherently better than the others [168]. However, in practice, only one of these solutions is usually selected as the final decision. Often, the knee point—which represents the best marginal balance between conflicting objectives—can be a reasonable choice when no clear preferences are defined. When preferences are known, MCDA methods can be applied to rank and select the most appropriate non-dominated solution according to the decision-maker's priorities (e.g., assigning 70 % weight to cost and 30 % to GWP).

Zou Y et al. [156] developed a hybrid optimization model to determine the optimal trade-off between embodied and operational carbon across different design phases. The design variables were defined based on each design phase, and generated through orthogonal experiments, covering a range of possible values and variations. A Least Squares Support Vector Machine (LSSVM) model was then trained using the generated dataset to learn the relationship between design variables and GWP at each design phase. This LSSVM model acted as a meta-model (or surrogate model), providing an implicit function that approximates the behaviour of the design variables on GWP—thus replacing full simulations and enabling a faster and less computationally intensive MOO process. This model achieved a high accuracy with a coefficient of determination (R^2) of 0.91 and 0.92 for embodied and operational impacts respectively in early design. Slightly lower R^2 values were observed in detailed and construction design, ranging from 0.81 to 0.85. The model was trained and validated using an 80/20 data split and tested on unseen data, supporting reproducibility. The NSGA-II was then applied to generate the Pareto front, and the TOPSIS method was applied to rank the Pareto-optimal solutions and select the best trade-off point between embodied and operational carbon. Similarly, Zong et al. [157] applied NSGA-II to optimise material thickness and combinations, using TOPSIS to rank solutions. Mowafy et al. [37] combined parametric design, NSGA-II, and Data Envelopment Analysis (DEA) to select optimal materials for walls, floors, roofs, and windows. Chen et al. [158] used MOO with the Weighted Sum Method, assigning different weights to LCC, primary energy demand, GWP, and ozone depletion potential based on expert surveys.

Furthermore, predictive models can also support decision-making; however, only one article adopted this approach. Martínez-Rocamora et al. [159] developed a method to generate environmental benchmarks for building typologies by simulating 240 combinations of façades, partition walls, and roofs. A Random Forest (RF) regression model was used to predict GWP and other indicators, identify outliers, and evaluate the influence of each variable. The model achieved high accuracy ($R^2 = 0.9999$) and enabled the definition of minimum and maximum GWP values for the typology analysed. The authors noted that the model was trained using the full dataset due to its limited size (with Out-Of-Bag samples used for validation), while acknowledging that this approach is less robust than using a separate test set.

On the other hand, Sensitivity and Uncertainty analyses enhance decision-making in LCA by quantifying the impact of design variables and reducing uncertainties related to model assumptions, input data, and practitioner expertise [160,161]. 16% of the articles applied sensitivity or uncertainty analysis.

Sensitivity analysis was primarily used to identify the most influential design variables [107,161]. For instance, Rostamiasl et al. [129] incorporated scenario and Sensitivity analyses to identify cost-sensitive parameters. Other studies employed Sensitivity and Uncertainty analysis to assess LCA result reliability, examining how BoQ variations impact environmental results [77,107,124,162,163]. For instance, Harter et al. [160] examined how uncertainties vary depending on the LOD. Zhou Y et al. [161] and Gao et al. [164] used Monte Carlo simulations to assess uncertainty in material quantities and calculated the probability distribution of total GHG emissions.

4. Discussing the existing gaps and future directions

The above research findings assessed current research into integrating BIM and LCA. In this section, we analyse the challenges and gaps in this field, discuss what previous research has addressed and, explore potential future research directions to fill these gaps and respond to these research questions: **RQ1 -** What obstacles hinder the decision-making in BIM-based LCA? **RQ2 -** What solutions have been developed to address these challenges? **RQ3 -** What challenges remain overlooked, and how can they be addressed? Table 6 provides a structured overview, linking each challenge (RQ1) to existing solutions (RQ2) and identifying further research needs (RQ3), organised into themes such as early design, LCI/LCIA automation, LCA for building renovation, and decision-support.

4.1. LCA in early design and continuous LCA

Several studies have addressed the specific challenges of applying LCA during early design stages, particularly the lack of material specifications, the use of assumptions by practitioners, and the limited availability of representative LCA data. To mitigate these issues, researchers proposed strategies such as the use of predefined F&T for prefabricated components [49,50], and the combination of absolute quantities extracted from BIM models with relative material quantities from external databases—following a logic similar to shoebox modelling in early energy simulations (e.g., using surface area instead of volume) [33,54,62].

Other solutions involve enriching BIM models with external knowledge databases containing technical and LCA data or developing hierarchical LCA databases that correspond to the LOD and include generic, average, and specific LCA data, as well as minimum and maximum GWP values for each building assembly [51,52,54,56,57,59–61]. As well as, using EPDs with safety and range factors (min, max, average, median) to improve the quality and representativeness of input data at the early stages [53].

Together, these methods reduce uncertainty in early-stage BIM-LCA and lay the foundation for more consistent and traceable data integration across subsequent design stages.. However, establishing robust links with external data sources depends on the adoption of consistent data structures and semantic alignment, either based on the internal ontology of BIM authoring tools or the IFC schema, when models are exchanged.

Despite these advances, further research is needed to establish a standardised mapping between LODs and LCA applications, such as Screening, Simplified, and Complete LCA. Additionally, understanding the deviations in material quantities between design stages could inform the development of conversion factors, adjustment methods, or estimation techniques to address missing or uncertain data during early design phases—particularly relevant for Screening LCA, as suggested by [46].

Future research could enhance early-stage LCA by training ML models on past projects to automatically apply typical assumptions when assigning materials. Decision trees, gradient boosting (e.g., XGBoost), or support vector machines might effectively predict material choices based on building typology, geometry, and function. In more complex scenarios involving sequential decision-making, such as determining optimal material substitutions or refinement over time, reinforcement learning (e.g., Deep Q-Networks or Proximal Policy Optimization) may help guide early design decisions by suggesting material improvements that reduce environmental impact and fill in missing or uncertain data over time.

Another ML-based approach involves training models to predict environmental impacts (e.g., GWP, embodied energy) directly from simplified early-design inputs, such as overall geometry, number of storeys and proposed construction systems, using neural networks or regression-based models. However, as noted by Hollberg [48] such methods depend on the availability of large datasets containing as-built BIM models linked with LCA results. At that time, no such database existed; now, there are some efforts to create an open-source database, for example, the Built Environment Carbon Database by BECD [169].

Additionally, BIM-LCA tools that support continuous monitoring of environmental impacts from early to construction design are gaining attention. These tools should be capable of storing and managing project history, generating structured datasets throughout the project lifecycle. These datasets could then be used to train ML models—such as recurrent neural networks (RNNs) to model temporal dependencies, or graph neural networks (GNNs) to capture relationships among building components and typical material assemblies during early design. Furthermore, generative AI models (e.g., GANs or diffusion models) show great potential in conceptual and early design phase by generating optimised building geometries and configurations optimised for environmental performance. Such approaches could significantly improve the accuracy of LCA results across design stages, reduce uncertainty, and support decision-making when data is incomplete or undefined.

4.2. Data extraction and exchange and automation degree

There are multiple methods for BIM-LCA integration, each with advantages and limitations, as highlighted in this and previous literature reviews. Prior to 2021, Type 1 (data export to spreadsheets) was the most common approach. Manually editing the BoQ and manually inputting data into LCA software is becoming less frequent as the use of knowledge databases to complement BIM data, compliance with exchange requirements and standardised information management within BIM models becomes standard practice. Type 2 (BoQ import into LCA tools) and Type 3 (BIM add-ons) have gained popularity due to their user-friendly interfaces, particularly in commercial tools like OneClick LCA and Autodesk Tally.

However, dedicated LCA tools with a Type 2 data exchange require

Table 6
Summary of Challenges and Gaps (RQ1), Current developments (RQ2) and Development needs (RQ3).

Topic	Challenges | Gaps (RQ1)	Current developments (RQ2)	Action type	Development needs (RQ3)
BIM-LCA during early design and continuous LCA	**i)** Limited data in early design (only geometric data, no material specifications). **ii)** Lack of standardised LCA methods/tools for early design assumptions. **iii)** Generic LCA data may not be representative. **iv)** Existing tools focus either on early or detailed design phases, limiting continuous impact monitoring.	1) Predefined F&T for prefabricated building projects. 2) Use absolute BIM quantities + relative material quantities from a database (parametric modelling). Real-time control of variables. 3) Use a knowledge database containing all the necessary data, such as technical material and LCA data. 4) Implement a hierarchical database correlated to the LOD and LCA data type (i.e., generic, average and specific data). 5) Use minimum and maximum GWP for building assemblies in early design. 6) Use EPDs with Safety Factors & Range Factors (min, max, avg, median) in early design. 7) Use dynamic data extraction, as this allows model changes to be automatically reflected in the LCA results. 8) Conduct sensitivity analyses to understand the impact of each design variable in each design phase.	Automation & Digital Tools	**A)** ML to learn from past projects to apply typical assumptions for placeholder materials during the early design.
			Automation & Digital Tools	**B)** ML to predict environmental impacts during early design.
			Automation & Digital Tools	**C)** Develop a dynamic data extraction approach independent of proprietary BIM software, able to store and track project history.
			Data & Standardisation	**D)** Standardise LOD for different LCA applications (Screening, Simplified, Complete LCA).
			Data & Standardisation	**E)** Create local databases with typical construction assemblies and processes.
Automation during LCI	**v)** Manual BoQ input and edit during LCI due to incomplete or inadequate BIM models.	**9)** Automation during LCI has increased. Only 7% of the reviewed articles still relied on manual processes. **10)** Use a knowledge database containing all the necessary data, such as technical material and LCA data to complement the BIM model data when necessary **11)** IDM and MVD for LCA. Propertied datasets and PDT for BIM-LCA data.	Automation & Digital Tools	**F)** BIM validation tools to ensure models are compatible with quantity take-off and LCA.
			Automation & Digital Tools	**G)** Dynamic data extraction methods independent of BIM proprietary software, capable of storing and tracking project history.
Automation degree during LCIA	**vi)** Lack of unified data structures between BIM and LCA tools.	**12)** Data structure through a Construction Classification System (CCS) and naming conventions.	Automation & Digital Tools	**H)** Further research on ML algorithms for object classification and LCA data assignment.

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Table 6 (*continued*)

	vii) Mapping BIM and LCA data is time-consuming and prone to errors.	**13)** Only two articles use ML for BIM object classification & LCA data assignment.	Automation & Digital Tools	**I)** Use ML to classify the available entries in LCA, LCC and S-LCA databases. Classify EPDs and new entries for these databases with CCS.
			Automation & Digital Tools	**J)** Further research on web semantics to connect BIM with LCA data and enable SPARQL-based queries.
			Data & Standardisation	**K)** Digital and machine-readable EPDs.
Renovation Projects	**viii)** Limited research on BIM-LCA for renovation and retrofit models. **ix)** Existing BIM-LCA tools do not address renovation-specific challenges.	**14)** Generation of multiple renovation scenarios & identifying renovation measures for each building element [113]. **15)** Scan-to-BIM approaches for the identification and modelling of existing structures.	Automation & Digital Tools	**L)** Machine Learning for classification of point cloud data.
			Automation & Digital Tools	**M)** <u>ML models</u> to predict end-of-life scenarios based on material degradation and component interdependencies.
			Data & Standardisation	**N)** Standardised property sets (Psets) and data templates for renovation-specific BIM/IFC attributes.
LCA and other indicators	**x)** Few studies combine LCA with other environmental, economic & social indicators. **xi)** LCA impact savings from Circular Economy (CE) principles are often overlooked.	**16)** LCA & LCC integration is common, but few studies include Social LCA (S-LCA). **17)** Indicators such as the MAC and the MDC link low-impact actions to economic savings. **18)** Some BIM-based tools for CDW management and DfD integration have been proposed.	Automation & Digital Tools	**O)** More research on BIM-based tools for LCSA (LCA + LCC + S-LCA).
			Automation & Digital Tools	**P)** Use sensitivity analysis and ML to understand how CE indicators, i.e., DfD and DfA, impact LCA results.
Dynamic LCA	**xii)** Most studies apply static LCA, which fails to capture temporal variations in building performance.	**19)** Three studies incorporate dynamic LCA, considering: → Grid mix scenarios → Temperature changes → Glass façade heat transfer → Elevator energy recovery → Recycling rates → Material replacement cycles	Data & Standardisation	**Q)** Further research on dynamic LCA modelling that incorporates temporal and spatial variability, including time-dependent inventory data, characterisation factors, and impact weightings, to more accurately reflect changes in building performance and environmental impacts over time.
Decision Making	**xiii)** Difficulty in identifying optimal solutions due to conflicting environmental, economic, and social objectives. **xiv)** Lack of regional or local benchmarks.	**20)** Use of MCDA and MOO methods to prioritise and identify optimal solutions across multiple sustainability indicators. **21)** Only one study applied a meta-model to approximate GWP based on design variables and reduce the computational load of MOO.	Decision-making	**R)** Use meta-models to reduce MOO computation.
			Decision-making	**S)** Use parametric design and ML to benchmark each building component and define the minimum and maximum LCA impacts (predictive modelling).

(*continued on next page*)

Table 6 (*continued*)

		22) Only one study used a predictive model to estimate LCA impact categories of different building elements.	Decision-making	**T)** Apply ML, such as reinforcement learning, to suggest design improvements and alternatives at the component and building levels.
			Decision-making	**U)** Combine continuous LCA, dynamic data extraction, meta-models, MOO, and MCDA to support integrated and iterative decision-making
			Data & Standardisation	**V)** Develop a regional database with Building LCA results for benchmarking and define budget-based targets scaled to a regional, national or European reference.

the entire workflow to be repeated when the BIM model is updated, a limitation that static and dynamic approaches could mitigate. Static approach, through IFC GlobalIds can maintain a consistent link between LCA data and specific elements or materials, reducing the need for manual updates; however, only 18% of the articles used IFC for data transfer (see Fig. 5 section 3.2). In contrast, dynamic integration offers an even more efficient workflow by automatically updating LCA results in real-time as BIM models evolve, making it particularly beneficial for continuous LCA assessments throughout the design process.

Despite its advantages, dynamic integration is currently limited to Type 3 (BIM add-ons), Type 4 (VPL scripts), and Type 6 (BIM object libraries), all of which depend on proprietary software. While results can be linked to BIM objects and exported to IFC, no open BIM tool supports full dynamic BIM-LCA integration, only static approaches. This raises a key question: How can different project specialities—such as architectural, structural, and MEP models developed in different authoring software—be assessed dynamically using a unified BIM-LCA approach?

Regarding automation degree, researchers have developed add-ons, VPL scripts, and knowledge databases to improve the LCI phase, avoiding manual editing and input of the BoQ into LCA software. However, the LCIA phase—specifically the mapping between BIM objects and environmental impact data—remains manual and prone to errors. Although structuring BIM models using Construction Classification Systems (CCS) and consistent naming conventions has helped improve semantic alignment and interoperability, these approaches still depend heavily on manual data verification and assignment. In this SLR, two studies implemented ML to automate the mapping of BIM objects with LCA datasets using an NLP-based semantic model healing [56,92].

Future research should focus on developing and training ML models capable of automatically classifying BIM elements and associated materials, using inputs such as CCS codes, object metadata (e.g., type, function, dimensions), and geometric or parametric features. Supervised learning algorithms—including Random Forests, Support Vector Machines (SVMs), and Gradient Boosting methods like XGBoost—are particularly well-suited for learning from labelled datasets that link BIM components with environmental product data. For this approach to be effective, both BIM elements and LCA databases must be classified using a common system such as CCS. This would facilitate cross-referencing between datasets, minimise semantic discrepancies, and reduce errors associated with multilingual or inconsistent terminology.

Additionally, integrating BIM and LCA through web-based semantic architectures—using technologies such as SPARQL queries, linked open data, and domain ontologies—could provide further benefits (e.g., dynamic querying of external LCA repositories directly from BIM environments [87].

4.3. Renovation projects

The integration of BIM and LCA in renovation projects remains limited, accounting for only 14 % of the articles analysed in this SLR. Renovation workflows introduce additional layers of complexity that are not typically addressed by standard BIM-LCA tools. These include the need to differentiate existing from new elements, account for the current condition of existing materials, and model selective demolition and material recovery.

A critical aspect of LCA of renovation projects is the high level of information required. BIM models typically need to reach LOD 400–500 to enable the identification of individual components, their physical condition, and potential end-of-life destination. When IFC is used as the data exchange format, it should include standardised property sets — ideally aligned with data templates as defined in ISO 23387 -that cover key renovation-related attributes such as the identification of existing structures, material recoverability, disassembly potential, and reuse condition. As previously discussed, these should be complemented by well-defined Information Delivery Manuals (IDMs) and Model View Definitions (MVDs).

Future research directions should explore Scan-to-BIM approaches, such as those proposed by Kim et al. [114]. The integration of machine learning with point cloud data can automate the identification and classification of building elements, using models such as PointNet or 3D CNNs, and assess their condition through image-based CNNs or Bayesian models [170]. Additionally, decision trees, graph neural networks, or reinforcement learning could be employed to predict end-of-life scenarios based on material degradation, and component interdependencies.

4.4. LCA and other indicators

Regarding the use of LCA and other economic, environmental, and social indicators, we conclude that few studies have integrated LCA with LCC and S-LCA. While LCA and LCC are widely applied to quantify environmental and economic impacts, S-LCA, which assesses social aspects such as working conditions and the well-being of stakeholders, remains underexplored.

In parallel, some studies have started to explore how Circular Economy (CE) principles—such as Design for Disassembly (DfD) and Design for Adaptability (DfA)—can be integrated into BIM-based LCA and LCC tools. For example, several tools have been developed to quantify construction and demolition waste (CDW) and evaluate how different CDW management approaches influence both environmental impacts and economic performance. However, only two studies have conducted a quantitative assessment of DfD or DfA interventions [121, 122]. Further research is needed to use BIM-based LCA and LCC tools to analyse the potential environmental and economic savings associated with implementing CE principles in construction design. This includes integrating Sensitivity analysis and ML techniques to better understand how DfD and DfA strategies influence life cycle impacts and support more informed decision-making.

On the other hand, most studies carried out a static LCA, which does not take into account time-dependent factors affecting building performance, which can lead to an overestimation of the environmental impact by up to 66.7 % [133]. Only four studies have explored dynamic LCA methodologies that consider variations in the electricity grid mix, fluctuations in outdoor and indoor temperatures due to climate changes, heat transfer coefficients of glass curtain walls, energy recovery efficiency of elevators, recycling rates, and material replacement cycles [132–135]. Dynamic LCA is likely to gain attention in the coming years. More research is needed into dynamic parameters, processes and methodologies, considering the evolution of energy production, distribution and use, material flows, technological advances, waste treatment and social factors.

4.5. Decision-Making support

MCDA and MOO integration into BIM-LCA remains rare, with only 21 % of studies applying one of these methods. In most cases, LCA is used solely to report environmental impacts (79 %), and design alternatives are compared qualitatively, leaving decision-making to practitioner judgment. This is likely due to the lack of such functionalities in commercial tools, the limited availability of integrated research-based solutions and the computational demand, especially in MOO.

Sensitivity and Uncertainty analyses also play an important role in improving the robustness of LCA-based decision-making. These methods help identify critical design variables and assess how input variability in early design stages can affect final LCA outcomes. However, only 16 % of the studies applied these analyses, which may reflect both the lack of support in commercial BIM-LCA tools and the methodological complexity of implementing them. An example of advanced implementation is the “PhD” version of SimaPro, which includes Monte Carlo simulation capabilities to assess output variance and result robustness [171].

Future research should focus on simplifying and embedding MCDA, MOO, and Sensitivity analysis into BIM-LCA tools, making them more accessible and practical for iterative design and optimisation. One promising direction is the use of meta-models or surrogate models to reduce MOO computation demand. Moreover, Reinforcement Learning can support sequential and adaptive decision-making in BIM-LCA, by learning to suggest design alternatives or improvements at both the component and building level, based on defined environmental or economic reward functions.

The combination of continuous LCA with dynamic BIM-LCA integration, and AI-enhanced MOO and MCDA offers a promising foundation for automated workflow and iterative decision-making. In this approach, continuous LCA enables the tracking of environmental impacts throughout all design phases, while dynamic data extraction ensures that updates in the BIM model are reflected in real time. Coupling these with AI-driven optimisation and decision-support methods allows for real-time feedback, enabling designers to evaluate trade-offs and select optimal solutions early and efficiently in the design process.

On the other hand, the lack of benchmarks and context-specific reference values remains a key barrier to informed decision-making. It is often unclear whether a building’s environmental performance is acceptable or whether significant improvement is possible. One study attempted to address this gap using parametric modelling and machine learning to simulate a wide range of material combinations for each building element [159]. A Random Forest regression model was trained to learn the relationship between design variables and GWP, enabling the definition of minimum and maximum impact ranges (benchmarks) for specific components.

Meanwhile, initiatives like the one by Röck et al. [172] have made valuable contributions by providing embodied carbon benchmarks and a dataset covering LCA results of different European buildings. Nonetheless, further efforts are needed to develop datasets that reflect regional construction practices, climate conditions, energy grids, and material supply chains. These improvements are essential to enhance the accuracy, comparability, and relevance of BIM-LCA results, and to ensure that environmental targets are realistic and regionally aligned.

5. Conclusion

This research examined the current state of decision-making in BIM-based LCA. A total of 115 research papers published between 2019 and 2024 were analysed through a systematic literature review (SLR). The analysis identified key challenges related to automation and decision-making in BIM-LCA, as well as corresponding future research needs, structured across four thematic areas: early design, LCI/LCIA automation, LCA for building renovation, and decision-support.

The results indicate notable advancements in the integration of BIM and LCA compared to previous literature reviews, particularly in data availability and uncertainty in early design, automation of LCI processes (e.g., BoQ export and import into LCA tools without the need for manual input), and the development of hierarchical databases that align LOD variations, range, and safety factors to enable continuous LCA throughout the design process.

However, manual data mapping between BIM and LCA remains a major limitation during the LCIA phase, despite ongoing efforts to improve interoperability and data structure through CCS and a naming convention between the LCA and BIM data.

Decision-making methods such as Multi-objective Optimization (MOO), Multi-criteria Decision Analysis (MCDA), and Sensitivity/Uncertainty analyses are rarely integrated into BIM-LCA tools, even though they have the potential to improve stakeholder decision-making, especially non-LCA experts—by supporting structured trade-off analysis between environmental, economic, and social indicators. Additionally, the integration of LCA with LCC, S-LCA, and circular economy indicators remains limited, and current BIM-LCA tools are not yet fully adapted to the requirements of renovation and retrofit projects.

Future research should focus on advancing automation, standardisation, and AI-supported decision-making within BIM-LCA workflows. First, ML algorithms could be trained on past projects to recognise typical material assumptions, assisting in material assignment and early-phase LCA calculations, while also minimising data ambiguity. ML techniques should also be applied to classify BIM objects and map them to expanding LCA databases using CCS, helping to automate currently manual processes. Establishing standards for LOD in screening, simplified, and complete LCA, and implementing dynamic data extraction aligned with Open BIM principles, would further support interoperability and workflow efficiency.

Moreover, combining continuous LCA with real-time data extraction, surrogate models, and AI-supported MOO and MCDA offers a promising foundation for iterative and informed decision-making. ML techniques such as reinforcement learning could be used to suggest design alternatives at the component or building scale, based on defined environmental or economic targets.

Parametric design combined with ML could simulate a wide range of material assemblies, supporting the benchmarking of material options and defining minimum and maximum LCA impact values for each building element. These approaches depend on the availability of large-scale, machine-readable datasets structured with LCA, LCC, and S-LCA results—resources that could also support budget-based target setting and ML-driven comparative analysis across building projects.

Further research is also needed to develop quantitative indicators for assessing Design for Disassembly (DfD) and Design for Adaptability (DfA), as well as their contributions to environmental, economic, and social impacts. Additionally, greater attention should be paid to dynamic LCA modelling, which better reflects real-world variations across the building life cycle.

The results of this study provide insights for researchers and practitioners, offering a systematic overview of the current challenges and advancements in BIM-LCA integration. This study is part of a broader research effort, the second part of which explores how AEC professionals adopt BIM-LCA integration, how they make informed decisions based on its outputs, and their specific needs and challenges—ultimately to guide future research and support the development of user-centred BIM-LCA tools.

Credit authorship contribution statement

Sara Parece: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Ricardo Resende:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Vasco Rato:** Writing – review & editing, Data curation, Supervision.

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

While preparing this work, the authors used Grammarly to correct the English grammar. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

CRediT authorship contribution statement

Sara Parece: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ricardo Resende:** Writing – review & editing, Validation, Supervision, Data curation. **Vasco Rato:** Writing – review & editing, Supervision, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Sara Parece reports financial support was provided by Foundation for Science and Technology. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.buildenv.2025.113248.

Data availability

The content analysis of the 115 articles is presented in Appendix B.

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