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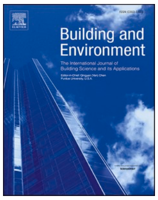

# Building sustainability through a novel exploration of dynamic LCA uncertainty: Overview and state of the art

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ABSTRACT

Life Cycle Assessment is necessary for evaluating the environmental impacts of buildings throughout their life cycle, considering factors such as energy consumption, emissions, and resource utilization. However, Dynamic Life Cycle Assessment introduces a temporal dimension, acknowledging that a building's environmental performance evolves due to technological advancements, occupancy behavior, and changing environmental conditions. This paper reviews DLCA, focusing on uncertainties arising from parameter, scenario, and model variability, and emphasizes the integration of technologies like Building Information Modeling, the Internet of Things, and machine learning to enhance real-time data collection and predictive analytics. An extensive review of 430 papers, refined to 180, reveals that 55 % of publications are in environmental sciences, with significant contributions from the United Kingdom (27.8 %), France (24.1 %), and China (18.1 %). Key findings include significant variations in embodied greenhouse gas emissions for materials like aluminum and the dynamic aspects of transportation impacts, which extend beyond traditional metrics to include operational efficiency over time. Uncertainties in all LCA stages (A1 to D) are addressed, focusing on service life, operational energy and water use, and transportation needs. Advanced methodologies, including a proposed framework for a hybrid LCA approach that integrates process-based and input-output methods, are suggested to enhance the comprehensiveness of assessments. The integration of real-time monitoring and predictive analytics further improves the adaptability and precision of LCA models, emphasizing the necessity of continuous updates and scenario analyses to capture future conditions accurately. This study paves the way for future research aimed at mitigating major sources of uncertainty, promoting more sustainable building practices, and advancing the field of dynamic LCA.

## 1. Introduction

In today's rapidly evolving world, the construction industry stands at a crossroads of innovation and sustainability [1]. Within this dynamic landscape, the practice of Life Cycle Assessment (LCA) has emerged as a key instrument for evaluating the environmental impact of buildings throughout their entire life cycle [2]. LCA, as a holistic methodology, is renowned for its ability to thoroughly analyze the environmental implications associated with material selection, construction processes, occupancy patterns, and eventual disposal or recycling [3]. It plays a pivotal role in shaping decisions aimed at creating sustainable and resource-efficient built environments.

Building Life Cycle Assessment, often referred to as Building LCA, is the vanguard of sustainability in the construction sector [4]. It offers a comprehensive lens through which it is possible to analyze the environmental performance of buildings. Considering a myriad of factors, including energy consumption, emissions, and resource utilization, Building LCA presents a comprehensive view of a building's environmental footprint [5]. It assesses the ecological consequences of a building from its inception, through its construction, occupancy, maintenance, and ultimately, its end-of-life. As a result, Building LCA has become an invaluable tool for architects, engineers, and policymakers, guiding the development of sustainable building practices.

Yet, amidst the achievements of traditional Building LCA, a critical dimension remains relatively unexplored, the temporal dimension [6]. Dynamic aspects within LCA consider how a building's environmental performance evolves over time [7]. This perspective acknowledges that the environmental impacts of a building are not static but fluctuate in

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response to a multitude of factors. For instance, as a building ages, its materials can degrade, leading to an increase in the U-value (thermal transmittance) of its envelope. This degradation means that the building will require more energy to maintain comfortable indoor temperatures, thereby increasing its energy consumption and associated environmental impacts. These factors include the advancement of technology, shifts in occupancy behavior, and changes in environmental conditions [8], commonly referred to as climate change, which results mainly from the anthropogenic emissions of greenhouse gases (GHGs). The recognition of this temporal dimension heralds the concept of dynamic LCA, where the evolution of a building's environmental profile is at the forefront of analysis.

Moreover, uncertainty in DLCA is a significant challenge due to the inherent variability and complexity in evaluating the environmental impacts of products throughout their life cycles. Various sources of uncertainty, including parameter uncertainty, scenario uncertainty, and model uncertainty, contribute to this complexity [9]. Parameter uncertainty arises from the variability in data inputs [10], scenario uncertainty stems from different possible future conditions [11], and model uncertainty results from the limitations of the models themselves [12]. Addressing these uncertainties is necessary for enhancing the reliability and credibility of DLCA outcomes.

Understanding and managing uncertainty in DLCA is critical for informed decision-making regarding the environmental sustainability of products. Effective uncertainty analysis helps in identifying the key parameters that significantly influence the assessment results, guiding efforts to prioritize data collection and model refinement. Studies like those by Chen et al. (2018) demonstrated the importance of representing and visualizing data uncertainty to support decision-making in LCA. By leveraging an array of publicly available data, they developed methods to quantify and propagate uncertainty, enhancing the reliability of LCA models [13]. Furthermore, a critical perspective by Lo Piano and Benini evaluated the approaches for uncertainty appraisal and sensitivity analysis in LCA, emphasizing the need for comprehensive methods to address both stochastic and epistemic uncertainties to support robust decision-making [14]. Additionally, Herrmann et al. discussed strategies to confront and manage uncertainty in LCA used for decision support, suggesting that incorporating quantitative uncertainty analysis into LCA can significantly enhance its reliability as a decision-support tool [15].

The integration of new technologies represents another frontier in the evolution of LCA. Innovations such as Building Information Modeling (BIM) [16,17], the Internet of Things (IoT) [18], machine learning (ML) [19,20], and digital twins (DT) [21] have revolutionized the way we design, construct, and operate buildings. These technologies empower real-time data collection, predictive analytics, and data-informed decision-making. They bridge the gap between static LCA and dynamic LCA by providing a continuous stream of data on a building's performance [22]. This connection between LCA and emerging technologies opens new vistas for environmental assessment and management throughout a building's life cycle.

Furthermore, the combination of LCA with ontological frameworks promises to elevate the field [23]. Ontologies offer structured and formalized knowledge representations, enabling seamless data integration from diverse sources and domains [24,25]. In the context of LCA, ontologies facilitate data interoperability, semantic querying, and the representation of intricate relationships between building components, processes, and environmental impacts [26]. They hold the potential to enhance the precision and coherence of LCA studies.

However, it is essential to acknowledge that the integration of dynamic aspects, new technologies, and ontological frameworks into Building LCA is not without its challenges. Uncertainty looms large in these domains, stemming from the dynamic nature of the systems involved, the complexity of real-world scenarios, and the inherent limitations of data and models [27]. Effectively understanding and managing uncertainty are paramount to ensuring the credibility and reliability of LCA results.

With these considerations in mind, this paper aims to address critical gaps in the field of Building LCA and introduces methodological approaches for improving its applicability and accuracy. Its objectives encompass.

- Investigate the uncertainties inherent in dynamic Life Cycle Assessment for buildings during the whole life cycle from extracting raw materials to recycling.
- Explore how technologies like BIM, IoT, ML, and DTs can enhance the accuracy and relevance of LCA in buildings.
- Examine how ontological frameworks can structure LCA data to facilitate knowledge sharing and stakeholder collaboration.

## 2. Review paper selection methodology

A meticulous and comprehensive methodology was employed in this review paper (Fig. 1), aimed at exploring the uncertainty of dynamic Life Cycle Assessment (DLCA) and the integration with the emerging technologies, and ontological frameworks within sustainable building practices. The approach involved an exhaustive search across three renowned academic databases: 1) Google Scholar, 2) Scopus, and 3) Web of Science, with the objective of collating and analyzing a broad spectrum of scholarly literature pertinent to these interrelated areas.

An extensive and iterative search strategy was devised, ensuring thorough coverage of the relevant literature. This included the formulation of search queries that effectively encompassed the core aspects of dynamic LCA. These queries were intricately composed, utilizing a blend of keywords, phrases, and Boolean operators. Each was specifically tailored to conform to the unique syntax and search functionalities of the different databases.

For example, a representative query in Scopus was structured as follows: ("Dynamic Life Cycle Assessment" OR "Dynamic LCA") AND ("Building" OR "Construction") AND ("Emerging Technologies" OR "BIM" OR "IoT" OR "Machine Learning" OR "Digital Twins") AND ("Ontological Framework" OR "Semantic Integration") AND ("Sustainability" OR "Environmental Assessment").

The criteria for inclusion ("OR") and exclusion ("AND") were precisely defined to ensure the relevance and quality of the literature. Consideration was limited to peer-reviewed journal articles, PhD thesis, master thesis, conference papers, and relevant book chapters published in English. Publications that did not directly relate to the focal topics, or their application in sustainable building practices were excluded.

A systematic screening process followed the initial search, involving an evaluation of the retrieved publications based on their: 1) titles, 2) abstracts, and 3) keywords. Duplicate records were methodically removed to guarantee the dataset's uniqueness. Initially, the dataset comprised 430 papers, including 100 from Scopus, 203 from Google Scholar, and 127 from Web of Science without any overlapping.

After an exhaustive refinement process focused on ensuring thematic relevance and methodological quality, the dataset was carefully narrowed down to 180 papers, representing a 58 % reduction from the initial collection. This selection was guided by strict inclusion criteria centered on each paper's contribution to the evolving field of dynamic life cycle assessment (LCA). Key themes for inclusion encompassed innovative methodologies for dynamic inventory analysis, the integration of temporal variability in impact assessment, and case studies that demonstrate the application of dynamic LCA in real-world scenarios. Each selected study was evaluated based on its citation impact, showcasing its influence within the dynamic LCA community, methodological rigor, particularly in handling time-dependent environmental impacts, and its direct relevance to advancing the understanding and application of dynamic LCA. This rigorous selection ensures the review comprehensively addresses the forefront of research and development in dynamic LCA, providing a solid foundation for future investigations into the temporal dimensions of environmental sustainability. These selected publications were systematically synthesized to identify key themes,

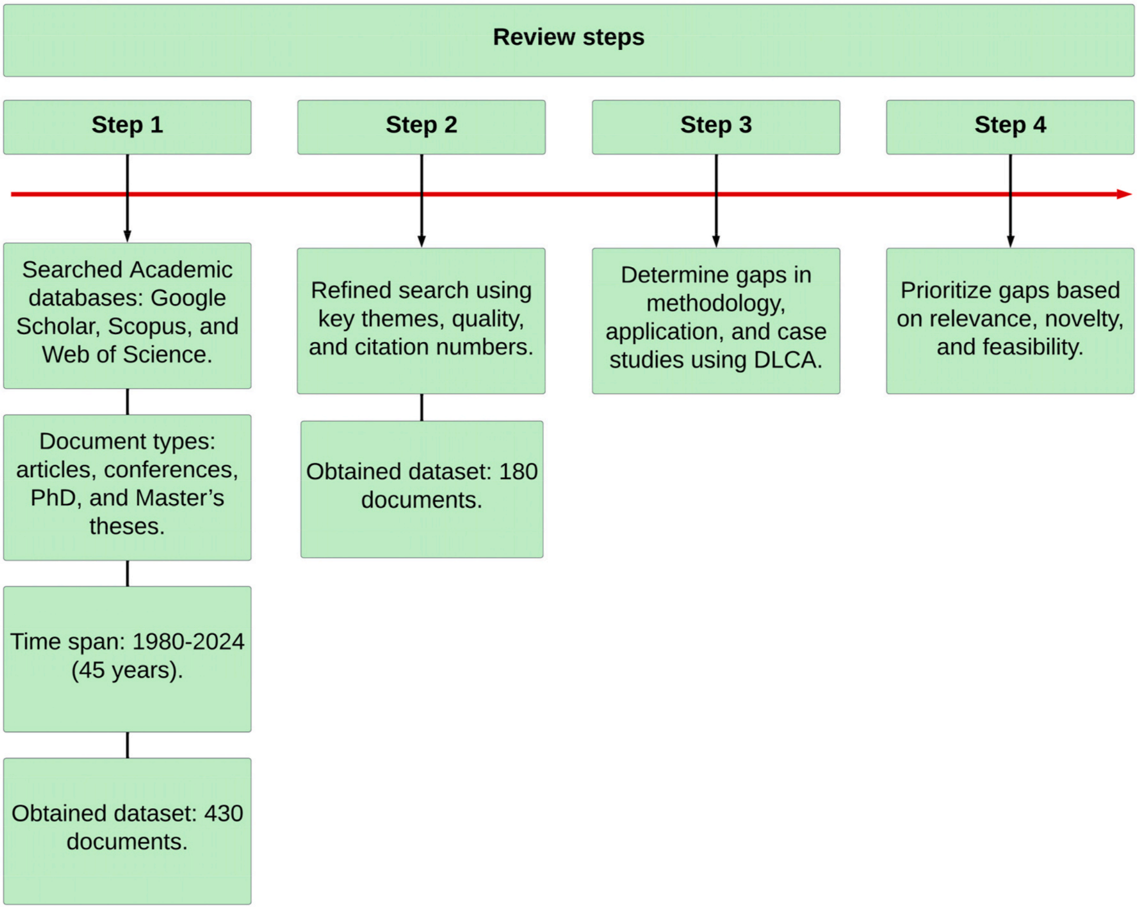

**Fig. 1.** Systematic literature review process.

trends, and insights in the field. This process involved categorizing the literature into relevant subtopics, highlighting significant findings, and identifying gaps or areas of ongoing research. Additionally, quality assessments were conducted to evaluate the rigor and credibility of the research, considering factors such as methodology and data sources. Citation analysis was integral to identifying seminal works and influential articles within the scope of the review.

To ensure the robustness and accuracy of our findings, particularly the figures developed from multiple sources in the results, the authors adhered to a systematic and careful methodological approach. The process began with the comprehensive collection of data from a variety of sources, including environmental product declarations (EPDs), databases, and literature. This diverse data pool enabled us to capture a wide range of values and uncertainties necessary for LCA. The developed work focused on ensuring that the functional units used for measurement were consistent across all data sources to facilitate direct and meaningful comparisons of material impacts.

Clear system boundaries that encompassed all relevant lifecycle stages were defined, including raw material extraction, transport, and manufacturing phases. By that, it was ensured a holistic analysis that considered the entire lifecycle of the materials studied. Additionally, to account for temporal variations in technology and practices, the data was normalized to a common timeline. This step involved aligning older data with more recent standards and practices, ensuring that the performed comparisons accurately reflected technological advancements rather than inconsistencies in data collection periods.

To quantify and represent the uncertainties inherent in LCA studies, statistical methods were employed. For each figure and analysis, error bars to illustrate the range of uncertainty derived from the diverse data sources were used. This statistical modeling allowed to capture the variability and provide a more nuanced understanding of the impacts.

## 3. Bibliographic analysis

In this section, the bibliographic analysis of the reviewed papers is shown in different dimensions based on the publication source, country, and topic.

The depicted publication trends in Fig. 2 reveal a significant increase in research activity within the LCA field from 1980 to 2021, peaking around 2021, likely driven by technological advancements and emerging trends. This peak indicates a culmination of efforts and heightened interest in the field. However, the subsequent decline in publication numbers post-2021 marks a notable departure from the previous growth trend. This downturn necessitates a thorough investigation into potential causes, with a particular focus on the impact of global events like the COVID-19 pandemic. The pandemic led to the closure of laboratories, restricted access to research facilities, and delays in ongoing projects due to lockdowns and social distancing measures. Funding priorities also shifted, with significant resources redirected towards immediate public health concerns and vaccine development, potentially diverting funds away from other research areas, including LCA.

Fig. 3 illustrates a steady growth in publications within the top 10 academic journals from 1980 to 2024, showcasing sustained scholarly dedication and inquiry in our domain. The criteria for ranking and selecting the top-10 journals were centered on publication volume, a quantitative measure reflecting the number of articles each journal published on the topic. This steady rise not only reflects a consistent academic commitment but also reveals the varied landscape of academic publishing. Some journals have been mainstays throughout this period,

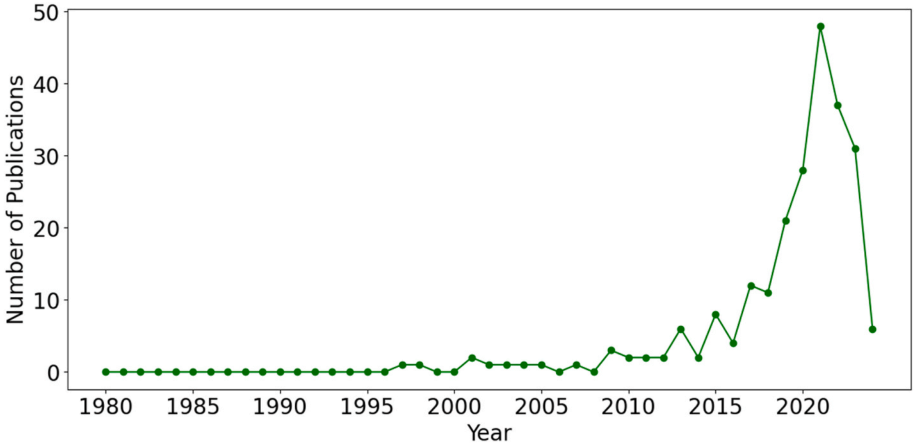

**Fig. 2.** Publication trend over time for from 1980 to 2024.

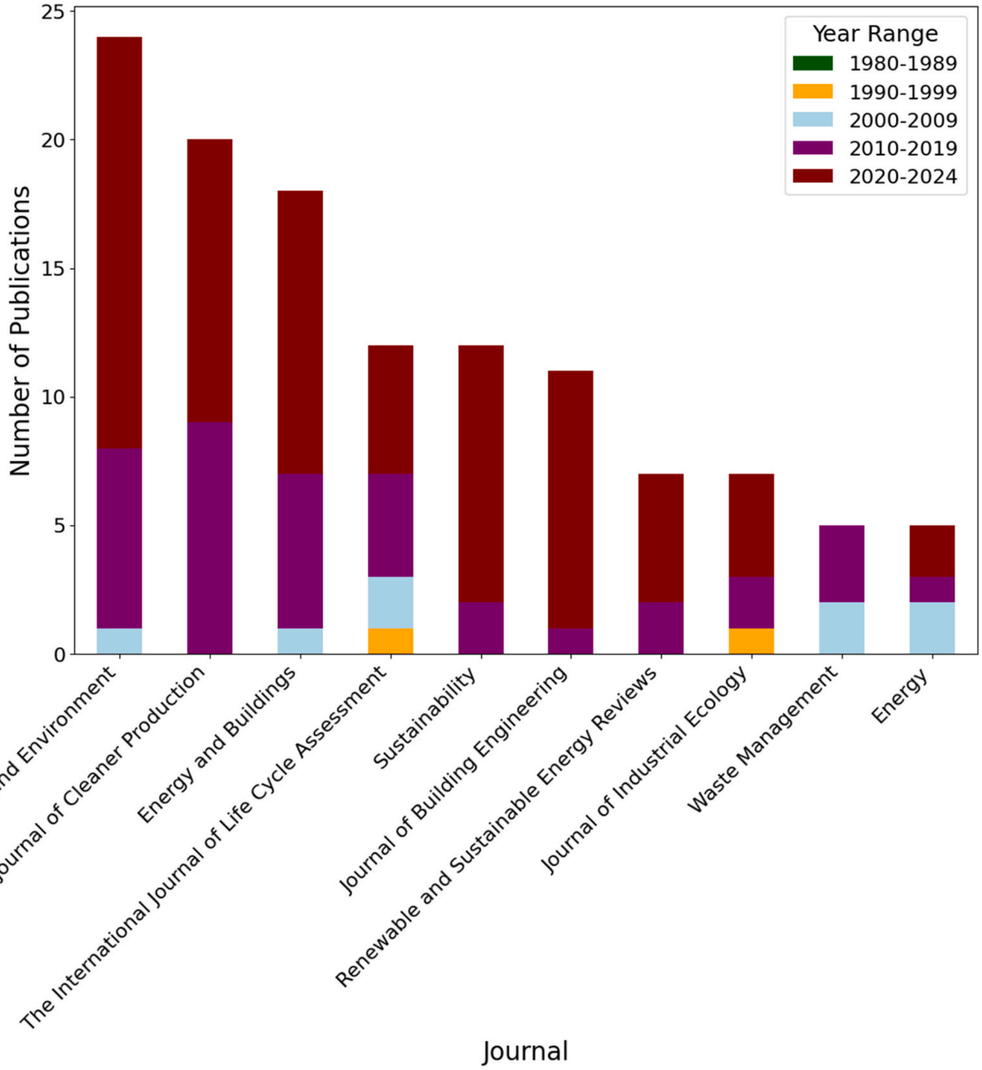

**Fig. 3.** Distribution of publications in top 10 academic journals by year range.

while others have seen their publication volumes vary, indicating shifts in research priorities or editorial directions. Notably, the Building and Environment journal stands out for its significant contribution, consistently ranking at the forefront in terms of publication volume. Close behind, the Journal of Cleaner Production is recognized for its crucial impact and relevance in academic conversation. Other journals, like Energy and Buildings, exhibit fluctuating publication counts, hinting at evolving research interests or changes in editorial focus over the years.

In addition, an analysis of the distribution of uncertainty-related publications across various subject areas, as depicted in Fig. 4, offers

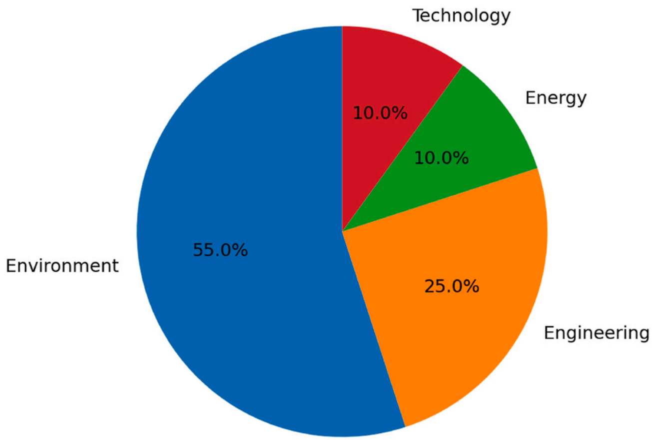

**Fig. 4.** Distribution of uncertainty-related publications by subject area.

insightful revelations about the academic dialogue on this critical research facet. During the period under review, several patterns have emerged, showcasing shifts in academic focus and output across different fields. The environmental sciences stand out significantly, consistently capturing the largest portion of publications, at 55 %. This persistent focus highlights the complex and important role of uncertainty within this domain. Moreover, fields like Engineering (25 %), Energy (10 %), and Technology (10 %) also see a high level of publication activity, reflecting a broad-based interest and scholarly commitment to exploring uncertainty in these areas.

To identify the uncertainty-related publications from previous dynamic DLCA studies, the approach shown in Fig. 1 and section 2 was adopted. The initial search results were subjected to a thorough screening process. Titles and abstracts were reviewed to filter out publications that did not explicitly address the incorporation of uncertainty in the context of DLCA. Following this preliminary screening, a detailed full-text review was conducted on the remaining papers to ensure their relevance and focus on uncertainty within DLCA methodologies and applications.

The subject area information for these identified publications was sourced from multiple reliable channels. Primarily, the metadata provided by the academic databases during the literature search was utilized. These databases categorize publications based on the journal's scope and the keywords specified by the authors. Additionally, the classification of the journals in which the selected publications were published were considered, as journals are typically associated with subject areas such as environmental science, engineering, energy, and technology. To further refine the categorization, the keywords and abstracts provided by the authors of the selected publications were reviewed. This involved analyzing the primary focus and context of each study, as indicated by the authors' keywords and abstract content. This approach enabled to visualize the distribution of uncertainty-related publications across various subject areas, as depicted in Fig. 4, and to draw meaningful insights about the academic dialogue on this critical research facet.

The distribution of the articles by country is illustrated in Fig. 5, where top countries were identified. The United Kingdom has the highest rank (27.8 %), followed by France (24.1 %) and China (18.1 %). Australia (8.3 %), and South Korea (6.0 %) are in the next places for having the highest publications in this area.

The top 10 topics by count within our dataset, highlighted in Fig. 6, form a crucial basis for the forthcoming analysis. These topics represent key areas of inquiry that have stood out in our research efforts, distinguished by their prevalence within the field. Their ranking, based on the frequency of their occurrence, offers a window into the dominant themes that permeate the literature, shedding light on the focal points of scholarly interest and investigation.

## 4. Dynamic LCA analysis- qualitative content examination

### 4.1. *Fundamental concepts and uncertainties in dynamic LCA*

### 4.1.1. *A dynamic LCA uncertainty in assessing embodied energy in building construction*

In the examination of uncertainties within the embodied energy assessment of building construction, particularly through a dynamic LCA lens, attention must be directed towards the phases of raw material extraction (A1), material transportation (A2), material manufacturing (A3), transportation to the site (A4), and construction (A5) (Fig. 7) [28–30]. The dynamic LCA approach, while providing a comprehensive view, introduces significant complexities in these stages, primarily due to the evolving nature of the construction processes and the external influences affecting them [31].

During the raw material extraction, processing, and manufacturing stages (A1-A3), the uncertainty primarily stems from variations in

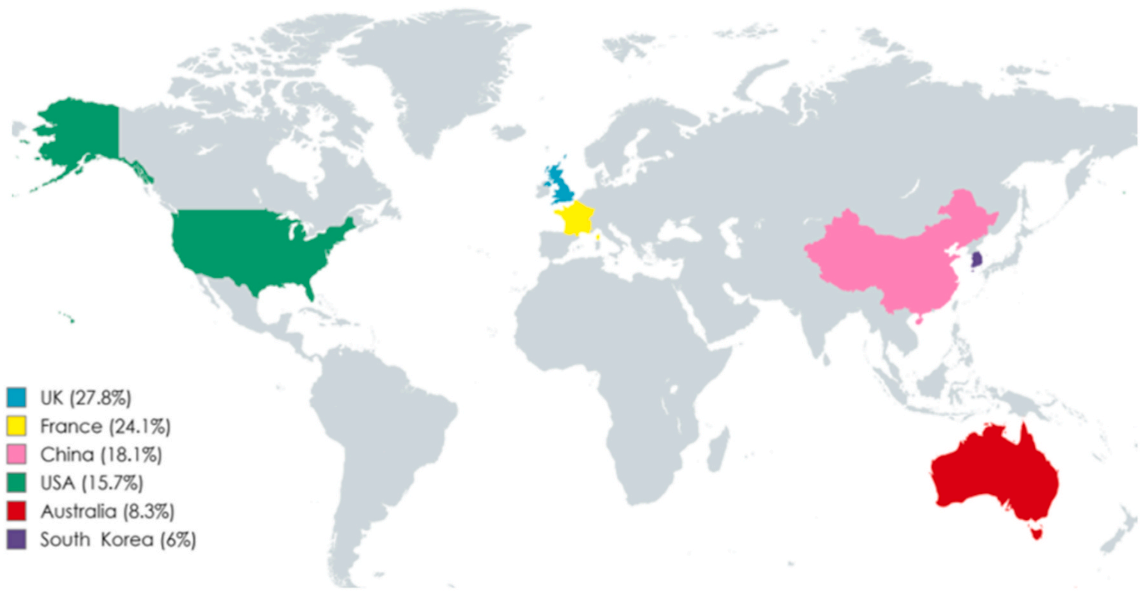

**Fig. 5.** Distribution of journal articles by country.

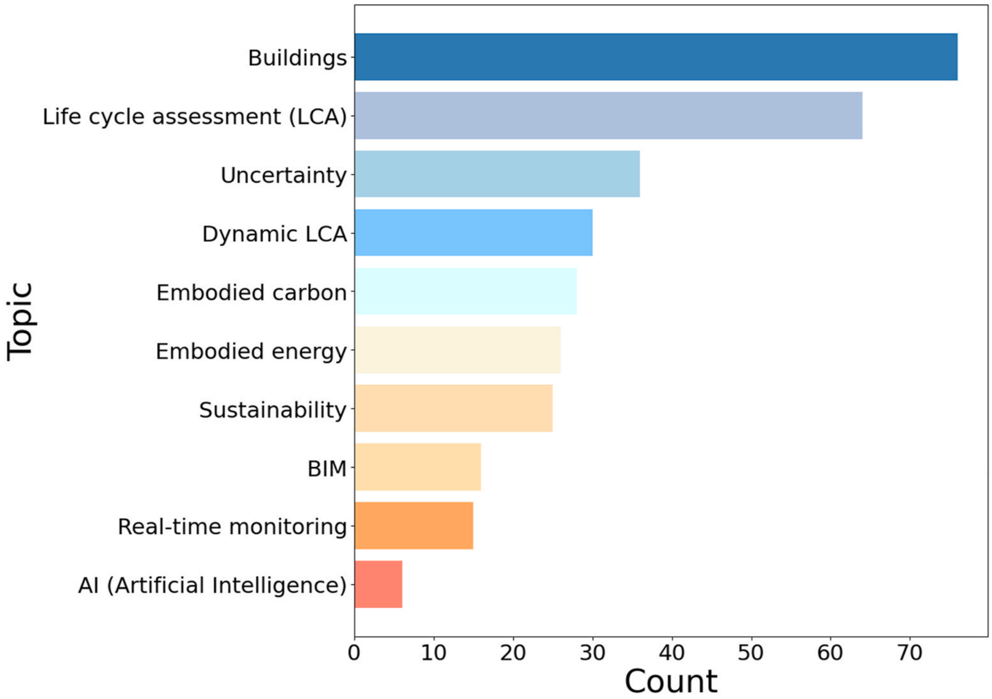

**Fig. 6.** the top 10 topics by count in our dataset.

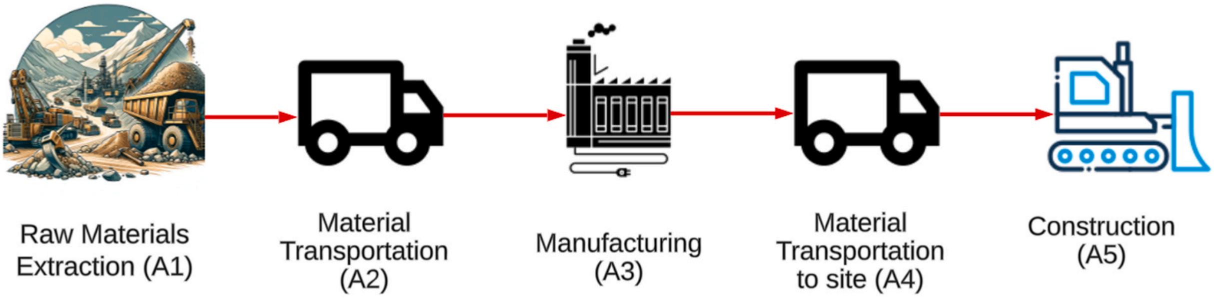

**Fig. 7.** illustrating the Life Cycle Assessment (LCA) categories A1 to A5.

energy sources and technological advancements [8,32]. As newer, more energy-efficient methods are introduced, the embodied energy associated with these phases can decrease, although predicting the rate and impact of these advancements involves a high degree of uncertainty [33]. Additionally, the extraction and processing methods vary greatly based on geographic location and regulatory environments, further complicating the assessment [34].

The transportation to the site (A4) adds another layer of complexity. The energy consumption in this phase is influenced by the distance materials travel, the modes of transportation used, and the efficiency of the vehicles including the aging of the vehicles [35]. These factors are subject to change over time, especially with the introduction of greener transportation technologies and optimization of logistics networks.

In addition, the on-site installation phase (A5) is impacted by the efficiency of construction practices, the skill level of labor, and the use of energy-efficient machinery [36]. The variability in these factors over time, influenced by advancements in construction techniques and training methods, introduces uncertainty in the assessment of embodied energy during this phase [37].

#### 4.1.2. *Assessing data quality, variability, and uncertainty in dynamic LCA*

This section aims to distinguish and assess the interplay of data quality, variability, and uncertainty concepts within the context of dynamic LCA, highlighting how they influence the reliability and robustness of the assessment results.

Data quality in dynamic LCA pertains to the accuracy, relevance, and timeliness of the data used in the analysis [38]. In a dynamic setting, where the environmental impacts of a building are evaluated over its life span, the quality of data plays a pivotal role. This includes up-to-date information on material properties, energy usage, and technological advancements [39]. High-quality data ensures that the LCA reflects current realities and provides a credible basis for decision-making [40].

Variability, on the other hand, relates to the natural and inherent changes in data over time and across different scenarios [41]. In dynamic LCA, this variability can arise from factors like fluctuating energy mix in material production, changes in occupancy patterns, and evolving construction practices [42,43]. Variability is not an indication of poor data quality but rather a characteristic of the real-world scenarios that LCA seeks to model [44,45]. Recognizing and quantifying this variability is crucial in dynamic LCA, as it affects the interpretation of results and the identification of environmental hotspots., for example, high-energy consumption during the manufacturing of building materials, emissions from transportation, or the generation of construction waste.

Uncertainty in dynamic LCA is linked to both the quality of data and its variability [46]. It encompasses the range of possible outcomes due to limitations in data, methodological choices, and inherent unpredictability in future scenarios [47,48]. For instance, forecasting the future energy efficiency of building materials involves uncertainty due to potential technological breakthroughs and policy shifts [49,50]. In addition, the future weather files that can be used in the BES modelling to determine the energy consumption through the considered lifespan of the LCA [51] also affected by the variability of all the inputs that the meteorological models – global and regional – take into account when obtaining the meteorological parameters, such as air temperature, within the wide range of time considered [52]. Differentiating uncertainty from variability is essential; while variability is a measure of the range of data points, uncertainty pertains to the confidence in the results given the known variability and data quality. Table 1 summarize the aspects that impact DLCA in the context of building construction.

#### 4.1.3. Multidimensional uncertainties in dynamic life cycle assessment

In DLCA, the exploration of uncertainty is crucial for ensuring the reliability and applicability of the findings. Various types of uncertainty studies are conducted to address the complexities and inherent unpredictabilities in assessing the environmental impacts of buildings over their lifecycle. These studies can be broadly categorized into four main types: 1) parametric uncertainty, 2) model uncertainty, 3) scenario uncertainty, and 4) temporal uncertainty.

*4.1.3.1. Parametric uncertainty.* Parametric uncertainty focuses on the uncertainties in input parameters such as material properties, energy consumption, and emission factors [46]. These uncertainties are addressed by varying the input values within a defined range, which is derived from available data or expert judgment [53]. This approach helps to identify the sensitivity of the LCA outcomes to changes in input parameters, thereby highlighting which parameters most significantly influence the results.

*4.1.3.2. Model uncertainty.* Forms another crucial part of the uncertainty analysis in dynamic LCA [15]. This type of study scrutinizes the uncertainties associated with the choice of models and methodologies in the LCA process. Different models might employ varied assumptions, system boundaries, and impact assessment methods, leading to incomparable outcomes [54–56]. Comparing the results derived from different models, researchers gain valuable insights into the influence of these methodological choices on the LCA outcomes. This comparison helps to understand the reliability of the results across different modelling approaches.

*4.1.3.3. Scenario uncertainty.* Scenario uncertainty studies are particularly pertinent, given their focus on future scenarios [57–59]. These studies involve exploring the uncertainties associated with potential future developments, such as technological advancements, policy changes, and shifts in user behavior. Analyzing various scenarios allows for an assessment of the robustness of LCA results under diverse future conditions. This enhances the relevance of the LCA in long-term planning by providing insights into how different future pathways might impact the environmental performance of buildings.

*4.1.3.4. Temporal uncertainty.* Temporal uncertainty, while distinct in its focus on the dimension of time, is equally significant in the context of DLCA [50,60,61]. Temporal uncertainty studies investigate how environmental impacts vary over the lifespan of a building due to factors such as aging, maintenance, and end-of-life scenarios. Similar to parametric, model, and scenario uncertainties, temporal uncertainty involves assessing the sensitivity of LCA outcomes to changes in time-related factors. This type of uncertainty analysis provides insights into the dynamic nature of environmental impacts and highlights the importance of considering the temporal evolution of buildings' environmental performance.

The assessment outlined in Table 2 underscores a critical consensus within the field of DLCA for buildings: uncertainties, particularly those inherent in early design stages, ISO standards application, and the prediction of future changes in technology and policy, profoundly affect LCA outcomes. These uncertainties challenge the accuracy and reliability of LCA results, emphasizing the need for robust methodologies, such as multi-Level of Development (LOD) analysis, taxonomy development, and dynamic LCA methodologies, to assess and mitigate their impacts. Key findings highlight the importance of addressing these uncertainties through systematic reviews, methodological innovations, and integration of sustainability dimensions in building information modeling (BIM), paving the way for more reliable and comprehensive environmental assessments of buildings throughout their lifecycle.

#### 4.1.4. Addressing uncertainty in dynamic LCA during early building design stages

In the exploration of DLCA, the early stage is critical as decisions made here can significantly influence the overall environmental impact of the building.

The inherent uncertainty in the early stages of building design primarily stems from incomplete information and the provisional nature of many design decisions [70]. At this stage, many aspects of the project, such as material choices, building techniques, and energy systems, are not fully determined [71]. This lack of detail introduces a high level of uncertainty into the LCA process. The dynamic nature of LCA, which considers the building's life cycle in its entirety, further amplifies this uncertainty due to the long-term projections and assumptions that must be made about future conditions and technologies [7,72,73].

While the uncertainty treatment methods discussed here can also apply to traditional LCA, their importance in DLCA is particularly pronounced due to the focus on long-term environmental impacts and changes over time. For instance, specifying key materials or energy systems early helps manage uncertainties in DLCA and improves the accuracy of long-term projections. One approach to managing this uncertainty is through specifying the most influential parameters while leaving less influential parameters less defined. This method allows for a focus on elements that have a greater impact on the environmental footprint, thereby reducing the overall uncertainty in the assessment [65,74,75].

**Table 1**
Impact of data quality, variability, and uncertainty on DLCA.

| Aspect | Impact on Dynamic LCA | Example in Building LCA | Cause | Characteristics |
|---|---|---|---|---|
| **Data Quality** | Ensures LCA reflects current realities, providing credible decision-making basis. | Up-to-date information on material properties and energy usage. | Methodological approaches, data collection techniques, and data source selection. | Reflects the present state of knowledge and information accuracy. |
| **Variability** | Affects interpretation of LCA results and identification of environmental hotspots. | Fluctuations in energy mix for material production, changes in occupancy patterns. | Natural progression of technology, policy, and market conditions. | Dynamic and often predictable within a certain range. |
| **Uncertainty** | Affects confidence in LCA results and informs decision-making under conditions of risk. | Forecasting future efficiency of building materials considering technological and policy shifts. | Inherent in predictive modeling, extrapolations, and assumptions in data. | Inherent in any analysis involving future scenarios or incomplete data. |

**Table 2**
Overview of selected literature on uncertainty factors in DLCA.

| Reference | uncertainty in inputs | Key Focus | Methodology | Main Findings |
|---|---|---|---|---|
| [62] | Uncertainty in building information during early design stages affecting Life Cycle Energy Assessment (LCEA) outcomes. | LCEA in early design stages | Uncertainty analysis, multi-Level of Development (LOD) | Method for assessing and reducing uncertainty impact on LCEA |
| [56] | Focuses on uncertainties related to application of ISO standards, spatiotemporal realities of construction, nature of the construction industry, and characteristics of infrastructure projects. | Infrastructure LCA uncertainty | Taxonomy development | Identification of key uncertainty drivers in infrastructure LCA |
| [42] | Discusses the variability in dynamic variables impacting DLCA, like changes in energy consumption, emissions over time, and technology advancements. | DLCA in buildings | Literature review | Overview of DLCA studies and identification of dynamic variables and assessment models |
| [63] | Uncertainty associated with changing electricity generation mixes and grid-building interactions over time. | DLCA of NZEB | Dynamic LCA methodology | Evaluation of electricity decarbonization on NZEB's life cycle impacts |
| [64] | Uncertainties related to the prediction of future changes in parameters like energy mix, technological improvements, and environmental policies. | Dynamic parameters in building stock modelling | Systematic review | Identification of dynamic parameters and prediction methods |
| [65] | Involves uncertainties in the service life estimates of building elements, influencing LCA & LCC outcomes. | Uncertainty in building elements' service lives | Stochastic framework, new service life database | Influence of service life uncertainty on LCA & LCC |
| [66] | Highlights discrepancies in previous LCA studies due to different methodologies, system boundaries, and input parameters. | Benchmarking in building LCA | Systematic review | Comparative analysis of LCA results in building case studies |
| [67] | Uncertainty in the analysis comes from the definition of product stage and service life parameters in the LCA of building elements. | Uncertainties in building LCA | Monte Carlo simulation | Analysis of product stage and service life uncertainties |
| [68] | Uncertainties stem from the varying methodologies and data sources used to assess embodied energy and carbon in building materials and types. | Embodied energy and carbon in buildings | Meta-analysis | Benchmark creation and guideline development for reducing environmental impact |
| [69] | Uncertainties related to integrating different dimensions of sustainability (environmental, economic, social) and the data requirements for this integration in BIM. | LCSA integration in BIM | Systematic literature review, methodological approach | Method for integrating LCSA into BIM during design stages |

Additionally, the use of a probabilistic approach helps identify the most influential factors contributing to total impacts [76]. Prioritizing data collection and specification efforts on these key areas, the assessment can yield more accurate results with less effort. This probabilistic approach is essential for DLCA's focus on changes in materials and technologies throughout a building's lifecycle. Studies have shown that a significant portion of a building's total environmental impact can be represented by a relatively small percentage of the total materials and processes involved, highlighting the effectiveness of this targeted approach [77–79].

However, one of the challenges in applying dynamic LCA at the early design stages is the absence of certain metrics, such as cost considerations, which can be fundamental in decision-making [80,81]. This gap points to the need for more integrated approaches that combine environmental impact assessment with economic analysis. These methods address DLCA's specific challenges, such as technological changes and evolving user behaviours, making DLCA more reliable and useful for long-term planning.

Fig. 8 reflects the interplay between materials with high contribution to the whole building LCA and those with high variability. For example, wood comes from various species of trees, each with different growth rates, densities, and mechanical properties [82]. These characteristics can change depending on the climate, soil quality, and forestry practices, which adds variability to the environmental impact assessments. Also, the processes of treating, curing, and manufacturing wood products can vary greatly, leading to differences in energy use and emissions. On the other hand, the production processes for materials like concrete and certain types of insulation are more standardized and less subject to change than those for wood. This standardization leads to more predictable and consistent environmental impact assessments. However, the concrete has high contribution to the emissions. While Steel has high uncertainty and contribute to the emissions significantly.

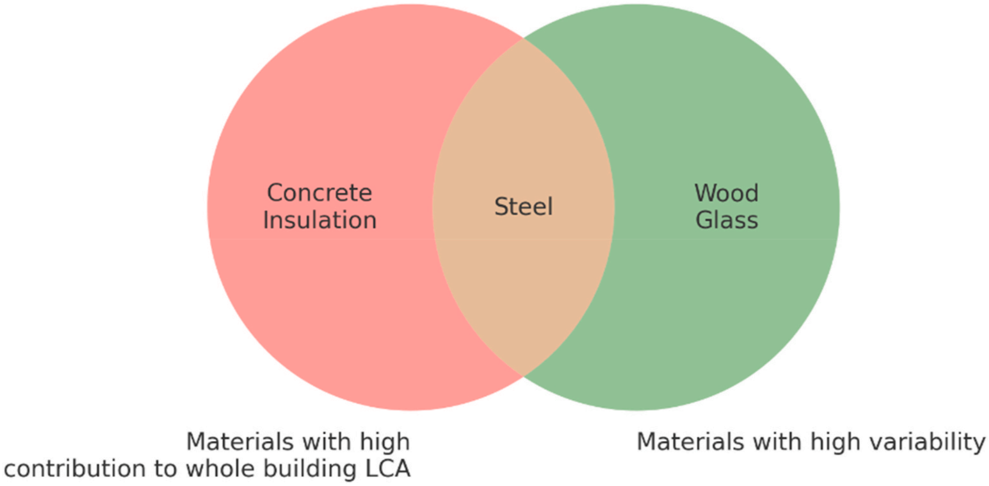

**Fig. 8.** Venn diagram that represents the material-related aspects that influence the accuracy of dynamic LCA results (this diagram is based on [8,83–85]).

### *4.2. Specific applications of dynamic LCA in building lifecycle*

#### *4.2.1. Dynamic LCA of building materials (A1-A3)*

The complexity of manufacturing processes for building materials introduces significant uncertainty in the LCA of buildings, particularly during the early material stages of A1 to A3. The type of technology used, such as various kilns for brick making, directly affects the energy consumption and emissions of the production process [86]. Even with the same equipment, efficiencies can differ based on operational factors, impacting the accuracy of LCA [87,88]. The energy sources powering these machines, ranging from solar to nuclear power, further contribute to the variability in emissions profiles, highlighting the multifaceted nature of uncertainty in these stages [89,90].

Embodied energy intensities, critical to LCA studies, are derived from diverse sources including environmental product declarations (EPDs) [91], databases [92], and literature [93], or directly from manufacturers [94]. Statistical distributions are employed to model this uncertainty, often assuming specific ranges around nominal values [8]. However, this approach can lead to underestimation, prompting the use of different statistical models to better characterize uncertainty [95]. Studies have identified significant variations in embodied greenhouse gas emissions for materials like aluminum, indicating that recycling content and dataset differences can notably impact LCA outcomes [96–98]. Additionally, advancements in manufacturing efficiency over time can lead to discrepancies between older and newer datasets, affecting total life cycle energy calculations and the comparative environmental ranking of materials [99].

To clarify that, significant variations in embodied GHG emissions for aluminum, particularly during the raw material extraction (A1), transport (A2), and manufacturing (A3) phases, can be attributed to a combination of factors. The type of energy sources used (renewable versus fossil fuels), the efficiency of production processes, geographic location of extraction and manufacturing, and differences in supply chain practices contribute to these discrepancies. For instance, aluminum production relying on renewable energy and advanced smelting technologies in regions with stringent environmental regulations will typically have lower embodied GHG emissions compared to those using fossil fuels and operating in areas with laxer standards.

Moreover, the uncertainty in LCA software arises when modeling materials not present in the Life Cycle Inventory (LCI) databases [100] or when approximating global values to local contexts [101]. Electricity usage, often averaged annually, introduces additional variability, particularly significant in assessing the energy-intensive phases of buildings [102]. Moreover, the selection of electricity mixes can drastically influence the LCA results, underscoring the need for consistent system boundary conditions [103,104].

The heterogeneity in simplification strategies and the inherent variability in impact categories due to the complexity of LCI flows further challenge the comparability and reliability of LCA studies [105,106]. The human factor also plays a role in the uncertainty of LCA outcomes, emphasizing the need for comprehensive and traceable methodologies in LCA databases and software tools [107]. Fig. 9 illustrates the embodied energy values for steel and aluminum, along with their associated uncertainties over time. The error bars indicate the range of uncertainty, highlighting how advancements in technology and changes in manufacturing processes can lead to reductions in embodied energy. Recognizing this change is vital to ensure that LCA dynamically reflects the current and evolving reality of building material production and its environmental impact.

Furthermore, to check the uncertainty in LCA software, many comparative studies have been investigated to assess and compare the environmental impact assessments generated by two LCA tools: One Click LCA [115] and SimaPro [116]. These studies aimed to evaluate the differences in results, particularly focusing on key impact categories such as Global Warming Potential (GWP), Ozone Depletion Potential (ODP), Acidification Potential (AP), and Eutrophication Potential (EP). This analysis aimed to provide valuable insights into the contrasting outcomes produced by these two-life cycle assessment software tools (Fig. 10). For example, the score of ’100′ in the GWP category for One Click LCA indicates its relative environmental impact, which is compared against SimaPro’s score of ’97′ in the same category. Fig. 10 shows that, in this particular study, One Click LCA predicts a slightly higher potential impact on global warming than SimaPro. The differences in values across the two tools (across all categories) highlight the variability and uncertainties inherent in LCA software tools.

The variations in results between SimaPro and One Click LCA, particularly in terms of GWP, ODP, AP, and EP, can be attributed to several key factors. One significant factor is the inclusion of the Refurbishment (B5) stage in One Click LCA, which is absent in SimaPro due to a lack of data. This stage involves energy-intensive activities during building refurbishment, contributing to higher impacts in GWP and AP categories in One Click LCA. Additionally, the release of volatile organic compounds (VOCs) during refurbishment significantly influences the ODP and AP results in One Click LCA, as these emissions are known to be

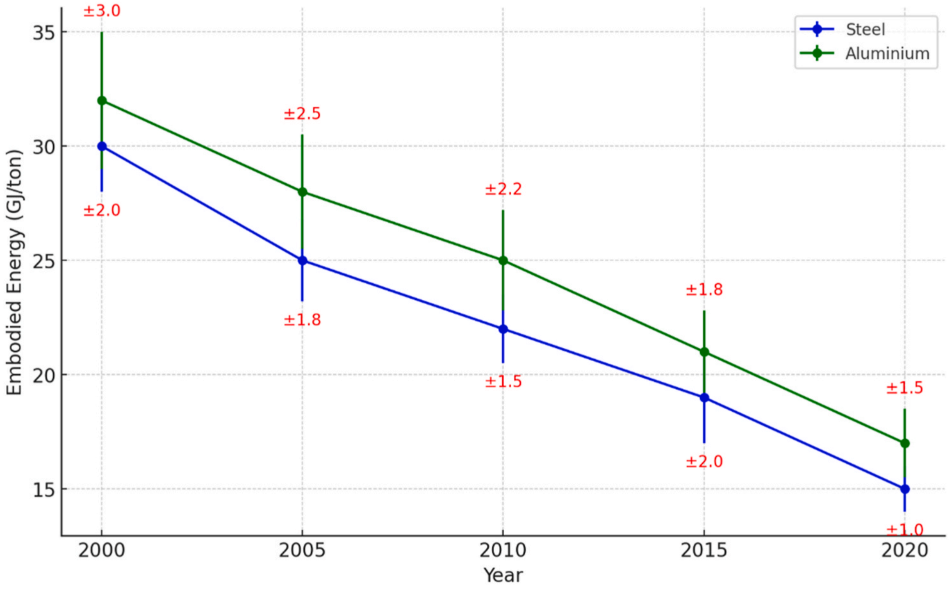

**Fig. 9.** *Comparative Analysis of Embodied Energy and Associated Uncertainty for Steel and Aluminum Over Time based on* [108–114].

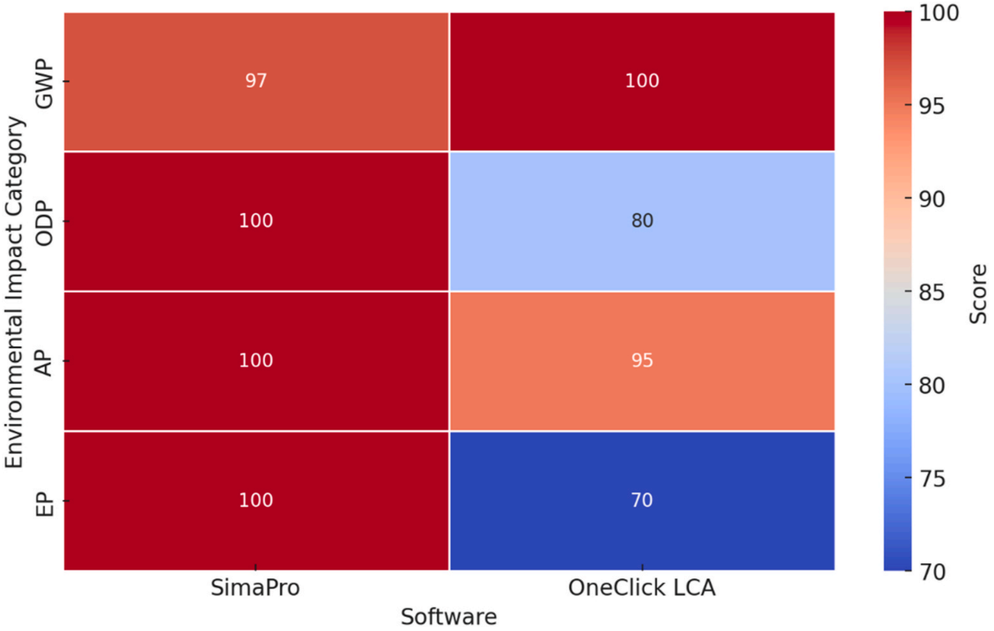

**Fig. 10.** Comparative Analysis of Environmental Impact Indicators Using SimaPro and One Click LCA Tools based on [119–121].

elevated in newly constructed or refurbished buildings. Differences in data inventories and geographic data quality also play a role, as they can lead to variations in characterization factors and reference materials used in the assessments. These multifaceted factors collectively account for the disparities observed in GWP, ODP, AP, and EP between the two LCA software tools.

In addition, the inherent variations in EP values between SimaPro and OneClick LCA confirms the uncertainty commonly encountered in life cycle assessment (LCA) outcomes. SimaPro's reliance on comprehensive databases like Ecoinvent [117] and its application of sensitive impact assessment methodologies such as the ReCiPe approach [118] can lead to higher EP values and reflect an intricate depiction of environmental impacts. This level of detail, while valuable, introduces complexity and variability that can amplify uncertainty in interpreting results. OneClick LCA's potentially different aggregation methods or databases could yield lower EP scores, which while being streamlined, might not capture the full scope of environmental impacts, thus adding another dimension of uncertainty. The discrepancy in results between these LCA tools highlights the importance of recognizing and critically evaluating the underlying assumptions, data quality, and methodological choices that contribute to the uncertainty in LCA studies. When comparing EP values from different software, researchers and practitioners must account for these uncertainties and consider them when making decisions based on LCA findings, ensuring that the inherent variabilities are communicated and factored into any conclusions or subsequent recommendations.

Moreover, in Fig. 11, more features are represented to illustrates the uncertainty in the LCA tools. User-friendliness, database size, BIM integration, cost-effectiveness, and customization are evaluated, with scores ranging from 5 to 10. These variations reflect the inherent uncertainties in the application and effectiveness of the tools. For instance, SimaPro's lower score in user-friendliness indicates less intuitive navigation, adding uncertainty to the ease of use for new users. Conversely, its higher score in database size where a more extensive repository of

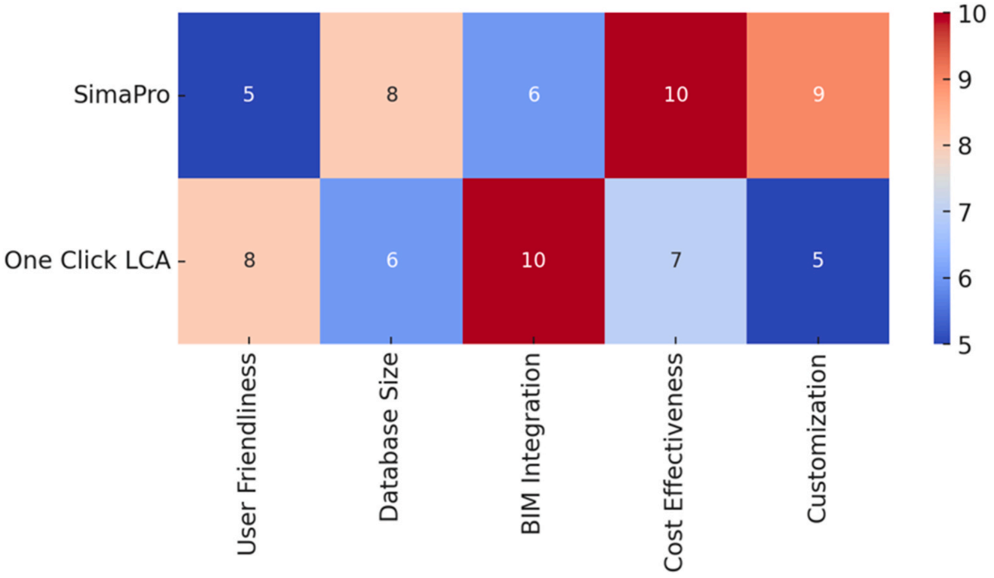

**Fig. 11.** Variation in scores between SimaPro and One Click LCA tools reflects inherent uncertainties in their application and effectiveness based on [122–125].

data, although this comes with the complexity of ensuring the reliability and relevance of the data used. OneClick LCA scores much higher in BIM integration, yet the difference in cost-effectiveness and customization could result from diverse methodologies and user.

#### 4.2.2. Dynamic LCA of building transportation and construction (A4-A5)

The intricacies of the transportation phase in dynamic LCA extend beyond the conventional tonne-kilometer metric, going into the nuanced operational life and efficiency of transport vehicles [126]. There is uncertainty associated with the deterioration of fuel efficiency over time. Over time, the fuel efficiency of trucks, pivotal in material transit, deteriorates, affecting fuel consumption estimates [127]. As trucks age, their energy demands for the same distance can escalate, rendering early-life data less reflective of long-term fuel usage [128]. This temporal degradation of vehicle efficiency is seldom captured in static LCA models, necessitating a dynamic approach that regularly updates these parameters to maintain the accuracy of the assessment [129].

Additionally, the transportation phase is subject to a wide array of indirect energy use, as evidenced by case studies in diverse geographic contexts like Australia and Sweden [130–132]. These studies illuminate that the ancillary energy consumption associated with freight transportation, encompassing vehicle manufacturing and maintenance, can constitute a substantial portion of the total energy profile. This introduces uncertainty as indirect energy use is often complex to quantify and incorporate accurately. This indirect energy use introduces another dimension of complexity, challenging the assumption that the production impacts of transportation means are trivial compared to operational impacts.

Furthermore, the environmental influence of transportation is contingent on the specific characteristics of the materials being moved. For instance, the transportation impact of concrete varies with the distance between the source of its constituents, like fly ash or recycled aggregates [133]. This variation highlights the uncertainty in assessing transportation impacts for different materials, especially those sourced from diverse locations or with significant import distances, transportation can have a pronounced effect on the total environmental impact [134]. These complexities underscore the need for a dynamic LCA approach that encompasses not only the direct emissions from transportation but also the broader systemic impacts, including the manufacturing of transport vehicles, the service life energy use, and the intricate web of the supply chain [135].

Incorporating these dynamic aspects into LCA requires a multifaceted strategy, using tools like scenario analysis and data from diverse sources to model the environmental impacts more comprehensively. This strategy must account for the variability and uncertainty in transport distances, the fluctuating nature of fuel efficiency over a vehicle's lifespan, and the changing emissions profiles due to evolving environmental regulations and energy sources. Through such an approach, dynamic LCA can provide a more accurate reflection of the environmental costs associated with the transportation and construction phases, capturing the complexity and temporal nature inherent in the life cycle of building materials.

In addition, the dynamic aspect of LCA in quantifying the material usage hinges on the variability and unpredictability of material wastage during construction [49]. Unlike a controlled factory setting, building sites are susceptible to a myriad of factors leading to material loss, such as weather conditions, storage issues, or mishandling [136]. This introduces uncertainty in material quantity estimation, as the traditional approach of relying solely on design drawings and constructor documents for material quantity estimation falls short in capturing the actual on-site usage and wastage [137]. Dynamic LCA models need to incorporate probabilistic approaches like triangular distributions to account for these variabilities [138]. However, studies suggest that uncertainties in material mass might not significantly impact the LCA outcomes compared to factors like service life and elementary impacts [139]. Thus, while important, the focus in dynamic LCA for material quantity should balance between precision and practicality, considering the varying influence of this uncertainty on overall results.

On-site construction activities, including refurbishment and mechanization levels, introduce another layer of complexity [97]. Rework, often due to design changes or construction errors, can lead to additional resource use and emissions [140]. The degree of mechanization affects energy efficiency and the speed of construction [141]. Models quantifying these impacts consider ecosystems, natural resources, and human health implications. The uncertainty introduced by varying levels of mechanization and rework needs to be integrated into dynamic LCA models, adapting to the changes and uncertainties in construction practices, and integrating predictive models that reflect current and future trends in construction methodologies.

The environmental impact of construction equipment, influenced by attributes like engine horsepower, model year, and load, is a crucial component in dynamic LCA [142]. The variability and uncertainty in fuel consumption and emissions due to these attributes necessitate detailed field studies and emission monitoring for accurate assessments. Dynamic LCA should also consider the life cycle of the equipment, including manufacturing and disposal phases, to provide a comprehensive view of its environmental impact. Case studies emphasizing the project, technology, and site-specific factors offer valuable insights into optimizing equipment use to minimize energy consumption and emissions.

One of the most significant uncertainties in dynamic LCA arises from the evolving nature of environmental regulations and technological advancements. As policies and technologies continue to develop, their impacts on fuel efficiency, emissions standards, and construction practices can vary widely, creating a moving target for LCA assessments. This regulatory and technological uncertainty requires dynamic LCA models to be adaptable and frequently updated to reflect current conditions accurately. Furthermore, the global nature of supply chains means that changes in one region's regulations or technological capabilities can have ripple effects worldwide, adding another layer of complexity and uncertainty to the LCA process.

#### 4.2.3. Dynamic LCA uncertainty of use stage (B1-B8)

*4.2.3.1. B1 to B5 stages.* A crucial factor here is understanding and accurately modeling the service life. Service life refers to the duration after installation during which a building or its components meet or exceed their performance requirements [143]. However, there is often a significant discrepancy between the designed service life and the actual usage period, influenced largely by user behavior [144]. This variance introduces considerable uncertainty in LCA, as the durability of materials, service conditions, maintenance, and user behavior during the use phase, as well as with factors like functional obsolescence and aesthetic changes, all play pivotal roles [145]. The usage patterns and installation quality also determine component longevity, where inappropriate use or improper installation can lead to a reduced lifespan [65,145]. In LCA, service life is typically modeled based on data from various sources or specific databases, usually following a normal distribution [146]. This aspect is vital as the value assigned to service life substantially affects LCA results, particularly in terms of building emissions. The modeling choices related to service life can lead to high variations in LCA outcomes, making it essential to approach service life estimation on a case-by-case basis. The uncertainty associated with service life accounts for up to 20 % of the overall GWP of a building, emphasizing the need for precise and dynamic modeling in environmental impact assessments [147].

In the context of dynamic LCA, the service life of various building types and components takes on additional complexity. For instance, post-tensioned concrete buildings are more influenced by the lifetime of building products than mass timber buildings due to the greater volume of temporary formwork involved [32]. The replacement and maintenance stages of a building's life cycle are also critical, often significantly impacting the total GHG emissions. Factors like the frequency and intensity of maintenance, environmental indicators used, and the nature of replacements (whether frequent or major) all contribute to this impact and introduce uncertainty [148]. Moreover, the assumptions about a building's service life alter the relative importance of different life cycle stages, with methods like geometric service life modeling [149], Markov deterioration curves [150], and statistical analysis [151] used to predict service life. The chosen Reference Study Period (RSP) for LCA, which analyzes the time-dependent characteristics of a building, also influences the results and introduces another layer of uncertainty [152]. Extending the RSP can shift the relative importance of life cycle phases and potentially reduce the life cycle energy for buildings, though factors such as early demolition due to policy changes or natural calamities can affect this [153].

*4.2.3.2. B6 (operational energy use) stage.* This phase encompasses the energy consumed during the operational life of the building, including heating, cooling, lighting, and the running of appliances and systems [154]. In a dynamic LCA context, this operational energy use is not just a static measure but a fluctuating one, influenced by numerous factors that evolve over time [155]. These factors include changes in building occupancy patterns, technological advancements in energy-efficient devices, shifts in energy sources, and climate change impacts, all of which introduce significant uncertainty in heating and cooling demands [156–159]. The dynamic nature of operational energy use necessitates a sophisticated modeling approach that can adapt to these changing conditions over the building's lifespan, integrating real-time data and predictive algorithms to forecast future energy needs and impacts accurately [160–163].

Furthermore, the interplay between operational energy use and other life cycle stages, particularly maintenance and replacement cycles, is crucial in a dynamic LCA. For example, the replacement of inefficient systems with more energy-efficient ones, or the replacement of deteriorated or inefficient insulation layers with new ones, can lead to significant fluctuations in operational energy use over time, adding another layer of uncertainty [164–166]. Additionally, regulatory changes, such as stricter energy efficiency standards, and shifts in user behavior, like increased consciousness about energy consumption, contribute to the uncertainty in determining the operational energy footprint of a building [167].

This dynamic and integrative approach in assessing operational energy use in LCA allows for a more accurate and holistic understanding of a building's environmental impact, reflecting both current conditions and future scenarios. It ensures that sustainability assessments and decision-making processes are based on comprehensive and evolving data, crucial for developing strategies aimed at reducing the environmental footprint of buildings throughout their entire life cycle.

Table 3 synthesizes key findings and dynamic aspects considered in different papers, providing a comprehensive perspective on the influence of operational energy use in building life cycles. The studies explore various dynamic elements such as the impact of climate change, energy mix variations, and operational uncertainties, contributing novel insights into the field of sustainable building design and assessment.

*4.2.3.3. B7 (operational water use) stage.* Operational water use, classified as B7 in LCA taxonomy, is a critical component in the dynamic LCA of buildings [180]. This phase addresses the consumption of water during the operational lifespan of a building, encompassing activities like sanitation, heating, cooling, and irrigation. In a dynamic LCA, operational water use is recognized as a variable and evolving aspect, subject to a multitude of influencing factors that change over time. These include demographic shifts affecting occupancy and usage patterns [181], advancements in water-saving technologies [182], changes

**Table 3**
Overview of recent dynamic life cycle assessment (LCA) studies on operational energy use in buildings.

| Reference | Key Findings | Dynamic Aspect(s) Considered | Uncertainty |
|---|---|---|---|
| [168] | Major contributor to life cycle energy (LCE) and life cycle carbon emissions (LCCE) during B6 stage | Influence of operational life stage on LCE and LCCE | Not explicitly mentioned |
| [169] | Dynamic LCA of energy renovation shows different decisions than static approach due to varying operational energy use and energy mix | Influence of changing operational energy use and energy mix | Uncertainty in future operational energy use and energy mix variations |
| [63] | Dynamic LCA captures the effect of lowering emission factors for electricity generation in NZEB | Effect of electricity decarbonization on LCA of buildings | Uncertainty in future emission factors for electricity generation |
| [170] | Long term changes in electricity mix influence the life cycle environmental impact of buildings | Influence of long-term changes in electricity mix on operational energy use | Uncertainty in long-term electricity mix changes |
| [171] | Focuses on the regulations for energy performance during operational stage in buildings | Operational energy use in building life cycle | Uncertainty in future regulatory changes |
| [62] | Addresses the uncertainty in building information influencing LCEA in early design stages | Uncertainty in operational energy use assessments | High uncertainty in initial building information and its impact on operational energy use |
| [172] | Analysis of the energy consumption stages in Chinese buildings | Energy consumption in building operation stage | Uncertainty in predicting energy consumption patterns |
| [42] | Overview of current scenario of DLCA studies in the building field | Dynamic variables in building life cycle assessments | General uncertainty in dynamic variables |
| [173] | Development of a dynamic life-cycle modeling framework for cross-laminated timber | Dynamic impacts in life cycle assessments of sustainable materials | Uncertainty in the long-term performance of sustainable materials |
| [174] | Analysis of dynamic LCI studies, particularly in Industry 4.0 applications | Dynamic components in life cycle inventory, especially electricity consumption | Uncertainty in electricity consumption patterns and technological advancements |
| [175] | Comprehensive life cycle perspective assessment of building energy | Building energy analysis from a life cycle perspective | Uncertainty in comprehensive life cycle energy assessments |
| [176] | Multi-objective optimization algorithm combined with BIM and LCA for embodied and operational energy | Trade-off between embodied and operational energy in building life cycle | Uncertainty in optimization outcomes and trade-offs |
| [177] | LCA performed through BIM software for operational energy use in buildings | Carbon footprint and operational stage carbon emissions in building life cycle | Uncertainty in BIM data accuracy and its impact on carbon footprint calculations |
| [178] | Life Cycle Assessment of EPS-based products | Impact of operational energy | Uncertainty in the performance and |

(continued on next page)

**Table 3** (*continued*)

| Reference | Key Findings | Dynamic Aspect(s) Considered | Uncertainty |
|---|---|---|---|
| | including operational energy use stage | use in life cycle of EPS-based products | energy use of EPS-based products |
| [179] | Comparative LCA between buildings with green walls and facades and a reference building | Impact of operational stage on environmental impacts in buildings with VGS | Uncertainty in the long-term performance of green walls and facades |

in local water availability and climate conditions [183], and evolving regulations and standards related to water conservation [184], all of which introduce significant uncertainty.

The dynamic nature of operational water use demands an adaptive and forward-looking modeling approach within the LCA framework. This approach should ideally incorporate real-time water usage data [185], and projections about future water scarcity. Predictive modeling is essential here, allowing for the anticipation of future trends in water use and the assessment of potential impacts on overall water resources. Such modeling must account for anticipated advancements in water-efficient appliances, changes in landscaping practices for water conservation, and the implementation of rainwater harvesting and greywater recycling systems, all of which add layers of uncertainty [186]. Moreover, the interrelation between operational water uses and other life cycle stages, such as the sourcing and treatment of water and the disposal of wastewater, is critical in dynamic LCA. For instance, the adoption of water-efficient fixtures can lead to changes in operational water use over a building's lifetime, adding another dimension of uncertainty [187]. This dynamic and comprehensive approach to assessing operational water use in LCA enables a more accurate and complete understanding of a building's environmental impact.

In general, the sources of uncertainty in operational water use is the unpredictability of future water availability and regulatory changes. Factors such as climate change can drastically alter local water supplies, while new regulations may enforce stricter water usage limits. Additionally, technological advancements in water conservation methods and changing user behaviors towards water usage can lead to unforeseen fluctuations in water demand. These dynamic and interrelated factors must be incorporated into LCA models to provide a realistic and adaptable assessment of water use impacts over a building's operational life, highlighting the necessity of continuous data integration and model updates to reflect current and future conditions accurately.

*4.2.3.4. B8 (operational transportation) stage.* This category focuses on the transportation requirements associated with a building's use, including the commuting of occupants, transportation of materials for maintenance and repairs, and other transportation-related activities necessary for the building's operation [188]. In a dynamic LCA, operational transportation is not a static factor but one that evolves over the building's life, influenced by a variety of changing conditions and trends, introducing significant uncertainty.

Key factors that influence operational transportation include urban planning and building location, which dictate commuting distances and available transportation modes [189]. As urban landscapes evolve, so do the transportation needs and patterns associated with a building. Additionally, changes in transportation infrastructure and the advent of more sustainable transportation options, such as electric vehicles and improved public transit, contribute to the uncertainty in transportation needs [190]. Dynamic LCA for operational transportation must also account for advancements in technology, such as the increased use of telecommuting [191] and virtual meetings [192], which can reduce the need for physical transportation.

Furthermore, dynamic LCA for operational transportation considers how changes in societal behavior and policy can impact transportation needs. For instance, shifts towards more eco-friendly commuting habits, like cycling or carpooling, and the implementation of policies that encourage such behaviors, directly affect the transportation-related environmental impact of a building, introducing variability and uncertainty [193]. The introduction of low-emission zones and incentives for using electric vehicles are examples of policy changes that can significantly alter the transportation footprint of a building over time [194].

#### 4.2.4. *Dynamic LCA uncertainty of end-of-life stage (C1-C4)*

In the analysis of the dynamic LCA for the End of Life (EoL) stages (C1-C4) of buildings, significant uncertainty was found, predominantly influenced by the variability in deconstruction processes [195], material recovery rates [196], and advancements in technology. While LCA is typically performed during the initial stages of building construction, assumptions about the EoL phase are often based on potential future technological advancements or changes in government policies related to recycling, which introduce a high degree of uncertainty [197,198]. These assumptions can greatly impact the LCA outcomes, with studies indicating that eco-efficient EoL management can reduce lifecycle impacts up to 17 % [199]. Key factors affecting LCA results include whether the EoL stage is considered, the choice between waste processing methods like recycling or incineration [200], modeling of disposal processes as consequential or attributional [201], and the technology assumed for stages C1-C4, ranging from today's average to low-impact technologies [202].

#### 4.2.5. *Dynamic LCA uncertainty of beyond End of Life stage (D)*

The analysis of the dynamic LCA for the Disposal Stage (D) of building materials reveals a significant degree of uncertainty, primarily stemming from the evolving nature of waste management practices and technologies [203]. This stage, which typically involves processes like landfilling, incineration, and recycling, is subject to a wide range of variables that affect the overall environmental impact assessment [204]. A critical factor contributing to this uncertainty is the variability in the efficiency and environmental performance of waste disposal methods. For example, the difference in greenhouse gas emissions between landfilling and incineration is substantial [205], and these emissions are further influenced by the energy recovery potential and the efficiency of the waste-to-energy technologies employed [206]. Furthermore, the dynamic LCA model highlights the uncertainty arising from future advancements in waste management technologies, which are difficult to predict and incorporate accurately into current LCA models. This unpredictability complicates efforts to determine the long-term environmental footprint of disposed materials.

In addition to technological factors, regulatory and policy changes significantly impact the LCA of the Disposal Stage [207]. Shifts in government policies regarding waste management, particularly concerning recycling and landfill regulations, introduce another layer of uncertainty. For instance, changes in recycling rates, driven by policy alterations or market dynamics, can lead to substantial variations in the environmental assessments of disposal methods. Moreover, the global trade of recyclable materials plays a crucial role in determining the actual environmental impact, as the movement of waste across borders affects both the environmental costs of transportation and the efficiency of recycling processes [208]. This highlights the need for a dynamic and adaptive approach in LCA modeling for the Disposal Stage, one that can accommodate future technological advancements and policy shifts to ensure a more accurate and comprehensive environmental impact assessment.

### 4.3. *Advanced methodologies and integration*

#### 4.3.1. *Impact assessment methods uncertainty*

The lack of harmony on a standardized method for DLCA introduces significant uncertainty, further complicated by the influence of regional and temporal factors [209]. Various impact assessment methods, including Eco-Indicator, and IMPACT, differ in their characterization models, normalization, and weighting processes [210]. An LCA practitioner must carefully consider the choice of impact assessment method and its suitability in each context. This is highlighted in the literature differentiating between site-generic, and site-specific characterization factors [211]. The deviation from actual impact patterns can be significant when generic characteristics are modeled instead of using site-specific data.

Furthermore, the spatial dimension of LCA emphasizes the importance of prioritizing inventory regionalization and spatialization efforts [212]. Sensitivity analyses comparing various impact assessment methods reveal substantial variations in results, particularly in impact categories other than GWP, thus highlighting the urgent need for consistency and quality-assured life cycle data to minimize uncertainty [213]. Furthermore, temporal uncertainty arises from the dynamic nature of environmental impacts over time. Integrating temporal dimensions into DLCA, such as time-dependent emissions and resource use, introduces complexities in accurately predicting future impacts. For instance, Bahramian et al. emphasize that simulations used in DLCA to account for temporal variations can lead to significant uncertainty in dynamic systems [214].

In addition, different methods yield varying results due to differing assumptions, scopes, and characterization factors. Hu et al. highlight that employing various methods to reduce uncertainty regarding upstream environmental impacts can lead to different environmental outcomes, emphasizing the importance of methodological consistency [215]. Alongside this, data uncertainty involves inaccuracies and variability in the data used for DLCA, including measurement errors, data gaps, and representativeness. High-quality, comprehensive data are essential for reliable DLCA outcomes. Banerjee et al. discussed how integrating patient-reported outcomes and wearable data can elucidate uncertainties in health-related DLCA studies, demonstrating the broader implications of data uncertainty [216].

These methods often yield different characterization factors and impact units for the same categories, introducing significant uncertainties into DLCA studies. A systematic evaluation using data from the US LCI and Ecoinvent databases found that discrepancies in total impact results are primarily caused by differences in total emission values included in the inventory, coverage of substances in the methods, and characterization factor values assigned to these substances [100]. While the global warming category showed relatively consistent results across different LCIA methods, other categories exhibited substantial variability, with maximum impact values for most categories found to be 10,000 times higher than the minimum values [100]. This vast range is attributed to differences in total emission values, coverage of substances, and characterization factors, underscoring the importance of considering multiple LCIA methods in DLCA studies to capture the full range of potential impacts and communicate these uncertainties clearly to decision-makers.

The study by Cherubini et al. investigates uncertainties in LCA arising from methodological choices, focusing on allocation approaches and LCIA methods [200]. This study compares several allocation methods, including economic allocation, mass allocation, and the substitution method, showing significant variability in impact categories such as climate change, acidification, eutrophication, and freshwater ecotoxicity. The choice of allocation method can greatly influence LCA outcomes, highlighting the necessity of conducting sensitivity analyses to understand the extent of these uncertainties [217].

Additionally, there are uncertainties arising from the selection of different LCIA methods, analyzing ReCiPe 2008, CML-IA, EDIP 2003, ILCD 2011, and TRACI 2.1 [200,218]. While results for climate change were relatively consistent across methods, other categories such as acidification, eutrophication, and freshwater ecotoxicity showed significant sensitivity to the chosen LCIA method. For example, freshwater ecotoxicity exhibited considerable variability, with EDIP 2003 showing results up to 24 % higher than ReCiPe [218]. This variability is due to differences in the number of substances each method considers, inclusion of fate modeling, and characterization factors used.

Scenario uncertainty is also linked to assumptions and choices made during the construction of LCA scenarios, and model uncertainty originates from the mathematical structures and relationships within the models. Both attributional LCA (ALCA) and consequential LCA (CLCA) have specific sources of uncertainty [219,220]. For instance, ALCA faces uncertainties related to allocation methods for multi-functionality problems, while CLCA is challenged by uncertainties from market-mediated substitution scenarios.

Addressing these uncertainties requires robust methodologies and consistent practices. Unfortunately, less than 20 % of LCA studies published between 2014 and 2018 included any form of uncertainty analysis [219]. Among those that did, parameter uncertainty was most frequently reported, despite the importance of scenario and model uncertainties. Common methods for propagating uncertainty, such as Monte Carlo simulations, were predominantly used, although they mainly address parameter uncertainty [221,222]. There is a significant need for standardized methods that account for all types of uncertainty, particularly those unique to ALCA and CLCA. Improved reporting and analysis practices are recommended to enhance the credibility and utility of LCA as a decision-support tool.

### 4.3.2. Development of a new hybrid LCA methodology

The evolution of LCA methodologies has been marked by a continuous effort to enhance accuracy, reliability, and applicability in diverse contexts [223]. In this pursuit, the development of a new hybrid LCA methodology emerges as a significant advancement, addressing the limitations of traditional LCA approaches. This hybrid methodology synergizes the strengths of both 'process-based LCA' [224] and 'input-output LCA' methods [225], aiming to provide a more comprehensive and nuanced understanding of environmental impacts.

The new hybrid approach is designed to overcome specific challenges inherent in the existing methodologies. Process-based LCA, while detailed and specific, often suffers from truncation errors due to its inability to account for the entire supply chain [226]. Conversely, input-output LCA, which covers the entire economy, lacks the specificity and detail necessary to accurately assess individual products or processes [227]. The hybrid LCA methodology bridges this gap by integrating the broad economic scope of input-output analysis with the detailed process-specific information. This integration enables a more holistic assessment, capturing both the direct and indirect environmental impacts of a product or service throughout its life cycle.

In Fig. 12, a novel approach to LCA through the hybrid LCA method is proposed. This method has been specifically designed to address the limitations inherent in traditional LCA methodologies, such as Input-Output LCA and Process-based LCA. The hybrid LCA method integrates the strengths of both approaches, offering a more detailed and comprehensive assessment of environmental impacts. The hybrid LCA method ensures that the data underpinning the LCA is accurate and comprehensive, by focusing on robust data collection practices, providing a more reliable assessment of environmental impacts.

In addition to robust data collection, the integration of dynamic data is a central aspect of this hybrid LCA method. Dynamic data incorporation includes real-time environmental data, production rates, transportation routes, weather conditions, building deterioration, and occupancy levels. Continuous updates to the LCA model with real-world changes allow for a better reflection of the dynamic nature of environmental impacts, significantly improving the accuracy of the assessments. The hybrid LCA method also distinguishes between attributional and consequential LCA within the context of handling uncertainty. Attributional LCA focuses on specific environmental burdens associated with a product, whereas consequential LCA considers broader system-wide impacts of changes in production or consumption patterns. This distinction provides a more understanding of environmental impacts and better management of uncertainties.

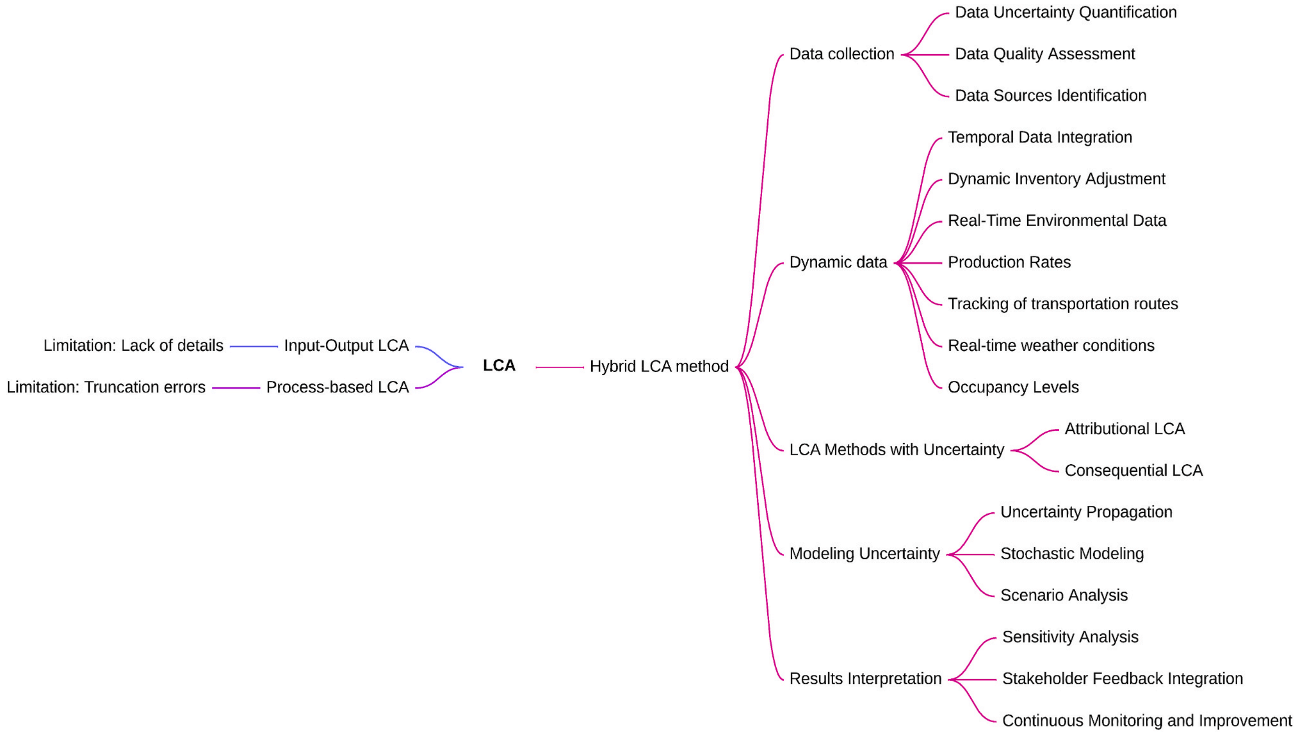

**Fig. 12.** Hybrid LCA methodology framework.

Modeling uncertainty is another critical aspect of the developed hybrid LCA method, ensuring that the assessments are robust and reliable. This involves using various advanced techniques to quantify and manage the inherent uncertainties in environmental impact assessments. Uncertainty propagation involves tracing how uncertainties in input data and model parameters influence the final LCA results, providing a comprehensive understanding of the reliability of the outcomes. Stochastic modeling introduces randomness into the model parameters, allowing for the simulation of a wide range of possible scenarios and providing a probabilistic understanding of potential environmental impacts. Scenario analysis explores different hypothetical situations and their impacts, enabling the assessment of how changes in key variables or assumptions might affect the results. Sensitivity analysis identifies which variables have the most significant influence on the LCA outcomes, helping to prioritize data collection efforts and improve the overall accuracy of the assessment. Together, these techniques form a robust framework for managing uncertainties in the hybrid LCA method, enhancing the credibility and utility of the environmental impact assessments.

Consider the construction of a new office building as an example to illustrate how the hybrid LCA method can be used, starting from data collection to the final results. For the office building project, comprehensive data collection can begin with gathering detailed information about the materials used. This can include types and quantities of concrete, steel, glass, insulation, and other construction materials. Energy data can focus on energy consumed during construction activities and projected energy use during the building's operational phase, such as heating, cooling, lighting, and other electrical systems. Transportation data can involve recording the distances materials are transported from suppliers to the construction site and the modes of transport used, such as trucks, trains, or ships. Additionally, data on construction processes, including the types of machinery and equipment used, construction techniques, and timelines, can be gathered. Operational data can also be essential, encompassing projected energy use, maintenance schedules, and occupancy patterns over the building's lifecycle.

With the initial data collected, the hybrid LCA method can integrate dynamic data to ensure the model reflects real-world conditions. Real-time environmental data can be incorporated, which can include current local weather conditions that affect the building's energy consumption for heating and cooling. Production rates can be dynamically adjusted based on actual construction progress and any changes in material usage. Real-time tracking of transportation routes can be implemented to account for any deviations from planned routes, capturing actual distances travelled and transport-related emissions. Occupancy levels can be updated based on actual usage patterns of the building, providing a realistic picture of energy consumption and resource use during the operational phase.

The hybrid LCA method can also incorporate techniques to manage and model uncertainty. For instance, uncertainty propagation can be used to understand how variations in input data, such as differences in material quality or fluctuating energy prices, affect the final environmental impact results. Stochastic modelling can introduce variability into key parameters to simulate a range of possible scenarios, providing a probabilistic assessment of potential environmental impacts. Scenario analysis can explore different hypothetical situations, such as changes in occupancy rates or energy efficiency improvements, to evaluate their effects on the building's environmental performance. Sensitivity analysis can identify which variables have the most significant impact on the results, guiding efforts to improve data accuracy and focus on critical areas.

Finally, the results of the hybrid LCA can be interpreted with the involvement of stakeholders, including architects, builders, and building owners. This interpretation can include a detailed analysis of the building's environmental impacts across its lifecycle, from construction to demolition. The assessment can highlight key areas where environmental performance can be improved, such as optimizing material choices, enhancing energy efficiency, or reducing transportation emissions. Continuous monitoring and feedback loops can ensure that the LCA remains up-to-date and relevant, with ongoing improvements made based on new data and evolving best practices. In summary, using the hybrid LCA method for the office building project can provide a comprehensive, dynamic, and accurate assessment of its environmental impacts.

#### 4.3.3. Incorporation of real-time monitoring and predictive analytics

The integration of real-time monitoring and predictive analytics into environmental assessment methodologies marks a significant evolution in the field of sustainability and LCA [228]. This incorporation is a response to the growing need for more dynamic, accurate, and proactive approaches in understanding and mitigating environmental impacts.

Real-time monitoring technology enables the continuous tracking of environmental parameters and resource utilization throughout a product's lifecycle [229]. By collecting data directly from processes and products in use, real-time monitoring provides a granular, up-to-date picture of environmental impacts. This level of detail is particularly beneficial in identifying hotspots of resource use or emissions, allowing for timely interventions. Moreover, real-time data collection helps in validating and enhancing the accuracy of LCA models, which traditionally rely on historical or estimated data [230]. This shift towards real-time data not only increases the reliability of environmental assessments but also enables more responsive and effective sustainability strategies.

Predictive analytics, on the other hand, brings machine learning and statistical modeling to forecast future environmental impacts based on current and historical data [231,232]. Integrating predictive analytics into LCA, practitioners can anticipate the future implications of present-day decisions, allowing for more informed strategic planning [233,234]. This predictive capability is crucial for assessing the long-term sustainability of products and processes, especially in industries characterized by rapid innovation and changing market dynamics. Predictive analytics can also play a pivotal role in scenario analysis, helping stakeholders explore various pathways and their environmental consequences, thereby guiding more sustainable design and policy decisions [235].

The synergy of real-time monitoring and predictive analytics in LCA methodologies represents a paradigm shift from reactive to proactive environmental management. It enables a dynamic approach to sustainability, where decisions are not only based on past and present data but are also informed by future projections. This integration is particularly relevant in the context of climate change and resource depletion, where understanding and mitigating long-term impacts are paramount. Table 4 shows the relevant literature in this case.

**Table 4**
Integration of real-time data in life cycle assessment (LCA) of buildings.

| Reference | Key Focus | Application of Real-Time Data |
|---|---|---|
| [236] | Framework for real-time environmental footprint in buildings | Semantic-based framework leveraging real-time data for dynamic LCA |
| [237] | Data-driven life-cycle optimization in building retrofitting | Integration of big-data for comprehensive assessment and optimization |
| [238] | Real-time monitoring using IoT and BIM | IoT for real-time data collection and integration with BIM |
| [239] | Information flow management in FM using BIM and cloud platform | Real-time communication and data access for FM operations |
| [240] | BIM-based decision-making tool for building construction solutions | Real-time decision support data integration in early design stages |
| [241] | Reality-based input data for LCA | Measured data usage for more accurate LCA results |
| [242] | Comparison of simulation model with monitored data | Real-time data for sustainable energy supply systems evaluation |
| [243] | IoT-integrated system for embodied carbon assessment | Automated real-time data collection for embodied carbon estimations |
| [244] | Integration of BIM with dynamic LCA | Use of BIM for data collection support in dynamic LCA |

#### 4.3.4. Application of BIM, ontologies and machine learning for LCA

The application of Building Information Modeling (BIM), machine learning, and ontologies in Life Cycle Assessment (LCA) heralds a new era of precision and efficiency in environmental impact analysis. Each of these technological advancements contributes uniquely to the refinement and accuracy of LCA, enabling more informed decision-making in sustainable construction and design.

Traditionally, project information was collected from two-dimensional (2D) drawings and on-site monitoring, with data manually entered into LCA software [244]. This conventional method is time-consuming and prone to errors and labor-intensive, which hinders the practical application of LCA in the building industry. The development of BIM has catalyzed a shift in this process, prompting numerous studies to explore the integration of BIM and LCA. BIM software can directly provide project data, eliminating the need for manual data re-entry and enhancing the efficiency and accuracy of data acquisition for LCA [245].

Using BIM, LCA practitioners can access a wealth of information about materials, construction processes, and building operations, which allows for more accurate and detailed environmental impact assessments. For example, Jalaei et al. integrated BIM with a decision-making approach to select optimal materials at the conceptual design stage [246]. Other studies have combined BIM with optimization techniques to find the best solutions for building components [247]. Some researchers have used BIM design tools and LCA technology to develop templates for assessing the embodied environmental impacts, such as Lee et al. who created a green template for this purpose [248]. These applications demonstrate that the synergy between BIM and LCA can effectively guide sustainable design decisions early in the project lifecycle. Also, Curry et al. utilized BIM to store cloud-based building data and manage the operational energy of office buildings [249], while Yang and Wang linked BIM to LCA to assess the operational energy consumption of residential buildings [250]. These studies highlight the capability of BIM to support comprehensive operational analysis and enhance energy efficiency throughout the building's lifecycle.

Some researchers have employed BIM-based models to estimate maintenance activities and demolition waste, but few have combined these models with LCA to quantify the related environmental impacts [251,252]. This gap indicates a need for further research to fully leverage BIM-LCA integration for maintenance and demolition phases, ensuring a holistic approach to building lifecycle management.

Based on the literature, three major conclusions can be drawn. First, BIM simplifies data acquisition for LCA studies and provides effective feedback tools, with numerous applications demonstrating the potential of BIM-LCA integration. Second, the adoption of DLCA is necessary and requires a greater amount of multidisciplinary knowledge compared to traditional LCA. BIM's ability to superimpose multidisciplinary information within a single model enhances the synergy between BIM and DLCA, creating opportunities to incorporate various sustainability measures. Third, while BIM supports LCA studies at different phases of the building lifecycle, most studies have focused on the design and operation phases. There is a scarcity of research on comprehensive, cradle-to-grave BIM-based assessment models that provide quantification and management across the entire building lifecycle. Addressing these gaps will enhance the application of BIM-LCA integration, promoting sustainable building practices from inception to demolition.

Fig. 13 represents a flowchart illustrating the stages of a process related to the integration of BIM with DLCA. The process starts with defining the goal and scope, which establishes the objectives, boundaries, time steps, and impact categories of LCA. This foundational stage ensures that the assessment is well-structured and focused, guiding the entire study to address specific environmental impacts and sustainability goals.

The next stage involves providing the BIM module, where comprehensive data can be extracted from 4D BIM models. This data encompasses types and amounts of components and materials, construction

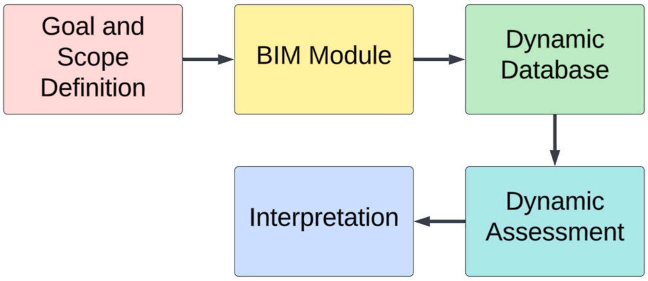

**Fig. 13.** BIM-DLCA integration (based on [244]).

schedules, building geometry, material properties, and component lifespans. This process creates a robust dataset that feeds into a dynamic database. In this database, software tools like Glodon Bill of Quantity and Green Building Studio process the BIM data [244].

With the dynamic database in place, the next stage involves dynamic assessment, where temporal elementary flows are collected, and inventory analysis, characterization, weighting, and normalization processes are conducted. This comprehensive assessment evaluates environmental impacts in real-time, providing detailed insights into the building's sustainability performance. The final phase, interpretation, involves analyzing these results to offer design guidance, compare schemes, suggest improvements, and support real-time decision-making.

Ontologies, which are structured frameworks for organizing information, play a crucial role in harmonizing data from diverse sources, including BIM and machine learning outputs [253]. Ontologies enable the integration of disparate data types into a cohesive LCA model by establishing a common language and set of concepts [254]. This integration is essential for ensuring that the LCA considers all relevant environmental impacts and interactions. Ontologies also facilitate the sharing and comparison of LCA results, contributing to a more standardized and transparent approach to environmental impact assessment [255]. Table 5 summarizes various studies that explore the integration of ontology and LCA.

Moreover, Machine learning (ML) has significantly impacted the field of DLCA by enhancing the accuracy and efficiency of environmental impact evaluations. ML algorithms are particularly useful in estimating environmental impact characterization factors and conducting sensitivity analyses, allowing for the development of surrogate LCAs that predict future products' full life cycle environmental impacts based on design-phase characteristics [264]. This integration of ML in DLCA facilitates data cleaning for life cycle inventories, improves the quality and quantity of data used for determining impact characterization factors, and generates inventory data for scenario analyses. Moreover, ML's ability to process large datasets rapidly and accurately makes it an invaluable tool for predicting system outputs and optimizing processes within the DLCA framework [265].

**Table 5**
Key studies on the Integration of ontology and LCA.

| Reference | Summary |
|---|---|
| [256] | Explores how the reuse of ontologies affects their life cycle, identifying dependencies and integration needs. |
| [257] | Uses ontology modelling to integrate exposure and life cycle inventory data for improved chemical exposure assessments. |
| [258] | Develops an ontology-based method for social life cycle assessment to facilitate data sharing and reuse in product development. |
| [259] | Proposes using Semantic Web technologies to create catalogues for LCA data, facilitating data integration and interpretation. |
| [260] | Introduces Temporalis, a method for dynamic LCA incorporating temporal information into inventory and impact assessment phases. |
| [261] | Introduces the HCOME methodology for the dynamic development and evaluation of ontologies, emphasizing user involvement throughout the lifecycle. |
| [262] | Evaluates the OIS ontology life cycle, focusing on testing and validation to ensure consistency and gather feedback for improvement. |
| [263] | Proposes novel methods for evaluating dynamic ontologies, focusing on syntactic correctness, semantic structure preservation, and pragmatic utility. |

Several studies have demonstrated the potential of ML in various DLCA applications. For example, the Temporalis method employs ML techniques to introduce temporal information into both the inventory and impact assessment phases of LCA, providing more accurate and dynamic assessments of environmental impacts [260]. Additionally, ML models such as long short-term memory (LSTM) networks have been used to predict the remaining useful life (RUL) of machines, which is essential for maintaining operational efficiency and reducing environmental impact [266]. The use of ML in DLCA is not limited to these applications; it also extends to estimating missing unit process data, optimizing resource use, and enhancing decision-making processes in environmental management [267]. The integration of ML in DLCA represents a significant advancement in the ability to assess and mitigate environmental impacts effectively.

This integration can significantly reduce uncertainty in environmental impact evaluations. ML algorithms can process and analyze vast amounts of data, identifying patterns and relationships that may not be apparent through conventional methods. ML improves the accuracy of environmental impact characterizations and predictions by enhancing data quality and quantity. For instance, ML techniques can fill gaps in life cycle inventories by estimating missing data points with high precision [266,267]. This ability to continuously update and refine models based on real-time data further reduces uncertainty, leading to more robust and reliable DLCA outcomes.

To give an example on how that can be used, let us say we have a commercial office building, and we want to implement DLCA and reduce the uncertainty. The process can start with creating a comprehensive BIM model that includes all relevant information about the building's materials, dimensions, construction processes, and operational systems. This BIM model serves as a centralized repository, capturing the building's details from inception through operation.

To integrate DLCA aspects into the BIM, specific LCA-related data can be embed such as the environmental impact of materials, energy consumption, and emissions data for different construction and operational stages. This data can be linked directly to the corresponding elements within the BIM model, providing a detailed mapping of the building's environmental footprint. For instance, the BIM model can include attributes for each material used, detailing its embodied energy and carbon footprint, as well as the expected lifecycle impacts based on usage patterns.

Real-time sensor data can further enhance the BIM model. Sensors may install throughout the building monitor variables like energy usage, temperature, humidity, and occupancy. This sensor data can fed back into the BIM in real-time, creating a dynamic model that reflects the building's actual performance. The BIM model can then provide a continuously updated view of the building's environmental impacts, which is critical for accurate DLCA.

ML algorithms then come into play, utilizing both the static BIM data and the dynamic sensor data. Supervised learning models trained on historical LCA data can predict the building's future energy consumption, waste generation, and emissions. Reinforcement learning can optimize construction schedules and operational practices to minimize environmental impacts by providing many scenarios. For example, the ML models can identify patterns in energy use and suggest modifications to reduce consumption or shift it to times when renewable energy sources are more available. This can be followed by sensitive analysis to check the results and interpret them in correct way.

Ontologies play a crucial role in generalizing this framework for implementation across multiple buildings. They provide a structured framework that harmonizes data from diverse sources, including BIM and ML outputs. Ontologies establish a common language and set of concepts that link specific building components in the BIM model to LCA categories and impacts. This ensures consistency and interoperability, making it possible to apply the framework across different projects and building types. For instance, an ontology can standardize how different insulation materials are classified and evaluated for thermal performance and embodied carbon, enabling uniform assessments across multiple buildings.

Closing the loop involves using the insights gained from the DLCA to inform decision-making processes. The dynamic feedback from the sensor data and ML predictions can be used to make real-time adjustments to the building's operation. For example, if sensors detect higher-than-expected energy consumption, the BIM model, informed by ML algorithms, can suggest adjustments to HVAC settings or lighting schedules. These recommendations can then be implemented to optimize the building's performance continuously.

## 5. Discussion and conclusion

This study intertwines the dynamic aspects of LCA in sustainable building practices with a structured exploration of uncertainties in building LCA, a crucial aspect often overlooked in traditional assessments. The integration of advanced technologies such as Building Information Modeling (BIM) and the Internet of Things (IoT) is crucial for enhancing LCA's responsiveness to environmental sustainability in construction.

Simultaneously, this detailed review identifies uncertainties into all building phases, and LCA methods. The study reveals that uncertainties can be notably reduced in the early design stage by refining input specifications. It also highlights the significant role of embodied energy intensity of materials, especially those recycled, in achieving accurate LCA results. Variations in material mass and transportation, along with the major replacement intensity during the replacement phase, emerge as key uncertainty factors.

Interestingly, the review indicates that changing the building's reference study period and the age of data can considerably affect life cycle energy outcomes. This points to the need for LCA practitioners to focus on relevant uncertain parameters, enhancing the reliability of results. Comparative LCA studies underline the influence of different databases and the importance of methodological choices on final outcomes.

This paper paves the way for future research aimed at developing methods to understand and mitigate major sources of uncertainty. Such an approach can significantly enhance the precision of LCA results, contributing to more sustainable building practices. The study also suggests exploring more comprehensive LCA techniques, like Input-output or hybrid LCA, to overcome limitations of process LCA.

Future review papers in this field could benefit from an expanded scope that includes emerging technologies and methodologies in sustainable construction. This could involve a deeper exploration of the integration and impact of innovative technologies such as advanced analytics, artificial intelligence, and augmented reality in LCA. Additionally, future reviews could focus on the evolving policies and regulations surrounding sustainable building practices and how they influence LCA methodologies. Another valuable area could be the comparative analysis of different LCA methodologies across various geographical regions and their adaptation to local environmental and socio-economic contexts.

## CRediT authorship contribution statement

**Haidar Hosamo:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guilherme B.A. Coelho:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Elsa Buvik:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing. **Sarra Drissi:** Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing. **Dimitrios Kraniotis:** Conceptualization, Funding acquisition, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing.

## Declaration of competing interest

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

## Data availability

The authors do not have permission to share data.

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