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CRITICAL REVIEW

Artificial intelligence meets LCA: a critical analysis from technical, ethical, and organizational perspectives

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Abstract

Purpose Artificial intelligence (AI) holds strong potential to automate repetitive and data-intensive life cycle assessment (LCA) tasks, thereby reducing costs, enabling scalability, and improving data access. This study critically analyzes the integration of AI into LCA from technical, ethical, and organizational perspectives. It aims to evaluate how AI can be implemented across LCA workflow steps to enhance efficiency without compromising effectiveness, inclusivity, and core LCA ethical values such as transparency and scientific integrity.

Methods We conducted a literature review to identify and characterize the technical approaches of current AI-LCA applications across academic research and commercial tools, complemented by a survey assessing current AI uptake in LCA practice and perceived ethical risks. Ethical risks, like accountability or fairness, were derived from existing AI ethical principles and analyzed for their potential conflict with LCA ethical values. Organizational implications including changes in work practices and regional disparities were explored, with attention to the role of AI in social LCA. Identified applications were critically assessed against four categories: technical maturity, potential to enhance LCA practices, operational feasibility, and ethical risks, and used to qualitatively derive criticality of ethical risks.

Results and discussion Most AI-LCA applications focus on predicting impact scores and estimating missing inventory data. Few are employing generative AI, while it is mainly used by practitioners for auxiliary tasks like compiling a literature review and report writing. Despite high automation potential, most publicly documented applications remain at proof-of-concept stage, and face operational barriers for inclusivity (coding skills, restricted access) resulting in low adoption. Most critical ethical risks relate to fairness, transparency, accountability and sustainability, driven by black-box models, poor documentation, and representation bias, threatening all core LCA values. Emerging commercial AI-LCA tools present a high potential to widen AI adoption in LCA, but present higher risks toward sustainability, transparency, safety and security. AI is expected to shift LCA stakeholders' roles from manual tasks to supervising algorithms and validating outputs, while potentially reinforcing regional disparities due to unequal access to AI tools, data, and expertise.

Conclusion AI can significantly enhance LCA efficiency and scalability, but without robust collaborative governance, it may undermine methodological rigor and ethical principles. Responsible integration requires need-based adoption, standardized protocols for evaluating AI models in LCA context, human-in-command validation for value choices, transparent documentation, and proactive attention to fairness and inclusivity. These findings provide a foundation for guidance toward effective, inclusive, and responsible use of AI in LCA.

Keywords Life cycle assessment · Artificial intelligence · Ethics · Automation · Efficiency · Organizations

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1 Introduction

Life cycle assessment (LCA) is increasingly recognized as a robust tool to quantify potential environmental impacts, identify hotspots, and potential trade-offs of products, services, and organizations. This is reflected through its inclusion into national policies (Sala et al. 2021), industry sectors, and major international frameworks such as Sustainable Development Goals (SDGs), the Global Framework on Chemicals and multiple United Nations Environment Assembly (UNEA) resolutions for sustainability decision-making. Alongside the ongoing development of conventional LCA (attributional LCA), diverse LCA approaches to overcome methodological challenges are rapidly developing (Guinée et al. 2018; Liu et al. 2024a). However, several key challenges still hamper LCA uptake preventing from full adoption into decision-making. The challenges include limited data availability and quality, reproducibility, lack of specialized expertise, time and labor-intensive process, lack of consistency and harmonization across studies, high costs and technical challenges in scalability (mass application for wide variety of products), inaccuracies resulting in uncertainty, and lack of effective communication and accessibility of LCA knowledge to non-LCA experts. To overcome these challenges, a balanced combination of efficiency and effectiveness-based solutions is required. Here, we define *efficiency* in LCA as the capacity to produce results with high speed and minimal resource use. In contrast, *effectiveness* in LCA refers to the capacity to produce results with *high quality* (accurate, robust, and methodologically sound), *high trust* (transparent, reproducible, and accountable, enabling decision-makers to rely on them and reviewers to verify them) and *high accessibility* (available to the practitioners and relevant decision-makers), such that the purpose of LCA of supporting sound and equitable sustainability decisions is fulfilled.

The pressing climate emergency, environmental degradation, and consumer environmental awareness have been driving industries, governments, and the LCA research community to perform faster and accurate environmental assessments for a wide variety of products on a large scale. These requirements resulted in increased integration of automation in LCA (e.g., process simulations, linking inventories with default datasets, integrating LCA results for EPDs, and automating the selection of most relevant LCI data) (Köck et al. 2023; Bertrand et al. 2025; Clos et al. 2025). It led to the development of automated and scalable LCAs (Arias et al. 2025) (e.g., screening, parametric, streamlined, process-based LCAs, hybrid LCA), and diverse environmental indicators and methodological improvements. These developments are primarily driven by *efficiency-based* improvements, such as reduced data requirements (Hester et al. 2018) or automating repetitive tasks, yielding benefits including time and cost reduction and resource optimization when performing an LCA task. However, *effectiveness-based* aspects such as improved accuracy (Haun et al. 2022), representativeness, data quality aiming at lowering uncertainty and producing high-quality results to inform decision-makers are equally of critical importance but have comparatively received less attention. Similar observations have been made across AI-augmented natural sciences research, i.e., increased publications and citations (*efficiency)* vs. reduced collective science's reach and collaborations (*effectiveness)* (Hao et al. 2026). The struggle to maintain the balance between efficiency and effectiveness while improving performance is an acknowledged challenge across many disciplines (Mandl et al. 2008; Hollingsworth 2013; Førsund 2017), as well as in LCA (e.g., contextualization vs. generalization, accuracy vs. speed of assessment, and quality vs. quantity of LCA studies). LCA performance can be enhanced by utilizing artificial intelligence (AI) techniques to maintain a balance between complementary efficiency (optimized use of resources and reduced manual human effort) and effectiveness (high quality and meaningful decision-making) perspectives. Efficiency improvements from automation can also be achieved without AI, for example through rule-based workflows. The popularization of AI has spurred the development of new AI applications in scientific research (Xu et al. 2021; Bianchini et al. 2026), including LCA and related disciplines, e.g., industrial ecology (Donati et al. 2022), IPCC assessment workflow (Al Khourdajie 2025), impact assessment (Bond and Dusík 2025), and sustainable development (Gohr et al. 2025).

AI is a branch of computer science encompassing any system that broadly aims at emulating human intelligence. Machine learning (ML) is a sub-branch of AI that includes many techniques aimed at learning patterns, deriving insights from available datasets to make predictions. One important subset of ML involves artificial neural networks (ANNs), which are structured networks of interconnected nodes inspired by the human brain. ANNs can approximate complex functions and have become especially powerful for tasks like image and speech recognition, and time-series forecasting (Schmidhuber 2015; Abiodun et al. 2018). ML has been instrumental in scientific breakthroughs with potential relevance for climate change mitigation and adaptation (Buck et al. 2026), including structure prediction of biomolecular interactions (Abramson et al. 2024), probabilistic weather forecasting (Price et al. 2025), and zero-shot time-series forecasting (Auer et al. 2025). Within ML, Generative AI (GenAI) aims at creating original content such as text, images, or video by learning from large existing datasets. GenAI systems exemplified by large language models such as GPT-4 or Claude, use ANNs to produce relevant

and human-like outputs (Vaswani et al. 2017; Ramesh et al. 2021; Liu et al. 2024b). This makes GenAI a powerful tool for summarizing information, processing unstructured data, and generating insights in natural language. It is important to note that GenAI models often require human oversight to validate their outputs, since they may produce incorrect or biased information, with the former commonly referred to as hallucination (Farquhar et al. 2024). An even greater level of automation can be achieved through AI agents and GenAI-based systems that can observe their environment autonomously, plan and execute actions to achieve defined outcomes (GOV.UK 2025; Sapkota et al. 2026). As the degree of autonomy and agency are not binary, one can consider that scores exist on a spectrum of autonomy and agency.

While potential benefits of AI are widely anticipated, divergent views on its systemic risks remain at the forefront of the discussion of its development and adoption (Bengio et al. 2025). Not all AI applications are aligned with environmental objectives, e.g., AI might lead to increased greenhouse gases emissions through the acceleration of fossil fuel extraction as it is increasingly leveraged to increase efficiency, cost-cutting (IBM 2025), and to enhance oil recovery (Wood Mackenzie 2025). Further, AI faces environmental sustainability challenges such as resource consumption and environmental impacts, technical challenges with model collapse (Shumailov et al. 2024), bias and hallucination (Huang et al. 2025); and ethical risks and social impacts including specialized skills, governance (OECD 2025), and safety (Gazos et al. 2025). Major ethical risks of AI, e.g. potential harm caused when AI conflicts with shared human norms of right and wrong, are associated with bias and fairness, transparency and explainability, privacy and security, accountability and sustainability (UNESCO 2022). Paying attention to the ethical risks is critical as they may lead to human rights violations, promoting discrimination, and causing damages to the natural ecosystems (UNESCO 2022; Kamila and Jasrotia 2025; Fiske et al. 2025). Similar perspective has been shared by domain experts on using GenAI applications in impact assessment practice (Khan et al. 2024). Identifying and taking action to mitigate the ethical risks of AI helps build trust in AI-based results, promote responsible work practices and tools, ensure preparedness to comply with existing or upcoming AI regulation. In addition, implementation of AI is reshaping work practices and roles. In the short term, AI is reshaping work by automating repetitive tasks, displacing substitutable and less experienced workers (Teutloff et al. 2025), requiring AI skills as baseline and creating new roles centred on AI. In long-term, it may lead to structural shifts in the world of work with a polarization on high-skill cognitive or non-automatable jobs which may prevent from achieving inclusive and equitable labor market (Ersanlı et al. 2025). The contradicting perspectives in the application of AI, i.e., the growing relevance of AI applications and their potential for resource optimization (*efficiency*) vs. the associated challenges such as biased outcomes leading to unintended effects (*effectiveness*), question their absolute benefit and demand for a well-regulated integration of AI applications in LCA, including the consideration of ethical and organizational challenges.

An AI application in LCA (hereafter referred to as AI-LCA application) refers to a method or tool at any maturity level (from proof of concept to commercial application), developed for the LCA community to perform some LCA tasks using AI, applicable to one or several LCA workflow steps. Evaluation of AI-LCA application outputs remains challenging due to the absence of standardized consensus protocols to determine the quality of AI-generated outputs for LCA tasks (Donaldson et al. 2025). This challenge stems from the fundamentally different approaches used for validation of model outcomes in AI and LCA. Validation in LCA is about methodological soundness and completeness; it includes internal and external reviews involving consistency and completeness checks, uncertainty and sensitivity analysis (ISO Library 2020; ISO 2024). AI model output validation is statistical and probabilistic, evaluated against data-driven ground truth through simulations, physical trials, model-centered assessments, and expert evaluations (Myllyaho et al. 2021). For semantic, predictive, or generative AI-LCA applications, validation should also address uncertainty quantification (He et al. 2026), explainability tied to a specific task and user (Doshi-Velez and Kim 2017), and robustness testing beyond aggregate accuracy (Zhang et al. 2022a). Validation should also establish whether the explanations of the AI results are usable by their intended audience (Rong et al. 2024). Finally, validation can assess which among human-only, AI-only, or human-AI configurations performs better, as the combination should not be assumed to be superior (Vaccaro et al. 2024). The potential benefits of integrating AI in LCA have been reviewed by many prior studies. Review papers on generic AI-LCA applications (Ghoroghi et al. 2022; Popowicz et al. 2024; Romeiko et al. 2024; Preuss et al. 2024; Sica et al. 2025; Salla et al. 2025; Neupane et al. 2025), as well as focusing on specific sectors, e.g., buildings and construction (Gachkar et al. 2024; Jalota and Ayazi 2025), and chemicals (Blanco et al. 2024), already exist. Several current and potential future applications of AI (primarily ML and LLMs) across different LCA stages have been identified and summarized. (Preuss et al. 2024) discussed various risks associated with the implementation of the identified opportunities, such as transparency, hallucinations, training data, accountability, and sustainability. Various benefits and limitations of different AI algorithms/methods and

their evaluation against several data quality requirements criteria (e.g., completeness, sensitivity, reliability, explainability, precision, and computational requirements) have been performed, exploring the role of human intervention in AI-LCA applications (Nwagwu et al. 2025). A few studies address ethical and organizational aspects of AI use in LCA, e.g., risk of bias in training data affecting social-LCA (S-LCA) results (Cole et al. 2025) and integrating digital technologies for environmental assessments from an organizational perspective (Popowicz et al. 2024). These aspects require thorough analysis for effective integration of AI in LCA. Overall, the existing literature extensively analyzes the technical opportunities and challenges of integrating AI in LCA. A comprehensive, multistakeholder evaluation that holistically addresses the technical, ethical, and organizational implications for LCA workflow steps is still lacking.

While AI and LCA both have their disciplinary perspectives on ethics, the ethical implications of using AI in the LCA context should be analyzed specifically for each LCA workflow step and stakeholders to better understand specific ethical risks and prevent unintended consequences, e.g., data integrity risks (inaccurate AI-generated data entering LCA databases), and governance and access concentration risks (sensitive proprietary industrial data being used for model training that may lead to unauthorized disclosure of proprietary industrial data). AI-LCA applications might increase inconsistencies and decrease accuracy and transparency. Similar ethical concerns are also framed as a significant challenge in the context of impact assessment and environmental data collection (Khan et al. 2024; Sandfort et al. 2024). In addition, the involved organizational changes should be identified in the short and long-term to adapt managerial practices and prevent any undesirable outcomes such as lack of inclusivity. The emerging concerns related to uneven and non-inclusive AI adoption across labor markets globally (Berg et al. 2024) are equally relevant for AI-LCA integration, given the unequal access to AI infrastructure, and proprietary LCA databases, which may further widen the existing digital divide. To the best of our knowledge, such risks are unaddressed in the current AI-LCA integration discussions.

Acknowledging these research gaps, this article critically analyzes AI-LCA applications from a holistic perspective. The diverse AI-LCA applications developed by academia and industry are identified and classified according to the LCA workflow steps, as this structure resonates with AI developers and fits the organizational perspective. Indeed, AI applications can cover the full LCA workflow, but they more often target specific workflow steps. The overarching objective of this work is to critically analyze the integration and adoption of AI in LCA from a multidimensional and multistakeholder perspective to evaluate the potential for an effective, inclusive, and responsible use, and to provide a foundation for future guidance. The specific sub-objectives are as follows:

1. Map current AI-LCA applications to identify technical opportunities and challenges for different stakeholders and workflow steps.
2. Identify ethical risks of using AI in LCA and assess their criticality levels.
3. Identify organizational implications for the LCA community.
4. Perform a stakeholder-wise critical analysis of AI-LCA applications with a focus on technical, organizational, and ethical dimensions.

The exploratory outcome of this research is relevant for LCA stakeholders, AI technology developers, and sustainability initiatives globally (such as Life Cycle Initiative, ACLCA, and ISO) as a basis to derive technical and ethical guidelines and support the future recommendations for the responsible integration of AI in LCA.

2 Methods

The general methodology to accomplish the stated objectives consisted of four steps (Fig. 1). First, current AI-LCA applications were identified using literature review by screening academic literature and industrial applications. To complement these findings, an online survey of LCA community was conducted. The purpose of the survey was to identify and assess common practices and actual uptake AI-LCA applications, as well as perceptions of their ethical risks. Second, the ethical risks of using AI in LCA were identified and their criticality levels were evaluated qualitatively. Third, various organizational implications for stakeholders across the LCA community are explored, extending a discussion on implications on work practices and regional disparities among others. Finally, a semi-quantitative evaluation of the identified AI-LCA applications was performed to present a critical analysis from a multiple-dimensional perspective (technical, ethical, organizational) targeting different LCA stakeholders, across LCA stages and workflow steps. Figure 1 presents an overview of the methodological steps for each sub-objective along with the tools/techniques used. The tools used included literature review, questionnaire survey, and expert interviews.

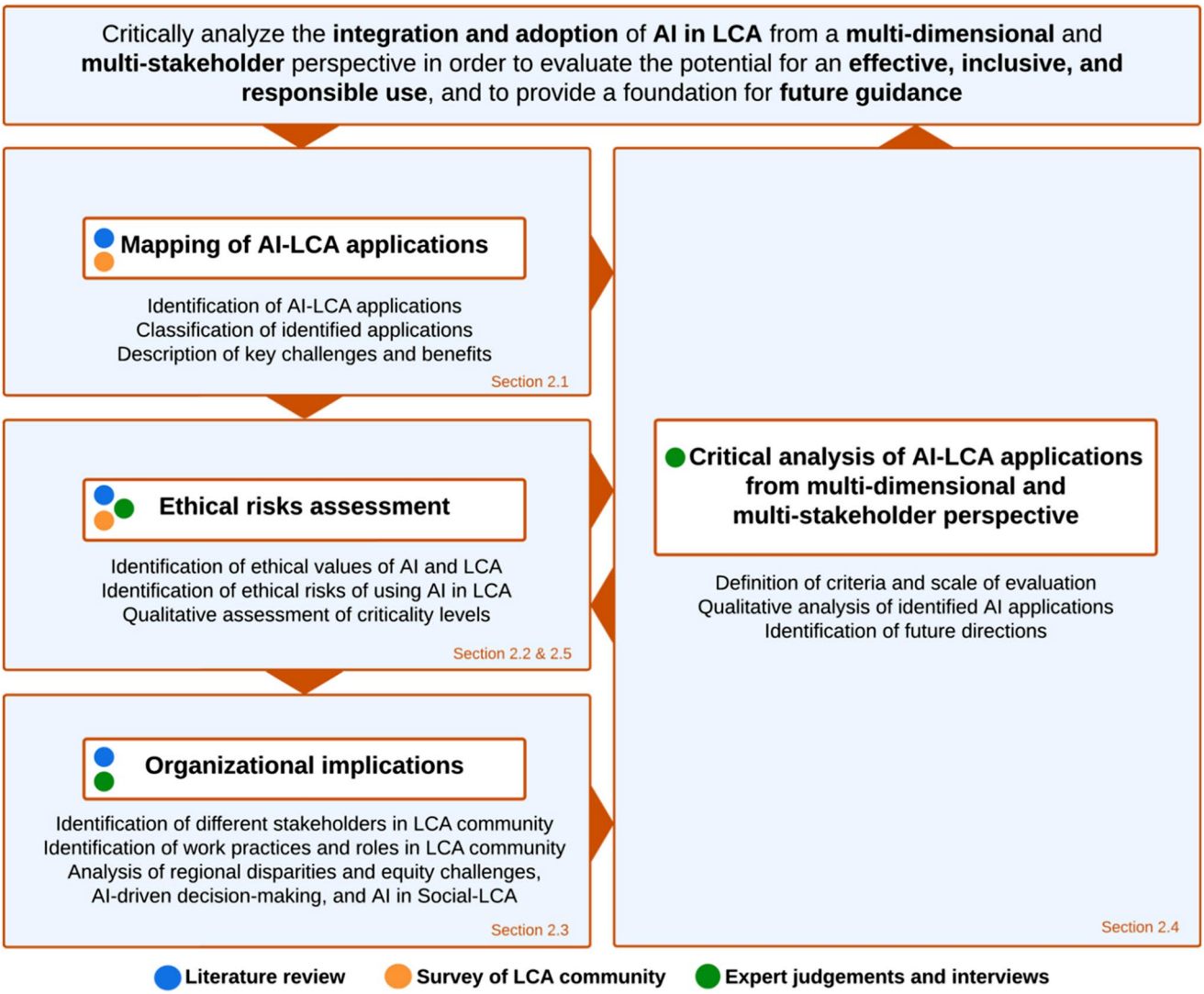


Fig. 1 Overview of the general methodology

2.1 Mapping of AI-LCA applications

2.1.1 Identification of AI-LCA applications using literature review

To address sub-objective 1, we conducted a semi-systematic review to identify academic and industrial AI-LCA applications. AI-LCA applications originating from majority of authors affiliated with academic institutions are defined as academic applications, whereas industrial AI-LCA applications are those developed by majority of authors affiliated with industrial or commercial software providers. The semi-systematic approach was preferred because of the abundance of recent literature reviews on the integration of AI in LCA (Nabavi-Pelesaraei et al. 2018; Barros and Ruschel 2021; ELOUARIAGHLI et al. 2022; Cornago et al. 2023; Ibn-Mohammed et al. 2023; Köck et al. 2023; Martínez-Ramón et al. 2024; Popowicz et al. 2024; Romeiko et al. 2024; Preuss et al. 2024; Mba Wright et al. 2024; Salla et al. 2025). Academic applications were therefore identified using backward snowballing, complemented by targeted searches in Google Scholar. Academic sources included journal articles, conference proceedings, and book chapters. Industrial applications were identified through web searches and social media review with an unstructured approach that relied on the authors' LinkedIn feed, rather than with a systematic search string. Since systematic searches did not prove useful, we acknowledge that this part of the study cannot be transparently reproduced. Additional industrial tools were identified during the academic literature review. The review was sector-agnostic, and identified applications were either generic or sector-specific. Only studies and tools that explicitly integrate AI techniques (e.g., machine learning, natural language processing) into LCA-related methodologies (e.g.,

full LCA, carbon footprints, EPDs, organizational LCA, or LCIA) were included; records addressing only AI or only LCA were excluded. For LCA workflow steps with limited coverage, targeted searches were conducted to assess the existence of relevant applications. All searches were last updated in December 2025; details are provided in the *supplementary information (SI)2*.

Each identified application was reviewed to extract information on the following topics: *specific LCA task*, *AI technology used*, *use of GenAI*, *technical challenges*, *benefits*, *relevant LCA stakeholders*, and *evaluation metric* (Table S1; SI 1) for a complete definition of each topic. *Relevant LCA stakeholders* identifies the LCA stakeholder category that would most likely use the application. *Evaluation metric* describes the metric used to validate the application outcomes. The information summarized in the table (see SI 2) further enables the critical analysis of the selected AI-LCA applications. Considering the primary target audience of this article (LCA practitioners, researchers and software developers), the identified AI-LCA applications were categorized according to the LCA stages inspired from ISO 14,040, and corresponding LCA workflow steps. LCA workflow steps refer to the specific sub-tasks (e.g. define the system boundaries, select background processes, develop characterization factors (CFs), predict impact scores, identify hotspots, produce the content of the report) to make an LCA study possible. The definition of LCA workflow steps and their corresponding LCA stages used in this study are listed in Table S2; SI 1.

Table 1 Definitions of ethical concepts

Term	Definition	Source
Ethical value	"A value in the context of human culture that supports a judgment on what is right or wrong"	(ISO 2022a)
Ethical principle	"A shared proposition about ethical values that members of a community can pursue and uphold" *For instance, a code of conduct, or a norm reflects ethical principles. If ethical values are objective, ethical principles are coded and subjective.*	(ISO 2022a)
Ethical risk	"A risk to ethical values"	(ISO 2022a)
Ethical risk of AI	A situation resulting from the development, deployment, and use of AI systems with potential negative consequences that conflicts with ethical values for trustworthy AI	Developed by the authors based on (European Commission 2019), and aligned with (ISO 2022a, 2023)
Ethical risk of LCA	A situation resulting from an application of LCA with potential negative consequences that conflicts with ethical values for robust LCA	Developed by the authors to mirror the definition of ethical risk of AI, as no definition of ethical risk of LCA exist.
Ethical risk of using AI in LCA	A situation resulting from the use of AI in LCA with potential negative consequences that conflicts with ethical values for robust LCA	Developed by the authors to aligning with other definitions of ethical risks.

2.1.2 Identification of prevalent AI-LCA applications using survey

An anonymous online survey was designed to gather data on three dimensions: (1) current uptake of AI in LCA, (2) perceptions of ethical values in LCA, and (3) perceptions of the ethical risks of using AI in LCA. The responses on the current uptake of AI-LCA applications were collected by including questions on motivation, purpose, frequency, and future interest in using AI (including GenAI and ML) in LCA practice. The questions on ethical dimensions are detailed in Sect. 2.2.2 and 2.5. The target audience was members of the international LCA community (LCA practitioners from academia, consultancy and industry, LCA researchers, LCI database developers, LCIA method developers, LCA software developers, etc.). The survey was distributed through various LCA community platforms, including the UNEP's Life Cycle Initiative, LCA lists newsletters as well as professional network channels (LinkedIn posts). The responses were collected from March 2025 to May 2025, involving 89 participants. The full list of questions and answers is available in Table S3; SI 1.

2.2 Assessment of potential ethical risks of using AI in LCA

To address sub-objective 2, we examined how existing ethical risks of using AI in LCA may negatively affect the ethical foundation of LCA. Our analysis focuses on building a theoretical framework grounded on ethical concepts defined in Table 1. In parallel, an empirical study was conducted in which answers from eleven large language models were evaluated by LCA experts to determine how often and under what conditions they produce misleading, inaccurate or poorly explained answers to LCA questions (Donaldson et al. 2025). For an empirical analysis of potential practical risks structured around ethical risks identified in this study, see Donaldson et al. (2025).

Our methodology, illustrated in Fig. 2, explores the ethical risks of using AI in LCA through four steps. First, we identify the ethical values that support trustworthy AI development and use by analyzing existing ethical principles for AI (Sect. 2.2.1). Second, we identify the ethical values

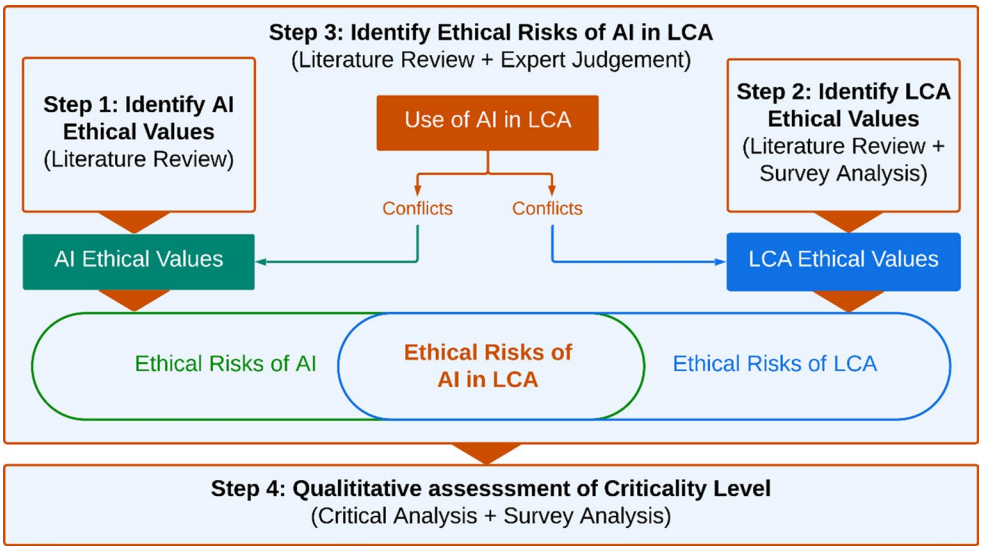


Fig. 2 Methodology to evaluate the ethical risks of the use of AI in LCA

Table 2 Ethical values for AI investigated in this study

Ethical values for AI	Definition	Source
Transparency	Appropriate disclosure to stakeholders of an AI system's purpose, design choices, assumptions, training data, known limitations, and degree of automation	Adapted from (ISO 2022b)
Accountability	Clear allocation to identifiable persons or organizations of responsibility for each stage of the development, operation, and management of an AI system, so that responsibility can be assigned when harms or concerns arise	Adapted from (ISO 2023)
Fairness	Absence of unjustified differential treatment that preferentially benefits certain groups over others, whether through biased system behavior or unequal access to the technology	Adapted from (ISO 2022b)
Data protection	Safeguarding of ownership, licensing, and authorized use of data — particularly proprietary, copyrighted, or restricted-access datasets — throughout training and use	Developed by the authors
Privacy	Ability of individuals to control the disclosure and use of information about themselves when interacting with an AI system	Adapted from (Westin 1968)
Safety and security	Prevention of unintended harmful behavior arising from system design or operation (safety) and of unauthorized use or manipulation through malicious action (security)	Adapted from (Qi et al. 2024)
Sustainability	Limitation of the environmental and social burdens generated across the life cycle of AI systems, from resource extraction and training to inference and end-of-life	Developed by the authors

underpinning robust LCA practice (Sect. 2.2.2). With both sets of values defined, we then examine how the use of AI in LCA may conflict with AI and LCA ethical values. To do so, we first identify situations in which the use of AI in LCA may conflict with AI ethical values. When such conflicts arise, we assess whether their consequences also affect LCA ethical values, thereby identifying the ethical risks of AI in LCA (Sect. 2.2.3). Finally, we qualitatively assess the criticality levels of these risks (Sect. 2.5) based on survey and critical analysis results (Sect. 3.2 and 3.3). This exploratory approach constitutes the first attempt to structure such an assessment and provides a foundation for future refinement by the AI and LCA communities.

2.2.1 Identification of ethical values for AI

The methodology used to identify the ethical values of AI involved three steps: (1) Reviewing multiple sets of AI ethical principles developed within the AI community (Finnveden 1997; Hertwich et al. 2000; Ekvall et al. 2005; Steen 2006; Goldstein et al. 2016; Freidberg 2018; Baitz 2019; Jobin et al. 2019) identified through the "AI Ethics Guidelines Global Inventory" (Algorithm Watch 2024); (2) Extracting the ethical values addressed in each set (Figure S1; SI 1), and (3) Selecting the most frequently recurring ethical values for further analysis (Table 2).

Four closely related terms recur throughout this paper and are used with distinct meanings. *Transparency* concerns what is disclosed about a system, i.e. its data, assumptions, design choices, and degree of automation (ISO 2022b). *Accountability* concerns who is answerable for the system's behavior and is established ex ante, during risk assessment and operational planning. *Explainability* concerns whether the important factors influencing a given output can be expressed in a way humans understand (ISO 2022b); in

an LCA context, this means being able to trace why a particular inventory flow, impact score, or interpretation was produced. Explainability underpins both of the preceding values: it is what makes disclosure substantive rather than nominal, and what allows a decision to be justified to those holding the system to account. *Auditability* concerns whether an independent party can verify that behavior ex post, during performance evaluation (ISO 2023). The distinction matters because these properties can be satisfied independently: a system can be transparent without being explainable, when documentation is complete, but decision pathways remain opaque, and explainable without being auditable, when outputs can be rationalized but no record allows independent verification.

2.2.2 Identification of ethical values for LCA

Although LCA practice is strongly anchored in ethical values, these values have not been explicitly defined. To identify ethical values for LCA for our analysis, we applied the following steps: (1) review academic literature on ethical values for LCA (Finnveden 1997; Hertwich et al. 2000; Ekvall et al. 2005; Steen 2006; Goldstein et al. 2016; Freidberg 2018; Baitz 2019), which revealed that no comprehensive set currently exists (Figure S1 and S2; SI 1); (2) review codes of conduct and practice developed by the LCA community; nine relevant sources were identified (SETAC 1993; European Commission et al. 2010; TOSCA 2011; Benoît Norris et al. 2020; ACLCA 2021; UNEP Life Cycle Initiative 2024; Aspire Sustainability 2025); (3) review ISO standards related to LCA (ISO 2006) (4) review survey responses (see Sect. 2.1.2) to the question "how would you define ethics as it applied to Life Cycle Assessment?"; and (5) synthesize findings from all sources to identify ethical values for LCA. This process led us to propose seven ethical values for LCA defined in Table 3, supported by our review (Figure S2; SI 1) and survey responses.

Table 3 Ethical values for LCA investigated in this study

Ethical values for LCA	Definition
Transparency and reproducibility	Clearly report all assumptions, choices and data sources in a structured and detailed manner to ensure that results can be consistently reproduced under the same conditions
Completeness	Being comprehensive to avoid problem shifting across life cycle stages and impact categories
Coherence	Being consistent with the goal and scope
Scientific integrity	Ensure unbiased and accurate assessment to be as close as possible to the reality, while acknowledging limitations, uncertainties, and potential conflicts of interest
Sustainable responsibility	Guide toward decisions minimizing sustainability impacts
Inclusivity and fairness	Ensure a good representativeness by considering interests and point of views of all stakeholders
Conformity	Respect the normative foundations of LCA, e.g. ISO 14040-44 (ISO 2006) and other legal obligations

2.2.3 Identification of ethical risks of using AI in LCA

To identify the ethical risks of using AI in LCA, we examine how the ethical risks of AI in an LCA context may translate into ethical risks of LCA. We first summarize the risks associated with each selected ethical value of AI based on literature review. Second, we discuss the extent to which these AI ethical risks are relevant to or manifest within LCA and what could be the associated potential negative consequences in the LCA context based on literature review and expert judgement of the authors. Finally, LCA ethical values that may be threatened by each AI ethical risk are identified based on our ethical risk assessment, hence reflecting the authors' analysis.

2.3 Identification of organizational implications of using AI in LCA

To address sub-objective 3, the organizational implications of AI integration on the LCA community can be evaluated by answering the following question: "*How may the usage of AI affect work practices and roles of the different stakeholders of the LCA community?*". To answer this question, we first identified the different stakeholders in the LCA community (Table S4; SI 1). Second, we examine how the use of AI in LCA may transform the LCA community in both the short and long term, drawing on the authors' judgment as well as trends identified in the literature, recent advances in academic research (as discussed in Sect. 3.1), and social networks highlighting developments in the professional landscape such as the emergence of end-to-end AI-LCA services. Finally, we discuss specific topics that we believe are of particular interest to the LCA community that, to our knowledge, have not yet been significantly explored: (1) implications at the regional level to identify potential regional disparities and equity challenges, (2) implications of AI-driven decision making, and (3) specific implications of using AI to perform S-LCA considering the specific nature of its goals, data and methods used.

2.4 Critical analysis of AI-LCA applications

To address sub-objective 4, we conducted a critical analysis positioning the current AI-LCA applications against several criteria reflecting thematics of interest for different LCA stakeholders. It aims to guide further development toward

an efficient and effective implementation and adoption of AI in LCA, as well as to contribute to the emerging debate on the integration of AI in LCA. This is a preliminary qualitative analysis based on the author's expert judgement. It should be strengthened in the future based on feedback from the broader LCA community.

Several criteria have been identified for the critical evaluation of the identified AI-LCA applications. The identified criteria are grouped into four thematic categories addressing technical, organizational and ethical dimensions: *technical maturity*, *potential to enhance LCA practice*, *operational feasibility*, and *ethical risks*. For each criterion, a semi-quantitative scale from 1 to 3 is defined with the highest value, (3) being the best or most desirable option. A detailed description of the criteria, category definitions and scale-wise evaluation is provided in Table 4. Criteria were defined to avoid overlap within each thematic category, but not across them, as each category aims to capture aspects relevant to different types of stakeholders. While LCA practitioners can be interested in all categories, LCA researchers, LCA tool developers (software, LCI databases, LCIA methods) and AI developers might be more interested in the *technical maturity* and *potential to enhance LCA practice* categories. The *potential to enhance the LCA practice* category also provides relevant insights for strategic positioning in LCA. The *operational feasibility* category could be of particular interest for LCA managers and LCA educators, and the *ethical risks* category is very relevant for LCA regulatory authorities, LCA reviewers, and LCA users.

Technical maturity has two criteria: *technical readiness* and *validation step. Technical readiness* captures the readiness level of AI-LCA application for being used by the LCA community and is inspired by Technical Readiness Levels (TRLs) defined by NASA (2023). *Validation step* criteria determine whether the application includes a validation step and whether it is automatic or human based. *Potential to enhance the LCA practice* category has two criteria: *output quality* and *contribution to workflow efficiency*. *Output quality* evaluates the improvement on the accuracy and robustness of outcomes of the application compared to current LCA practices. *Contribution to workflow efficiency* evaluates the resource and time savings induced using the application for conducting LCA compared with current practices. *Operation feasibility* category is divided into following criteria: *ease of use*, *level of integration*, *accessibility*, and *current level of adoption*. *Ease of use* evaluates the level of effort and expertise required to use an AI-LCA application. *Level of integration* of an AI-LCA application evaluates its compatibility with existing LCA software and data formats. *Accessibility* evaluates whether the application is open-access or not, so accessible to a wide audience or not. The *current level of adoption* reflects the audience size currently using the application and is evaluated based on the survey responses. *Ethical risks* are characterized by seven criteria based on the ethical risks for AI identified previously: *accountability*, *fairness*, *privacy*, *data protection*, *safety and security*, *transparency*, and *sustainability*. For each ethical risk, the likelihood of each application being exposed to this risk is evaluated using a binary scale. Example of practices used to help identify the level for each criterion along with a showcase example of evaluation are described in Table S4; SI 1.

To increase the coverage of the review and put the principles developed in this paper into practice, we used LLMs to assist with scoring and validated the scores. We created a prompt template for each set of criteria and provided the full text of the AI-LCA application to Claude Opus 4 or OpenAI GPT-5, operating under non-data-sharing versions of these tools. Furthermore, for each score assigned, we required that the model provided an explanation to justification of the score. To ensure that the model provided consistent and high-quality responses, we defined a data model for responses from the AI endpoint using the Pydantic AI framework (Pydantic 2025). Specifically, this data model ensured that a score within the valid range [1–3] was provided, and that a justification was given for each result. The model was also able to decline providing scores if it deemed a response to be invalid, providing a refusal mechanism to escape contradicting the task definition if irrelevant or malformed text was passed to the model. A human subsequently validated the scores and justifications against the application text and modified the score and/or justifications when disagreeing with the LLM analysis. The responses of Claude Opus 4 and OpenAI GPT-5 were not compared against each other directly, but were both reviewed and (if needed) adjusted by the same human reviewer, ensuring a degree of consistency in evaluation. Prompts were crafted such that both the documentation of the application to be scored and information in Table 4 were provided to the LLM for each application and criterion to be scored, along with examples of which attributes lead to which score (Table S6; SI 1), without exceeding the context window. The LLM was then asked to provide a score and an explanation of the score (details on prompt and methodology in Table S5; SI 1). Then, both the score and explanation were validated and corrected if needed by the authors. The evaluation of each criterion was performed following a conservative risk assessment perspective: even if an application met some requirements to have a better score (2 or 3), if it contained attributes leading to a lower score (1 or 2), then the lowest score has been chosen. 23 of the applications were assessed fully manually (5 academic and 18 industry applications). The review of the applications for which the LLM provided scores was conducted in two batches. For the first batch, the

Table 4 Description of the assessment criteria and their corresponding scales for evaluation

Thematic categories	Assessment criteria	Evaluation question	Scale of evaluation
Technical maturity	Technical readiness	Is the application ready to be used by the LCA community? Is it well integrated with existing tools?	3 = Production-ready with real-world use cases 2 = Beta-stage, limited functionality 1 = Experimental / Proof-of-concept
	Validation step	Does the application include validation steps?	3 = Automatic validation 2 = Human-in-the-loop/Human-in-command validation 1 = No validation
Potential to enhance LCA practices	Output quality	Are the outputs of the application robust, context-appropriate, accurate (i.e. being true), without errors?	3 = Higher accuracy than current practice 2 = Same accuracy as current practice 1 = Lower accuracy than current practice / no assessment of the accuracy performance
	Contribution to workflow efficiency	Does the application reduce time or resource needs when conducting LCA studies?	3 = Significant time or resource savings 2 = Moderate time or resource savings 1 = No measurable gain / increase of resource requirements / no assessment of the efficiency performance
Operational feasibility	Ease of use	How difficult is it to use the application? Is the level of effort and expertise to apply it adapted to an average LCA stakeholder?	3 = Easily usable by the average LCA stakeholder without specific skills 2 = Moderate expertise needed 1 = Difficult, requires high specialization (computing skills, etc.)
	Accessibility	Is this application affordable and easily accessible to all LCA stakeholders?	3 = open access application (code and documentation) + free-of charge or cheap operation 2 = open access application (code and documentation) + more expensive operation 1 = not open access
	Current level of adoption	Is the application currently widely used by the LCA community?	3 = Frequently used by most users 2 = Moderately used by some users 1 = Not used / only used by niche users
Ethical risks	Accountability	Can the application be exposed to challenges regarding explainability (how decisions are justified), liability (who is responsible for harm) or enforceability (how rules are enforced)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Fairness	Can the application be exposed to challenges regarding representation bias (Bias in AI-generated data) or the AI divide (unequal access to AI)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Privacy	Can the application be exposed to challenges regarding privacy (i.e. right to control personal information and protect autonomy and dignity)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Data protection	Can the application be exposed to challenges regarding data protection (i.e. proper use of proprietary, copyrighted, confidential data)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Safety and security	Can the application be exposed to challenges regarding safety (internal - unintended harmful behavior due to poor design) and security (external - malicious attack)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Transparency	Can the application be exposed to challenges regarding transparency (lack of disclosure of data or methods)?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk
	Sustainability	Can the application be exposed to challenges regarding its environmental or social impacts?	3 = No, most probably not exposed to risk 1 = Yes, most probably exposed to risk

manual review of the full 14 criteria across a sample of 89 applications (for a total of ~1246 scores), led to 84 scores being manually overridden. The refusal mechanism correctly identified seven articles as not relevant, which were excluded from scoring. The first batch helped us improve the prompt template and update a harness to ensure scores were more consistently measured in the second batch. The second batch only needed the adjustment of 14 scores which were not valid and was not further reviewed.

2.5 Qualitative assessment of criticality levels for ethical risks of using AI in LCA

To complete sub-objective 2 based on results from the previous sections, we assess the criticality levels for ethical risks of using AI in LCA along two complementary dimensions: (1) by LCA ethical values, i.e., the extent to which AI use in LCA may threaten each LCA value; and (2) by AI ethical values, i.e., the extent to which AI use in LCA may compromise each AI value. Risk levels are categorized as *high* (very likely), *medium* (likely), and *low* (unlikely). Risk levels by AI values are derived from the mean scores obtained in the critical analysis of AI-LCA applications in Sect. 3.5, representing the risk likelihood. Mean scores < 2.2 correspond to high risk level, 2.2–2.8 to medium risk, and > 2.8 to low risk, ensuring a conservative assessment. To determine risk levels by LCA values, we first identified which AI ethical risks plausibly threaten each LCA value based on our identification of ethical risks in Sect. 3.3. Each LCA value was then assigned the highest risk level among the AI values that could affect it.

We compared the resulting risk levels by LCA values to the perceived risks reported in the community survey (see Sect. 2.1.2), based on (a) the perceived importance of each LCA value ("*Can you rank the importance of the following values in LCA?*") and (b) the perceived risk of AI use in LCA for each LCA value ("*In your opinion*, *which ones of those LCA values will be most likely compromised by the use of AI in LCA?*"). LCA values perceived both highly important and highly at risk were classified as having a high perceived risk.

3 Results

3.1 Technical mapping of AI-LCA applications

A total of 145 AI-LCA applications were shortlisted for detailed evaluation. The shortlisted applications were manually categorized as per the relevant LCA stages and workflow steps (see Table 5). Approximately 88% of the reviewed applications were from academic publications and ~12% were industrial applications. The sources of the selected applications included original research articles (with or without demonstrated implementation/case studies), and industrial applications (white papers and scientific publications). The reviewed applications roughly cover 57% of the overall workflow steps and are applicable to the LCI and LCIA stages of LCA (99 applications, ~68%; and 80 applications, ~55%, respectively), predominantly focused on filling missing data gaps (45 applications) and predicting impact scores (72 applications). Applications focused on missing LCI data gaps include forecasting temporal data to overcome static annual averages (Cornago et al. 2020; Portolani et al. 2022; Dai et al. 2022), expanding geographical and technological coverage by predicting region-specific data (Meron et al. 2020; Froemelt et al. 2020; Dai et al. 2022), and approximating inventory data for emerging technologies (Hou et al. 2018). Similarly, AI-LCA applications for the LCIA stage focus on dynamic impact prediction (Cornago et al. 2020; Portolani et al. 2022), regionalized impact assessment (Froemelt et al. 2018, 2020), and hotspot analysis (Wernet et al. 2012). Further, a few applications have focused on the development of CFs (7 applications) and mapping background processes in LCI databases (16 applications). For example, text-based algorithms for automatic and efficient data collection for building sector LCA (Gachkar et al. 2025); using ML models to provide rough estimates of pesticide CFs for ecotoxicity and human toxicity in the ReCiPe method using physicochemical, toxicological and ecotoxicological properties from pesticide databases. Industry applications primarily focused on scaling up LCA activities, which include automating data collection, LCI generation, and emission factor selection and recommendation. For instance, large language models (LLMs) have been used to map product descriptions to North American Industry Classification System (NAICS) titles (Balaji et al. 2025a). An intermediate industry sector classification step is used to handle instances where database matches are insufficient, avoiding the need for extensive training data (Balaji et al. 2023a). A small number (~17%) of applications employ GenAI techniques, majorly from the industrial applications (15 out of 24 applications). The predominance of GenAI in industrial applications relative to academic research can be attributed to the earlier initiation of academic research on AI-LCA integration, as GenAI has gained significant prominence only recently. ANNs are the most common architecture used in the 57 (~39%) of the applications, followed by tree-based models (primarily random forests) with 24 (~16.5%), regression 28 (19%), LLMs (10%), and fuzzy logic and clustering (10%). A detailed summary of the AI-LCA applications and the associated information is provided in the supporting information (summary table sheet in SI 2) and (Figure S6; SI 1).

3.2 Use of AI by the LCA community: survey insights

The survey gathered insights from 89 respondents across the LCA community, including researchers (44%), practitioners in consultancy and industry (39%), LCI developers, software developers, and reviewers. Regarding the use of AI in LCA, 43% reported using GenAI "sometimes," 27% "often," and 30% "never." Non-generative AI or machine-learning tools show a lower adoption rate, with 62%

Table 5 Industry and academia focus on different LCA workflows, applications may be referenced more than once, if they cover more LCA workflows

LCA stage	LCA workflow [Total number of applications]	Academic applications	Industrial applications
Goal and Scope Definition	Define the goal and scope of the study [1]		(Agent Net Zero 2025)
	Conduct a literature review on similar LCA studies [1]		(EcoAgent 2025)
	Define scenarios to be assessed [1]	(Liu et al. 2025)	
	Define the main assumptions and modeling approach [1]	(Østergaard et al. 2018)	
LCI	Define the process tree [8]		(Carbon 2020; CarbonGraph 2021; ECOZE 2021; Carbon-Bright 2022; Context Labs 2024; Agent Net Zero 2025; EcoSemantic 2025; One Click 2026)
	Identify the data needed to model each process [5]	(Aslan et al. 2025; Kumar et al. 2025)	(Deng et al. 2023; EcoSemantic 2025; One Click 2026)
	Collect primary/internal data [8]	(Gachkar et al. 2025)	(Carbon 2020; Makersite 2024; Context Labs 2024; Agent Net Zero 2025; EcoSemantic 2025; CO2 AI 2025; One Click 2026)
	Collect secondary data (from suppliers or literature) [2]	(Turhan 2023)	(CO2 AI 2025)
	Estimate missing data / Fill data gaps [45]	(Sousa and Wallace 2006; Wernet et al. 2008, 2012; Wang and Shen 2014; Elhami et al. 2017; Ernstoff et al. 2018; Li et al. 2017, 2022; Hou et al. 2018; Nabavi-Pelesaraei et al. 2018; Froemelt et al. 2018, 2020; Perrotta et al. 2018; Lautenbach et al. 2019; Meng et al. 2019; Sharif and Hammad 2019; Thilakarathna et al. 2020; Cheng et al. 2020 b, a, 2021; Cornago et al. 2020; Liao et al. 2020; Meron et al. 2020; Naseri et al. 2020; Zhao et al. 2021; Olafasakin et al. 2021; Raeesi et al. 2021; Jian et al. 2021; Portolani et al. 2022; Khadem et al. 2022; Dai et al. 2022; Ascher et al. 2022; Ahmadi et al. 2022; Negri et al. 2022; Hajabdollahi Ouderji et al. 2023; Huntington et al. 2023; Polo-Mendoza et al. 2023; Xing et al. 2023, 2025; Cullen et al. 2024; Chen et al. 2025; Kumar et al. 2025)	(CarbonBright 2022; Deng et al. 2023; EcoAgent 2025)
	Evaluate the quality of the data (Data Quality Assessment) [1]	(MacMaster and Sinistore 2024)	
	Verify/validate LCI data [2]		(Carbon 2020; Context Labs 2024)
	Create parameters to be used in the model [1]	(Liu et al. 2025)	
	Map and input collected data in foreground processes [9]		(CarbonGraph 2021; Carbon-Bright 2022; Ailoop 2024; Makersite 2024; Context Labs 2024; Agent Net Zero 2025; EcoSemantic 2025; CO2 AI 2025; One Click 2026)

Table 5 (continued)

LCA stage	LCA workflow [Total number of applications]	Academic applications	Industrial applications
	Select/Map background processes from LCI databases (or emissions factors) [16]	(MacMaster and Sinistore 2024; Aslan et al. 2025)	(Carbon 2020; CarbonGraph 2021; ECOZE 2021; Carbon-Bright 2022; Balaji et al. 2023a, 2025b; Deng et al. 2023; Dumit et al. 2024; Makersite 2024; Agent Net Zero 2025; EcoAg-ent 2025; EcoSemantic 2025; CO2 AI 2025; One Click 2026)
	Calculate Allocation Factors [1]	(López-Andrés et al. 2018)	
	Calculate the LCI results [1]	(Cheng et al. 2020)	
LCIA	Develop characterization factors to cover new elementary flows [7]	(Slapnik et al. 2015; Marvuglia et al. 2015b; a; Hou et al. 2020; Servien et al. 2022a, b; Song et al. 2022)	
	Generate figures and tables for interpretation [1]	(Aslan et al. 2025)	
LCI and LCIA	Predict impact scores [72]	(Ozbilen et al. 2013; Khoshnevisan et al. 2013a, b, 2014a, 2014b; Taghavifar and Mardani 2015; Nabavi-Pelesaraei et al. 2016a; b, 2017a, b, 2019, 2023; Azari et al. 2016; Elhami et al. 2017; Mousavi-Avval et al. 2017; Khanali et al. 2017; Asif and Chen 2019; Duprez et al. 2019; Asif et al. 2019; Kaab et al. 2019; Karka et al. 2019, 2022; Feng et al. 2019; D'Amico et al. 2019; Romeiko et al. 2020a; Pishgar-Komleh et al. 2020; Płoszaj-Mazurek et al. 2020; Yan et al. 2021; Faridmehr et al. 2021; Tsay et al. 2021; Chen et al. 2021, 2023b; Hamida et al. 2021; Fleitmann et al. 2021; Martínez-Rocamora et al. 2021; Zhang et al. 2022a, b; Ghasemi-Mobtaker et al. 2022; Onyelowe et al. 2022, 2023; Singh and Sarkar 2023; Sun et al. 2023; Pan and Wu 2023; Liu et al. 2023; Naser et al. 2023; Teodosio et al. 2023; Morand et al. 2024; Zheng et al. 2024; Ahmed et al. 2025; Jha et al. 2025) (Song et al. 2017; Nabavi-Pelesaraei et al. 2018; Kleinekorte et al. 2019, 2023; Meng et al. 2019; Sharif and Hammad 2019; Xikai et al. 2019; Cornago et al. 2020; Zhu et al. 2020; Dabbaghi et al. 2021; Por-tolani et al. 2022; Koyamparambath et al. 2022; Akhshik et al. 2022; Turhan 2023; Kazemeini and Swei 2023; Polo-Mendoza et al. 2023; Mohammadi Kashka et al. 2023; Shekoohiyan et al. 2023; Chen et al. 2023a; Ross et al. 2023; Nikkhah et al. 2024; Płoszaj-Mazurek and Ryńska 2024; Baehr et al. 2024; Wang and Ye 2025)	
Interpretation	Identify hotspots [7]	(Wernet et al. 2012; Froemelt et al. 2018, 2020; Zhao et al. 2019; Abdella et al. 2020; Romeiko et al. 2020b; Abokersh et al. 2020)	
	Compare impact scores of ana-lyzed scenarios [8]	(Azari et al. 2016; Froemelt et al. 2018, 2020; Sharif and Hammad 2019; Dabbaghi et al. 2021; Akhshik et al. 2022; Kazemeini and Swei 2023; Mohammadi Kashka et al. 2023)	
	Identify parameters/scenarios for sensitivity analysis [2]	(Huntington et al. 2023)	(Context Labs 2024)
	Conduct sensitivity analysis [3]	(Ziyadi and Al-Qadi 2019; Feng et al. 2019; Abokersh et al. 2020)	
	Conduct uncertainty assessment [3]	(Ziyadi and Al-Qadi 2019; Feng et al. 2019; Baehr et al. 2024)	
	Grouping/Clustering of impacts for interpretation [1]	(Prioux et al. 2023)	
	Identify promising improvements of the system [8]	(Azari et al. 2016; López-Andrés et al. 2018; Turhan 2023; Chen et al. 2023a; Płoszaj-Mazurek and Ryńska 2024)	(Carbon 2020; ECOZE 2021; Gopalakrishnan et al. 2024)
Crosscutting	Learning and Training [1]		(EcoAgent 2025)

Table 5 (continued)

LCA stage	LCA workflow [Total number of applications]	Academic applications	Industrial applications
	Produce the content of the report [4]	(Zhang et al. 2025)	(CarbonBright 2022; Ailoop 2024; Makersite 2024)
	Communication and diffusion [1]	(Goridkov et al. 2024)	

reporting "never" using them. This current use is at odds with the applications described in Sect. 3.1, in which only GenAI is a small percentage. However, AI's current applications were primarily non-LCA specific such as literature reviews (58%) and report writing (43%) using mainstream general LLM models. This aligns well with current LLMs strengths and capabilities, which are well suited for producing structured text outputs such as report drafts or preliminary literature summaries based on limited input. Tasks that require more domain-specific knowledge like filling data gaps, automated mapping, and analyzing results are less commonly used among respondents, still they respectively represent 29%, 29%, and 25% of responses. Even considering the small sample size, this shows a good degree of trust in the capabilities of these applications. The main motivations for future use included reducing time-consuming tasks (88% of respondents) and improving the relevance and quality of assessments (54%), as well as facilitating the dissemination of LCA findings (37%).

Respondents widely agreed that ethics in LCA hinge on *transparency*, *scientific integrity*, *and* unbiased reporting, emphasizing the importance of clearly documenting assumptions, data sources, methodologies, and limitations. Many highlighted the practitioner's responsibility for safeguarding sensitive data, maintaining methodological rigor, and ensuring assessments are comprehensive enough to avoid burden-shifting across life cycle stages and impact categories.

When ranking core LCA values, transparency and reproducibility and scientific integrity emerged as top priorities, followed by completeness, coherence, and sustainable responsibility. Conformity with ISO standards was a low priority, albeit it showed the highest standard deviation in the score, which highlights disagreement within the pool of respondents. Considering diverse stakeholder perspectives, *inclusivity* and *fairness* were consistently rated as the least important. The respondents expressed concern that AI may compromise particularly transparency and reproducibility, and scientific integrity, citing challenges such as the "black-box" nature of AI models, reproducibility issues with generative tools, risks of biased or low-quality data, and inadequate documentation of AI-assisted workflows.

3.3 Identification of ethical risks of using AI in LCA

Ethical risks of using AI in LCA along with the LCA values that it may threaten are summarized in Table 6. The definition of each ethical risk for AI in general and its potential consequences in the LCA context are described below. For each risk, we then state explicitly which LCA ethical values may be threatened and through which mechanism.

Table 6 Synthesis of the analysis of ethical risks of the use of AI in LCA

Ethical value of AI	Summary of ethical risks of AI in broad terms	Summary of ethical risks of using AI in the LCA context	Ethical values of LCA threatened by AI in LCA
Transparency	Black-box nature of AI and lack of disclosure of training data/methods hinder transparency (disclosure of sources and methods, reproducibility, uncertainty quantification, and human supervision).	Transparency is a foundational LCA value, but AI introduces opacity in data sources and methods. Uncertainty quantification is rarely applied in AI-driven approaches, despite AI being inherently uncertain.	Transparency and reproducibility, Scientific integrity, Coherence, Completeness, Conformity
Accountability	Decision-making shifting from humans to algorithms complicates accountability. Ethical concerns center on explainability (transparent justification of decisions) due to opaque AI models, liability (who bears responsibility for harm) fragmented among AI stakeholders, and enforceability (upholding norms and regulations) remaining weak despite regulatory frameworks like the EU AI Act.	LCA accountability traditionally relies on ISO standards requiring explainability through transparency, placing liability on the LCA practitioner and ensuring enforceability through peer review. AI-driven LCAs create gaps in explainability and liability with risk of undetected errors leading to misguided sustainability decisions.	Transparency and reproducibility, Scientific integrity, Sustainable responsibility
Fairness	Two overlapping risks threatening inclusivity: representation bias (systemic imbalances in training data and model design) and AI divide (unequal access to AI technologies).	Bias in AI-generated data could undermine scientific integrity of LCA. Limited access to AI tools excludes certain LCA stakeholders, particularly from the Global South and senior professionals.	Scientific integrity, Sustainable responsibility, Inclusivity and fairness
Data protection	Data protection involves safeguarding proprietary and copyrighted data. Failure to maintain these protections could render AI applications illegal.	The conformity of LCA to law may be threatened if data are created or used illegally by AI. Ownership of synthetic LCA data remains undefined.	Transparency and reproducibility, Conformity
Privacy	Privacy means control over personal information. AI threatens this through intrusive data collection, profiling, and lack of user control.	Privacy is generally not relevant in environmental LCA since it focuses more on industrial processes than personal data. Could be more relevant for S-LCA or behavioral LCA.	Conformity
Safety and security	Failures in safety (unintended harm from poor AI design) and security (malicious attacks) can lead to disclosure of sensitive data, false content dissemination, and reputational harm. Potential amplification of fairness and data protection risks.	In LCA, malicious actors could exploit security failures in AI-LCA applications to falsify or bias LCA results, undermining trust in LCA and enabling greenwashing.	Scientific integrity, Sustainable responsibility, Inclusivity and fairness, Conformity
Sustainability	AI presents environmental impacts (climate change, metal resource depletion and water consumption) and social risks (child labor, precarious and unsafe labor, job displacement, widening of digital divide).	Direct impacts of using AI in LCA must not outweigh its LCA benefits. Full life-cycle environmental impacts and social risks, especially workforce reduction and exclusion of vulnerable practitioners, still require investigation.	Sustainable responsibility, Inclusivity and fairness

3.3.1 Transparency

As defined in Sect. 2.2.1, transparency for AI involves disclosure of sources and methods, reproducibility, uncertainty quantification, and human supervision. The black-box nature of most AI models makes decision pathways difficult to understand; as (Algren et al. 2021) note, "*there is often no way to mathematically represent the relationship between model inputs and outputs*," which complicates reproducibility. Similarly, most GenAI models face transparency issues due to lack of disclosure of training data and inference models. As with any data-driven approach, AI performance is fundamentally constrained by the quality of its training data, reflecting the "*garbage in*, *garbage out*" principle. Training data strongly influence model behavior and can perpetuate human biases (Treiman et al. 2024), yet proprietary training datasets used by most organizations limit external scrutiny of model limitations and biases. While open-source models can improve reproducibility, they depend on transparent disclosure of the model architecture and training data. For LCA, *transparency* is a core value and considered a moral and scientific obligation to ensure *scientific integrity* and reproducibility (Thomas 2023). AI challenges these values by introducing opacity in data sources, methods, and uncertainty. A review of studies using ML in LCA revealed that 35% of the studies did not report dataset splits between the training, validation and testing datasets, and 12.5% lacked validation details (Romeiko et al. 2024). These omissions matter for training or fine-tuning models but are not applicable when using pre-trained models without additional training. Uncertainty quantification, central to LCA (Heijungs 2024), is rarely applied when using AI in LCA, despite AI being "inherently uncertain" (Kaur et al. 2024). Techniques like uncertainty quantification exist in the AI field (Kaur et al. 2024) but are seldom implemented in LCA and remain disconnected from established practices. These consequences bear on several LCA values at once. Beyond *transparency and reproducibility* and *scientific integrity*, opacity threatens *coherence*, since the geographical, technological and temporal conditions under which a non-transparent AI-supplied datum or background process was derived cannot be checked against the goal and scope of the study; *completeness*, since AI-assisted scoping or gap-filling may silently omit life cycle stages or impact categories, leaving problem shifting undetected; and *conformity*, since ISO 14,044 reporting requirements on data sources and assumptions cannot be satisfied for choices that cannot be inspected.

3.3.2 Accountability

The integration of AI systems significantly complicates accountability dynamics by shifting the decision-making from human actors to algorithms. Ethical concerns surrounding accountability are centered on three main components: explainability (how transparently an AI system can articulate or justify its decisions), liability (who is legally or morally responsible for harms arising from AI-driven actions or outcomes), and enforceability (ensuring that norms, regulations, and ethical guidelines are upheld through oversight, monitoring, and sanctions) (Doshi-Velez et al. 2017; Novelli et al. 2024). Explainability is often compromised by the opaque nature of AI systems. Liability is fragmented among multiple stakeholders, including AI developers, manufacturers, and end-users, creating ambiguity in assigning responsibility for harm. It worth noting that the actors who are liable are not machine systems (Giannini 2023). This complexity is evident in domains such as autonomous vehicles and healthcare (He 2021; Terranova et al. 2024). Although regulatory frameworks like the EU AI Act (European Commission 2024) or Chinese AI regulations (Chun et al. 2024) attempt to define responsibilities and ensure compliance, enforceability of these frameworks remains weak due to resource-intensive audits and loopholes (Wachter 2023). Explainability in LCA has traditionally relied on transparency, data quality, and rigorous documentation, as defined by ISO 14040-44 standards (ISO 2006). These standards enable traceability and peer review, placing liability on the LCA practitioner and ensuring enforceability through audits of documented methods and data sources. However, the introduction of AI-driven approaches complicates this LCA's accountability structure, requiring practitioners to adapt or supplement existing frameworks. A gap persists in defining clear guidelines for AI accountability, which must be addressed before AI-driven LCAs can be considered trustworthy. Failure to do so risks propagating hard-to-detect errors (i.e. choice of an inadequate background processes, error in estimating a flow quantity, unjustified exclusion of some processes) with negative downstream impacts on sustainability policies and corporate strategies. Beyond these downstream consequences for the LCA value *sustainable responsibility*, the absence of an identifiable actor answerable for an AI-derived choice also threatens *transparency and reproducibility* and *scientific integrity*, since limitations, uncertainties and conflicts of interest are unlikely to be documented when no one is responsible for doing so.

3.3.3 Fairness

Fairness in AI requires that tools developed and deployed be inclusive by design, serving all population categories equitably rather than preferentially benefiting some over others. However, this principle becomes an ethical risk when AI systems fail to meet this requirement, leading to inequality, erosion of trust, and biased outcomes. Two risk categories can be distinguished: algorithm representation bias and AI divide (Yu 2020). Representation bias refers to systemic imbalances in how AI systems represent or treat different population groups due to biases in training data, model design, or deployment, which may lead to discriminatory outcomes such as replicating stereotypes in hiring recommendations (Belenguer 2022; Pasipamire and Muroyiwa 2024). The AI divide refers to disparities in access to AI technologies, infrastructure, digital literacy and representative training data, which limit who benefits from AI advancements. These risk categories often overlap, as AI divide can worsen representation and vice versa. UNESCO warns that AI diffusion may widen the existing digital divide (UNESCO 2022) and CSIRO highlights that GenAI could exacerbate fairness issues if the digital divide persists (Bentley et al. 2024). In the context of LCA, fairness risks manifest through representation bias and the AI divide. Biased AI-generated data may compromise scientific integrity in LCI or LCIA, while limited access to AI tools may deprive LCA stakeholders, particularly from the Global South and senior professionals, of opportunities to enhance their LCA practices (see Sect. 3.4.2 for more details). Representation bias therefore threatens not only *scientific integrity* but also *sustainable responsibility*, since comparisons distorted toward well-documented regions and technologies can favour the higher-impact option and shift burdens onto those under-represented. The AI divide, in turn, threatens *inclusivity and fairness*: stakeholders without access to AI tools, infrastructure or representative training data contribute less to the studies and tools being built, so the resulting body of AI-assisted LCA reflects a narrower set of interests and viewpoints.

3.3.4 Data protection

Data protection in AI involves safeguarding proprietary and copyrighted data and ensuring confidentiality for restricted-access datasets. The data may refer to either foreground industrial data often or data from background LCA databases. Copyright protects authorship rights, while proprietary data are protected for access and usage rights through contracts, licensing, or secret protections. Failure to maintain these protections could lead to unexpected divulgation of protected data during the AI model use phase if it has been used during training. This would ultimately render AI applications illegal (Longpre et al. 2024; Buick 2025). A critical unresolved issue is whether training AI on copyrighted material constitutes "fair use," a doctrine in U.S. copyright law that allows limited use without permission under certain conditions. This question is currently being litigated in cases such as Getty Images vs. Stability AI and NYT vs. OpenAI (Soiffer and Jain 2023), which will have far-reaching implications for AI ethics and legality. In the LCA context, a failure in data protection in AI applications may threaten the *conformity* of LCA to law if data are created or used illegally. Measures to ensure ethical data ownership and copyright protection are needed, particularly when AI models rely on proprietary databases such as ecoinvent. Currently, no license agreement defines ownership of synthetic data generated by AI, and existing frameworks like the Ecoinvent End User License Agreement only allow disclosure of "insubstantial amounts" of data under specific conditions (ecoinvent 2023), making the development of collaborative licensing frameworks essential to maintain compliance and fair use principles. Beyond *conformity*, these restrictions also threaten *transparency and reproducibility*, since license terms limiting disclosure of protected datasets, and the undefined status of AI-generated synthetic data, prevent practitioners from reporting where their data originate.

3.3.5 Privacy

Unlike data protection, which concerns safeguarding proprietary and copyrighted material, privacy focuses specifically on the protection of personal information and individual autonomy. Privacy, historically framed as "the right to be let alone" (Warren and Brandeis 1890), has evolved into the modern understanding of "the right to select what personal information about me is known to what people" (Westin 1968). This right is fundamental for the free development of one's personality, enabling individuals to make autonomous choices aligned with their interests and convictions and present different aspects of themselves to different audiences without fear of oppression (Bohn et al. 2004). The UN Declaration of Human Rights recognizes privacy as a prerequisite for personal freedom and diversity of thought (United Nations General Assembly 1948). The use of AI poses significant risks to these principles through intrusive data collection, profiling, and lack of user control over personal information, which can erode autonomy and trust (Andreotta et al. 2022). In contrast, privacy is not a major ethical concern in LCA, as its focus on industrial and commercial processes rarely involves personal data. Consequently, the integration of AI in LCA does not introduce meaningful privacy risks unless future practices incorporate

individual-level information. However, privacy risks might be higher for AI in.

S-LCA or in LCA modeling human behaviors as personal data can be involved. In particular, LCA-based tools calculating individualized impact score based on personal data (such as individual carbon footprint calculators) could be at risk regarding privacy. In these cases, the LCA value at stake is *conformity*, since processing personal data without adequate individual control breaches data protection law and hence the legal obligations of the study.

3.3.6 Safety and security

Safety and security in AI encompass two distinct but interrelated principles: safety aims to prevent unintended harmful behaviors or outcomes caused by poor AI design or operation, while security focuses on preventing unauthorized use or manipulation through malicious attacks (Qi et al. 2024). Failures may lead to the disclosure of sensitive information, dissemination of false content, or reputational damage, underpinning other ethical values such as fairness and data protection. Security issues pose a risk to LCA practitioners because they lead to inadvertent or intentional misrepresentation of LCA results, or unintentional disclosure of confidential data. While the burden of protecting users against these risks lies primarily in the hands of software and data providers, practitioners must be educated on and vigilant about potential risks specific to AI. Security vulnerabilities specific to AI systems include prompt injection, where malicious instructions override system guidelines, and model poisoning, where harmful behaviors are embedded during training (Owasp GenAI Security Project 2025). Prompt injection typically places responsibility on users and system integrators, while model poisoning requires AI providers to clean training data. One difficulty is that AI systems may act differently during testing than in real-world scenarios, making hidden behaviors difficult to detect (Lynch et al. 2025). It is not implausible to foresee a scenario in which misaligned or selfish actors use prompt injection or model poisoning to falsify or to bias LCA reviews of their products, which could cause a significant undermining of trust in product footprinting. Such manipulation threatens *scientific integrity* and, where falsified results support greenwashing, *sustainable responsibility.* It also threatens *inclusivity and fairness*, since an assessment manipulated in one actor's interest no longer represents the viewpoints of the other stakeholders it should account for, and *conformity*, where confidential data are inadvertently disclosed.

3.3.7 Sustainability

AI presents significant environmental and social risks across its life cycle, unevenly distributed across model types. Energy-related climate change concerns center on computationally intensive generative models, the primary drivers of the post-2022 surge in data centre demand. Transformer-based LLMs typically activate tens to hundreds of billions of parameters, leading to substantially higher training and inference energy demands than the task-specific ML models that dominate current AI-LCA applications (SI 2). Task-specific ML models often have negligible per-run energy burden on commodity hardware. Burden scales with model complexity, a gradient that architectures aimed at improving accuracy, such as retrieval-augmented generation, are expected to steepen (Bao et al. 2026). Although projected data-centre electricity use is expected to remain below 300 TWh by 2030 (Kamiya and Coroamă 2025; IEA 2025), the rate of growth is itself a concern, since demand for AI compute is outpacing grid infrastructure, renewable build-out and efficiency gains, creating demand for rapidly deployable fossil-based generation that offsets gains made elsewhere (Hosseini et al. 2025). Impacts also arise beyond operational energy. Device production carries its own burden (Lacoste et al. 2019; Bordage et al. 2021; Luccioni et al. 2023). The extraction of rare-earth metals for AI hardware raises concerns about resource depletion, which may be amplified by rebound effects (Luccioni et al. 2025). Mineral resource requirements and waste management challenges become more pertinent with the higher computation requirements of large-scale AI systems (Falk et al. 2026). Water consumption for server cooling and device manufacturing also affects water availability (Li et al. 2025), while communities near data centres are exposed to local air-quality and noise impacts (Gour et al. 2026; Wheeler et al. 2026). Social risks are less sensitive to model type, attaching to hardware supply chains and data work rather than compute intensity. These include unsafe mining conditions, child labor, low wages in manufacturing, and hazardous e-waste recycling (Subramanian and Yung 2018; Traverso et al. 2024; Carr-Wilson et al. 2024). Precarious labor in AI development, risks of job displacement and the widening of the digital divide by reinforcing inequalities further compound these social risks (Solaiman et al. 2023). Assessing these environmental and social impacts of AI use in LCA require closer examination, following the standardized frameworks such as ITU-T L.1801 recommendation (The International Telecommunication Union 2026), for which recent corporate assessments provide a useful foundation (Elsworth et al. 2025; Mistral 2025; Watershed 2026). These burdens create a distinctive tension with the LCA value of *sustainable responsibility*. In the LCA context, AI can support

sustainability by improving efficiency and knowledge dissemination (Rolnick et al. 2023). However, its direct environmental and social impacts must be carefully assessed to ensure that they do not outweigh these benefits (Horner et al. 2016; Bremer et al. 2023). Indeed, AI compute falls outside the system boundary of the assessments it supports, so the burden of an AI-assisted LCA is borne by the environment the study is meant to inform, without appearing anywhere in its results: a study may recommend a lower-impact option while its own burden is disproportionated to the decision at stake. In addition, social risks such as potential workforce reduction and the exclusion of vulnerable practitioners due to the AI divide (see Sect. 3.4.2) appear increasingly pressing: by concentrating AI-assisted practice among well-resourced actors, they threaten *inclusivity and fairness*, as the range of interests and viewpoints represented in LCA studies narrows accordingly. Levers to address these risks, including "Frugal AI" and matching model capability to task requirements, are elaborated in Sect. 4.3 and 4.4.

3.4 Identification of organizational implications of using AI in LCA

3.4.1 Expected transformations in LCA roles and work practices

The integration of AI in LCA is poised to transform LCA stakeholders' roles and work practices by automating processes, enhancing analytical capabilities, and reshaping decision-making structures. LCI database developers can use AI for large dataset handling, data preprocessing, harmonization, error detection, and gap-filling, reducing inconsistencies and improving reliability. LCIA method developers may refine impact characterization models for broader coverage of flows and regionalized CFs, while LCA software developers can introduce scalability through AI-assisted features like automated background data matching. These advances will boost practitioner productivity but also increase the volume of studies, requiring reviewers to develop strategies for validating AI-generated analyzes (AI4LCA Workshop 2026). As AI becomes embedded in LCA workflows, interdisciplinary training will be essential for increasing the AI literacy and computational skills of LCA stakeholders. Regulatory authorities must ensure transparency, methodological rigor, and ethical safeguards, requiring new guidelines for AI. Decision-makers and users will gain dynamic, real-time sustainability insights, accelerating LCA adoption in industry and policy. Public engagement may increase as AI simplifies sustainability reporting and product footprint communication. However, concerns about AI opacity, biases, and evolving skill requirements call for a balanced approach.

Recent progress in commercial AI-LCA applications for automating LCA tasks suggests that this trend may continue in the short term, however, validation of AI-generated results will still rely on human oversight, shifting roles from data collection to supervising algorithms and reviewing outputs. AI integration promises efficiency gains and wider LCA adoption by reducing resource needs. However, studies of AI-enabled knowledge work show that these efficiency gains frequently lead to work intensification, expanded task scope, and blurred boundaries between work and non-work, increasing the risks of cognitive overload and burnout if left unmanaged (Lee et al. 2026; Ranganathan and Maggie Ye 2026). With increased demand for LCA studies, employment levels should remain stable, but work roles will evolve significantly, and limited access to AI may deepen inequalities within the LCA community, particularly for stakeholders in the Global South and senior members (see Sect. 3.4.2). Rapid adoption in LCA software will highly facilitate accessibility but must avoid long-term interoperability issues. In the long-term, human intervention might be reduced, with roles shifting toward strategic interpretation (Xing 2025), alongside ethical concerns about AI autonomy in LCA studies. Therefore, education and regulations will be crucial to align AI use with LCA best practices.

3.4.2 Regional disparities and the AI-divide

The integration of AI in LCA offers opportunities to enhance LCA practices, but its uptake remains uneven globally due to the AI divide, i.e., disparities in access to relevant training data, AI infrastructure, AI expertise, and economic capacity (World Bank 2025). Restricted access to AI infrastructure and expertise is a direct consequence of the existing digital divide: while more than 90% of individuals in high-income countries used the internet in 2022, only one in four did so in low-income countries (World Bank 2025). In addition, the high licensing costs of LCA software and proprietary AI systems further limit AI uptake for LCA stakeholders from emerging economies, excluding them from innovation.

One major concern is the dominance of LCA data and methodological assumptions from developed countries, which shape AI training and outputs, embedding Western-centric biases in areas such as energy mix, industrial processes, and regulations (Georgiou 2025). This representation bias creates challenges for practitioners in the Global South, as most LCA studies and peer-reviewed data originate from developed nations (Amarasinghe et al. 2021; Aryan et al. 2023). It leads to biased AI outputs that replicate assumptions unsuitable for emerging economies, risking misleading or irrelevant results (Arena 2000; Brent et al. 2002). Therefore, AI models lack representativeness, overlook local supply chains, informal economies, and environmental

stressors, and often apply one-size-fits-all assumptions that ignore regional differences in infrastructure and electricity grids (Brown et al. 2025). Data scarcity further drives this representation bias, as systems default to European averages, reducing reliability and fairness (World Bank 2025).

Addressing these challenges requires promoting open-source LCA and AI tools, investing in local data generation, fostering regional and global collaborations to diversify databases, and establishing ethical guidelines prioritizing fairness and contextual accuracy (United Nations Executive Office of the Secretary-General (EOSG) 2023). Without such measures, regional disparities risk deepening existing inequalities in sustainability science and practice. AI-powered LCA can be transformative, even surpassing human expertise, which is also biased, but only if its foundations, i.e. data, access, and modeling assumptions, are equitable and inclusive.

3.4.3 AI-driven decision-making: autonomy vs. human oversight

AI involvement in decision-making can be viewed as a spectrum, ranging from full AI autonomy where decisions are executed entirely by AI without human oversight to human-in-command approaches, where humans retain control and AI acts as an advisor. Full autonomy allows automation, scalability and reduces human-induced bias, as AI can capture consensus better than humans as it can be trained on more data than an individual can personally experience (Celli and Spathoulas 2025). However, autonomous systems are vulnerable to computational biases caused by heterogeneous data, simplified representations, incorrect inputs, and algorithmic issues such as overfitting or outlier treatment, and may lead to systematically inaccurate results (Schwartz et al. 2022), or small errors cascading to cause systemic issues (Miedema et al. 2026). Human supervision may take different levels of involvement. Human-in-the-loop (HITL) systems involve the capability for human intervention in every decision cycle of the system (European Commission 2019). HITL systems provide transparency and allow users full control to override undesirable AI decisions, at the cost of introducing the risk of high time intensiveness and the risk of allowing human errors to propagate. Human-In-Command (HIC) systems provide the capability for humans to oversee the overall activity of the AI system (including its broader economic, societal, legal and ethical impact) and the ability to decide when and how to use the system in any particular situation, including deciding not to use a system. Practical use case of AI involves human evaluation throughout development and production and may take a higher or lower involvement level depending on the application or context in which it is used. However, to reduce the risk of errors and unethical behaviors especially when used in full autonomy, the performances of AI systems need to be evaluated, as demonstrated in a recent work on evaluating LLM performance in LCA (Donaldson et al. 2025). This early high-touch evaluation can inform design choices (e.g. adding more context or adding a citation-checking stage) that can mitigate shortcomings of models or mistakes in implementation or help determine under which circumstances a system adds value. For some LCA tasks, evaluation can be performed against labelled benchmark datasets. However, publicly available benchmarks risk data contamination, where the labelled answers leak into model training data, inflating measured performance. For other LCA tasks, what constitutes a good decision is complex in LCA, as many LCA decisions are inherently subjective. In some cases, value choices in LCA cannot be deemed true or false but only more or less justifiable (Weidema 1997). Therefore, AI decisions may be evaluated for plausibility, i.e. to align with what an LCA practitioner could reasonably have decided. Such LCA-specific AI evaluation framework has not yet been defined, and future work is needed to guide AI autonomy in an LCA context. Lastly, and possibly the key deciding factor in decision making is accountability. In most/all contemporary jurisdictions a human remains accountable for decision making, not an autonomous AI system (Giannini 2023). This makes granting of full autonomy by an organization to an AI system potentially highly problematic in the event of an issue ever arising.

3.4.4 Expansion of AI: shaping tomorrow's social LCA?

Despite the growing interest in AI across sustainability research, its application in S-LCA remains limited and largely exploratory. In contrast to environmental LCA, as S-LCA relies predominantly on qualitative, text-based information, making semantic interpretation and natural language processing (NLP) particularly important. AI has the potential to strengthen the robustness of social impact assessment, by addressing persistent challenges in collecting sensitive, dispersed, or context-specific data (Grubert 2018). AI can mine information from CSR reports, social media, worker feedback systems, surveys, interviews, and public records, offering insights where direct field data is scarce. Beyond data collection, AI enables pattern recognition across large qualitative datasets and rapid literature mapping, supporting the identification of stakeholder narratives and emerging social risks. NLP can automate the analysis of open-ended texts, making qualitative data processing more efficient and scalable, while enabling real-time monitoring of complex social trends and risks for informing more inclusive and evidence-based decision-making (Solaiman et al. 2023; Baldassarre et al. 2023). Where S-LCA differs

from environmental LCA is that systems might incorporate personal data and be subject to training on data carrying social biases, making privacy and accountability central risks that must be mitigated for. The feasibility of AI integration varies across S-LCA steps. As illustrated in Figure S3; SI 1, early phases such as qualitative data collection and stakeholder categorization require high human supervision and exhibit low trust levels due to ethical and contextual complexities. In contrast, structured tasks like system comparisons and reporting show higher trust levels, allowing AI to provide reliable support with limited validation. Potential applications include data mining for social indicators, automated stakeholder mapping with sentiment analysis, predictive modeling for impact forecasting, and scaling assessments across products or regions. NLP can also harmonize terminology and AI-powered interfaces could enable more interactive and accessible S-LCA tools. However, these innovations carry risks, including bias in training datasets, algorithmic opacity, and loss of local specificity. Overreliance on generalized models may obscure nuanced realities in socially complex contexts. Therefore, integrating ethical guidelines and participatory approaches is essential to ensure that AI-enhanced S-LCA tools remain inclusive, transparent, and context-aware.

3.5 Critical analysis of AI-LCA applications

Figure 3 displays the score distributions for 145 AI-LCA applications for each identified criterion for the thematic categories: technical maturity, potential to enhance LCA practices, operational feasibility and ethical risks. Correlation analysis across criteria (ranging from −0.62 to 0.47 with an outlier at 0.73) indicates that the criteria are largely independent, each providing distinct insights into the applications (Figure S5; SI 1). The only notable exception is the stronger correlation (0.73) between technical readiness and ease of use, suggesting that more mature AI-LCA applications tend to be easier for typical LCA practitioners to use without requiring specialized skills. The scores and explanations for each application and criterion are provided in SI 2.

Regarding *technical readiness*, most AI-LCA applications remain at the proof-of-concept stage and are not fully integrated into LCA workflows, reflecting the predominance of academic applications. In contrast, validation practices are relatively strong. Most applications, particularly from academia, implement automatic output validation, supporting robust result checking and LCA automation. Only 12% of the applications lack documented or implemented validation, indicating broad recognition of the importance of result verification. However, human validation is rarely considered (only 7%).

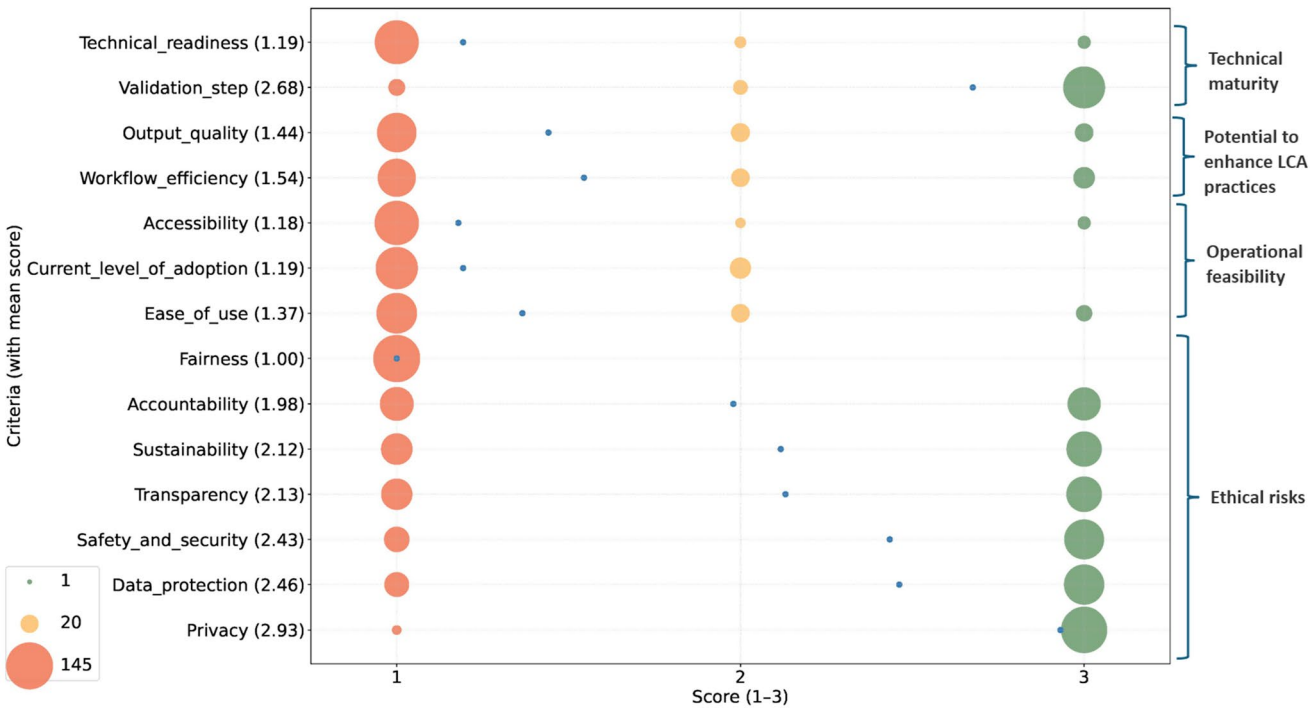


Fig. 3 Score distributions for AI-LCA applications across evaluation criteria. The distribution of scores (1 = lowest performance (red) to 3 = highest performance (green)) is shown for identified AI-LCA applications and for each criterion covering technical maturity, potential to enhance LCA practices, operational feasibility, and ethical risks. Bubble sizes are proportional to the number of applications receiving each score. Mean scores are indicated by the number following each criterion name and are represented by a blue dot

Although AI-LCA applications frequently claim gains in *workflow efficiency* and *output quality*, these improvements are rarely assessed quantitatively against current LCA practices. Only a limited number of academic studies explicitly measure *time savings* (Hou et al. 2020; Zhao et al. 2021; Balaji et al. 2023a, b, 2025a, b; Deng et al. 2023; Di Bari et al. 2024; Preuss et al. 2024; Gachkar et al. 2025; Xing et al. 2025) or demonstrate superior *output quality* relative to conventional approaches (Hou et al. 2020; Dai et al. 2022; Balaji et al. 2023b; Jain et al. 2023; Kleinekorte et al. 2023; Cullen et al. 2024; Xing et al. 2025; Wang and Ye 2025).

Operational feasibility remains a major barrier to inclusive adoption of AI in LCA. Most applications are neither easily *accessible* (code not open access, limited documentation, licensing fees) nor *easy to use* (need for advanced programming skills). Only a small subset of academic studies (Goridkov et al. 2024; MacMaster and Sinistore 2024; Płoszaj-Mazurek and Ryńska 2024; Aslan et al. 2025; Halli et al. 2025) provides user-friendly interfaces such as chatbots or online demonstrations, and a few offer fully open-source, well-documented, and low-cost solutions (Zhao et al. 2021; Portolani et al. 2022; Dai et al. 2022; Balaji et al. 2023a, b; Cullen et al. 2024; Morand et al. 2024). Consequently, overall *current level of adoption* remains low, as most applications represent early-stage research rather than deployed tools.

According to our pre-defined mean value intervals (defined in Sect. 2.5), *ethical risks* associated with AI use in LCA are assessed high for *fairness*, *transparency*, *accountability* and *sustainability*; moderate for *safety and security* and *data protection*; and low for *privacy* (see blue dots in Fig. 3). Low *fairness* scores for all the applications reflect structural barriers related to AI divide (limited accessibility, lack of user-friendly interfaces, English-only documentation), and representation biases for high income regions and incumbent companies in training data. *Transparency* is limited in approximately half of the applications due to black-box models, insufficient methodological documentation, missing performance metrics, or lack of uncertainty analysis. *Accountability* is also weak in roughly half of the applications, primarily due to the frequent limited explainability and absence of discussions on liability or enforceability. *Sustainability* risks are polarized, with lower scores for applications relying on energy-intensive large language models, non-open-source tools, or requiring advanced technical skills and higher scores for lightweight, low-computational approaches. *Data protection* is adequate in most applications (76%) as training data are transparent and properly licensed but remain weak where proprietary data or non-private AI platforms are used. *Safety and security* scores are low for 27% of applications due to missing reported safeguards (such as security protocols, access control, or human oversight) and reliance on public or pretrained AI models. In contrast, 73% score high because they use internally developed, low-exposure models, although security measures are often not explicitly documented (Slapnik et al. 2015; Marvuglia et al. 2015a; Song et al. 2017; Hou et al. 2018, 2020; Severson et al. 2019; Liao et al. 2020; Abdella et al. 2020; Zhao et al. 2021; Dai et al. 2022; Di Bari et al. 2024; Martínez-Ramón et al. 2024; Morand et al. 2024; Nikkhah et al. 2024; Jha et al. 2025). *Privacy* risks are minimal overall, except in a few cases involving identifiable personal data for emissions estimation or personalized recommendations (Zhao et al. 2019; Froemelt et al. 2020; Yan et al. 2021).

As 88% of the reviewed applications originate from academia, the overall trends described above largely reflect academic practices. While concerns related to fairness and accessibility are similarly high across academic and industrial applications, trends for industrial applications diverge for approximately half of the evaluated criteria (Fig. 4B). Most industrial applications report production-ready tools with real-world use cases, indicating high *technical readiness*. However, 65% receive low *validation* scores, as publicly available documentation seldom details validation procedures and full systems were not directly accessible for our review. Industrial applications primarily demonstrate gains in *workflow efficiency*, with substantial documented time and resource savings, whereas improvements in *output quality* remain less clearly documented. In terms of operational feasibility, 71% of industrial applications provide user-friendly interfaces. Their *current levels of adoption* are slightly higher than those of academic applications, with approximately 65% showing moderate uptake supported by customer stories, partnerships, or selective enterprise deployment. However, their *accessibility* seems constrained by licensing costs. Compared with broader trends, industrial applications exhibit higher ethical risks for *sustainability*, *transparency*, and *safety and security*. *Sustainability* risks arise mainly from widespread reliance on large language models with high computational and energy demands. *Transparency* risks stem from proprietary or undocumented training data, black-box models with limited technical disclosure, and the absence of uncertainty analysis. *Safety and security* risks are heightened by the use of public or pretrained models deployed via cloud-based APIs, which increase exposure to external vulnerabilities and often lack clearly documented safeguards.

Figure 4A focuses on the three most frequently addressed LCA workflow steps. Estimating missing LCI data and predicting impact scores are predominantly associated with academic applications and thus exhibit trends similar to those observed in academia (Fig. 4B). Conversely, mapping background processes is mainly represented in industrial

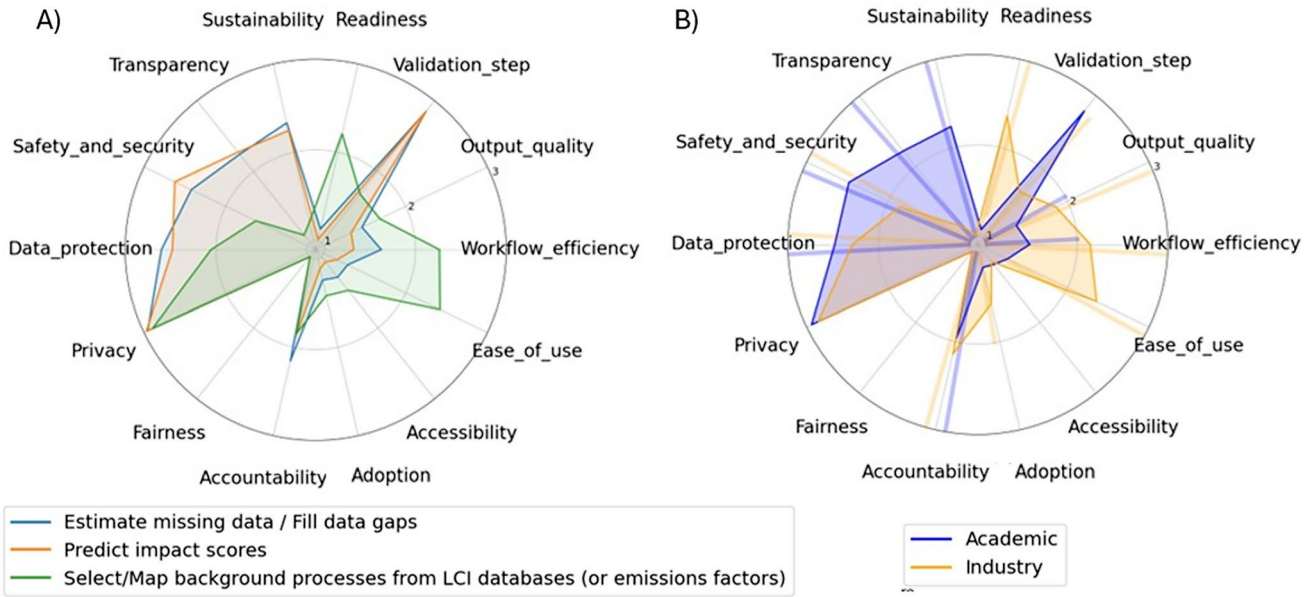


Fig. 4 Mean criterion scores for (**A**) a subset of AI-LCA applications covering only the three most frequently addressed LCA workflow steps (predicting impact score, estimating missing LCI data, and mapping background processes), and (**B**) all AI-LCA applications categorized as industrial or academic. For (**B**), the bars on each axis represent the interquartile range (first to third quartile) of scores for academic applications (blue) and industrial applications (orange). Readiness = technical readiness; Adoption = Current level of adoption

applications and shows corresponding industrial trends (Fig. 4B).

3.6 Criticality levels of identified ethical risks of using AI in LCA

The critical analysis indicates that AI-related risks of using AI in LCA concerning *accountability*, *fairness*, *transparency*, and *sustainability* are high. This is because most applications score poorly on these ethical risks, leading to mean values lower than 2.2 (Fig. 3). Altogether, these risks threaten all LCA ethical values. Therefore, AI use in LCA presents a high level of risk to all LCA ethical values (Table 7). Two LCA's core values, *transparency and reproducibility* and *scientific integrity* also emerged from the survey as the most important and most likely to be compromised, showing that the perception of the respondents is in line with these findings (see bottom lines of Table 7, and Table S3; SI 1). In contrast, the high LCA-related risk levels identified for *coherence*, *sustainable responsibility*, *inclusivity and fairness*, *completeness* and *conformity* exceed the risk levels perceived in the survey. This discrepancy likely reflects the lower importance attributed to these values by respondents and therefore the reduced concern, or "fear", associated with their potential compromise. For *conformity*, the difference may also stem from the survey's narrow definition (ISO conformity only), which may have led respondents to overlook its link with Data protection concerns.

4 Discussion

4.1 Limitations of our study

The review to identify AI-LCA applications for technical mapping and critical analysis covers literature published up to December 2025 and thus does not reflect more recent developments. The review was restricted to sources accessible by the authors or the public, constraining coverage of industrial applications that are often undocumented. Given the exploratory aim of providing a first, structured, and multi-dimensional assessment of AI integration in LCA to inform future guidance, a semi-systematic review was sufficient, while a more comprehensive and stakeholder-inclusive mapping is envisaged as a follow-up work to support broader standardization and governance efforts. The LCA workflow steps used to map AI-LCA applications reflect the authors' understanding of current practices and may not fully capture the consensus within the LCA community. Furthermore, the assignment of AI-LCA applications to LCA workflow steps represents the best estimates based on available documentation, which was often limited, particularly for industrial applications.

The survey results ($n = 89$) provide valuable insights into current perceptions and practices with the target for participants between 30 and 100 achieved for this early testing phase but are not statistically representative of the entire global LCA community. Indeed, the respondent pool is skewed toward researchers and practitioners contacted

Table 7 Risk analysis by LCA values and by AI values threatened by the use of AI in LCA

Level of risk by AI value (based on Figure 3)	**Ethical values of LCA** / **Ethical values of AI**	Transparency and reproducibility	Scientific integrity	Coherence	Sustainable responsibility	Inclusivity and fairness	Completeness	Conformity
High	Fairness		x		x	x		
High	Accountability	x	x		x			
High	Transparency	x	x	x			x	x
High	Sustainability				x	x		
Medium	Data protection	x						x
Medium	Safety and security		x		x	x		x
Low	Privacy							x
	Level of risk by LCA value	**High***	**High***	**High**	**High**	**High**	**High**	**High**
	Perceived importance of each LCA value (survey)	+++	+++	++	+	+	++	+
	Perceived risk of AI use in LCA for each LCA value (survey)	+++	+++	++	++	++	+	+

An "x" indicates that an LCA value is potentially threatened by a given AI-related risk when using AI in LCA (Sect. 3.3). The mechanism underlying each linkage is stated at the end of the corresponding subsection of Sect. 3.3. The perceived importance and perceived risk of AI use in LCA (from survey) are coded as +++ (high), ++ (medium), and + (low). The * symbol marks agreement between assessed criticality levels and perceived risk levels

Color Key: Red: High risk, Yellow: Medium risk, Green: Low risk

Symbols: +++: high, ++: medium, +: low

x: An LCA value potentially threatened by a given AI-related risk when using AI in LCA

through UNEP and ACLCA networks mostly, introducing a self-selection bias toward digitally literate professionals who are already engaged with global institutional frameworks. The survey was designed with some open questions to leave the respondents space to write and express their ideas on this novel aspect of AI in LCA. However, the use of ranking questions rather than category may have biased the perceived importance and risk levels of ethical values. Additionally, the absence of detailed background information and standardized definitions may have resulted in partially uninformed responses. Therefore, this survey provides a good first basis to better understand current perceptions and practices on AI in LCA, but the design of future surveys could be improved. As ethical values for LCA are not formally codified to our knowledge, the identification of LCA ethical values was exploratory and provisional. Further in-depth analysis would be required to strengthen and validate this identification. While many ethical risks of using AI overlap with known social impacts of AI (Paes et al. 2023), some social issues, such as usurpation of jobs by automation, technological overdependence, and injustice, remain only partially addressed, highlighting current blind spots in our ethical risk assessment (Figure S4; SI 1). Additionally, the criticality levels assigned to ethical risk by LCA values are strongly influenced by the two following points that could be refined in the future: (i) the authors' definitions of low, medium, and high-risk thresholds, and (ii) mappings between AI ethical risks and threatened LCA ethical values that reflect authors' interpretations as there is no consensus in the LCA community.

The literature on the organizational implications of AI adoption in LCA is scarce. Consequently, the identified implications largely reflect author-driven analysis informed by broader AI literature. Rapid advances in AI further limit the ability to anticipate long-term organizational impacts, underscoring the need for more structured and systematic analysis of future organizational implications.

Finally, the semi-quantitative approach for the critical analysis is inherently subjective and relies on criteria and evaluation scales that could be further refined. Validating AI-generated outputs, as captured by the validation step criteria, is a form of uncertainty management that could increase transparency scores; however, this interdependency is not accounted for in the present analysis. The evaluation partly relied on large language models, which made the work feasible within time constraints but also introduced sensitivity to prompt design, the context provided, and the level of human oversight. To mitigate these risks, most scores were manually validated as well.

Despite these limitations, this work offers an opportunity for reflexive assessment within the LCA community and contributes to clarifying existing workflows, which is an essential prerequisite for the development of efficient and trustworthy AI-enabled LCA automation.

4.2 Degrees of automation and influence on efficiency and effectiveness

The integration of automation into LCA workflows should be understood as a continuum of automation rather than a binary distinction between human-in-command and full autonomy. Different degrees of automation have distinct implications for efficiency and effectiveness and therefore require clear definitions and validation criteria tailored to LCA practice. Many efficiency bottlenecks in LCA stem from structural deficiencies such as the lack of standardized, machine-readable data formats, harmonized taxonomies, metadata conventions, and interoperable databases. An example is mapping product data or bills of materials (BOMs), one of the most time-consuming steps in many LCAs. This task does not inherently require AI but can be accelerated through rule-based automation, i.e., automation based on coding without AI. Where inputs and ontologies are not standardized, any model (AI or not) infers meaning from ambiguous information, increasing uncertainty and validation effort.

Replacing deterministic steps with opaque AI models risks weakening transparency and traceability. Core impact calculations are already executed rapidly through auditable mathematical operations; replacing them with black-box pipelines would undermines confidence in the results. Similarly, end-to-end AI approaches that directly predict impact scores from product characteristics bypass essential intermediate steps such as LCI and LCIA, obscuring modeling assumptions and sources of variability (Portolani et al. 2022; The Swiss Discussion Forum on Life Cycle Assessment 2026). For instance, using generalist AI models directly to estimate an LCA result for a product of a complex LCA model with minimal human input, may be quick and help fill data gaps where domain expertise is lacking. The drawbacks are that end-to-end systems can suffer from challenges in auditability, consistency, explainability and operational cost - especially if scaled. Modular AI architectures that comprise multiple components, including auditable deterministic components, specialized AI models/agents, and - if the problem is not well defined - additional iterative cycles of feedback from the user are likely to have higher upfront costs to design and build, and may have more confined input and outputs. On the other hand, modular systems are likely to be more explainable by being able to trace the path through each component to deliver a result, and more maintainable by leaning on tried-and-tested, introspectable software components. The latter also better aligns with requirements for transparency and reproducibility expected in LCA. The most actionable information for an LCA practitioner isn't in the result, but in the steps that lead to it.

AI-generated interpretations must remain explainable and auditable, particularly because LCA data quality involves not only completeness but also judgement regarding representativeness, proxy selection, modeling scope, and ethical data use. Effectiveness in LCA should be evaluated by whether automation strengthens the quality, transparency, and defensibility of LCA results, not merely their speed. Beyond efficiency gains, AI may also act as a lever to strengthen the LCA process itself by making workflow steps more explicit, formalizing ontologies, and encouraging critical reflection on modeling practices. In addition, the capability of AI to generate a high number of plausible scenarios could also be deliberately leveraged as an additional lens to explore and better understand uncertainty, rather than being treated solely as a drawback (AI4LCA Workshop 2026).

Because of the relatively easy development and the possibility to model a wide range of workflow steps, most industrial AI-LCA applications are based on GenAI. GenAI has improved in terms of performance but still has limitations, such as its stochastic nature and hallucinations. Human oversight currently remains essential wherever modeling requires context or involves value choices, but human validation remains rare (for only 7% of academic papers in the critical analysis).

Agentic systems can autonomously perform sequences of actions, for example, by supporting data collection, inspecting anomalous results, or coordinating multiple analytical tasks, but their increased autonomy also amplifies risks related to transparency, explainability, validation, and accountability. These risks are further compounded when multiple AI models or agents are chained together, requiring explicit attention to uncertainty propagation across the workflow.

Consequently, meaningful efficiency and effectiveness gains follow a sequential hierarchy to preserve auditability and accountability while redirecting practitioner time toward higher-value analytical tasks:

1. Support standardized data collection and reporting,
2. Apply rule-based automation for deterministic tasks, and.
3. Subsequently, integrate modular AI applications. AI can be integrated to augment expert judgment and interpretation while keeping human-in-command or human-in-the-loop validation where semantics and value choices are central.

4.3 Capacity building: driving AI readiness in the LCA community

AI-readiness means that members of the LCA community have access to resources, possess skills, and shared

principles needed to responsibly select and use appropriate AI tools for a given task, understand their limitations, and manage failures, whether AI is used for automated workflows or under human oversight. Key enabling conditions for AI-readiness in LCA include the following:

- **Technical infrastructure**: access to digital infrastructure and tools to run machine learning models and/or pre-trained (generative) AI models.
- **Skills and collaboration**: AI literacy through targeted training and collaboration between LCA experts and AI developers.
- **Data structure and interoperability**: standardized schemas and ontologies to structure LCA inputs and outputs to be machine readable to AI-enabled systems. This helps to increase the quality of outputs of AI systems and reduce the computational costs by making relevant information more easily retrievable.
- **Verification and auditability**: robust validation protocols ensuring that AI-assisted LCAs remain reviewable, reproducible, and compliant with LCA standards.
- **Evaluation framework**: Benchmarks to assess task-specific performance of different AI models over time, combining automated procedures with human-grounded evaluation where appropriate.
- **Computational proportionality**: the ability to select a model whose capability matches the task, and to estimate the resulting burden. Environmental burden scales steeply with model size and architecture, so a task-specific ML model that performs comparably to a general-purpose LLM within its domain represents a substantially lower-impact choice; where generative models are needed, reasoning effort, batching and model size are adjustable parameters rather than fixed properties of using AI.

Due to unavoidable interdependencies between stakeholders, AI-readiness cannot be achieved by individual stakeholders in isolation; rather, it must be developed collaboratively across the LCA community. Inappropriate or uncoordinated use of AI may generate inaccurate or misleading environmental footprints, leading downstream users to make poorly informed decisions and ultimately undermining the credibility of LCA in the whole market. Validation protocols and cross-stakeholder engagement (such as UN working groups, regulatory alignment and academia-industry partnerships) are therefore essential to address knowledge gaps of individual stakeholders and help ground AI ambitions in practice. When applied responsibly, AI can improve the accuracy, accessibility, and affordability of environmental footprints, potentially increasing their uptake by organizations and regulators. AI-readiness therefore also includes the judgement not to use AI, or to use a smaller model, where this is sufficient. The net benefit of AI-enabled LCA should thus be assessed in terms of its contribution to well-informed action relative to the additional environmental burdens it introduces, in line with the handprint concept (Pajula et al. 2021). Capacity-building efforts should therefore prioritize not only scaling LCA production but also ensuring that efficiency gains translate into more reliable results and greater real-world impact.

4.4 Toward building a global roadmap for a responsible use of AI in LCA

Responsible use of AI in LCA means integrating AI in ways that preserve core LCA ethical values, while avoiding bias, opacity, and misuse. Our analysis shows that the most critical AI-related risks (accountability, transparency, fairness, and sustainability) directly threaten these values, making it clear that guidance and governance for AI in LCA cannot remain optional. A coordinated global roadmap is therefore needed to ensure that AI strengthens, rather than undermines, the credibility and societal value of LCA. Such roadmap should translate general AI and LCA ethical principles into actionable and task-specific guidelines for the use of AI in LCA. Key elements include:

1. **Frugal and need-based use of AI**, deploying AI only where it demonstrably improves LCA practice (Evchenko et al. 2021; Gandikota and Osta 2025). Frugal AI treats resource constraints, cost-effectiveness, environmental impact and scalability as joint design criteria rather than as a trade-off against performance, which aligns closely with LCA's own commitment to sustainable responsibility. In practice this implies preferring rule-based automation for deterministic tasks, task-specific models for well-bounded predictive tasks, and reserving large generative models for tasks requiring open-ended language understanding, consistent with the sequential hierarchy proposed in Sect. 4.2.
2. **Clear documentation**, **reproducibility**, **and independent verification requirements** for AI-assisted LCA workflows, recognizing that these are already weak points in conventional LCA practice (e.g. no disclosure of sensitive data).
3. **Human-in-the-loop validation** for tasks involving contextual judgement or value choices.
4. **Standardized operational procedures and benchmarks** for AI model evaluation tailored for each LCA task (Chen et al. 2026).
5. **Explicit protocols for uncertainty quantification and reporting** in AI-assisted assessments.
6. **Standardized citations** and traceability of AI-generated data and outputs.

Table 8 An illustrative example of an organizational guideline operationalizing the ethical framework established within this paper, to cover points 3 and 4 listed in Sect. 4.4

Task type	Example task	Example of guidelines complying with ethical framework established in this paper
Deterministic tasks	Mapping product classification codes to emission factors / secondary LCIA data libraries	Automation, that could involve AI if needed, with strong testing in development and monitoring of performance in production
Generative tasks	LCA Report writing	Human review required. Ensure results can be independently verified. Ensure that confidential / proprietary data is processed using confidential AI endpoints that not train on data provided.
Value choices	Goal and scope definition, Determining weighting factors for social LCIA methods	High level of human agency required (ex. providing inputs and framing to AI, AI output validation) with participation of diverse perspectives to reduce risks of bias propagation. Ensure all impacted stakeholders, particularly those in socially or economically precarious situations, have sufficient opportunity to contribute to weighting factor determination.

Table 8 provides an illustrative example of how such principles can be operationalized at the organizational level across different task types (deterministic tasks, generative tasks, and value-laden decisions). Full guidelines should be more detailed and adapted to specific LCA applications, sectors, and tools.

In parallel, accountability frameworks must clarify roles and responsibilities across stakeholders (i.e. AI developers, LCA practitioners, software providers, reviewers, and regulators) supported by enforceable mechanisms for liability attribution. Effective governance will require a multi-level approach combining mandatory regulation, voluntary standards, and collaborative oversight, and may ultimately necessitate revisiting ISO 14040-44 to accommodate AI-enabled LCA workflows.

Finally, operationalizing such a roadmap requires continued attention to fairness and sustainability in practice, including equitable access to AI-LCA tools, diversity in training data, and assessment of the environmental and social impacts of AI systems themselves. Together, these actions provide the basis for a global strategy that balances innovation with responsibility and supports the long-term credibility of AI-enabled LCA. The foundation laid in this paper highlights the growing need for a robust strategy and practical guidance to continue evolving.

5 Conclusion

AI has the potential to improve the efficiency and scalability of LCA, particularly for automating repetitive or data-intensive tasks. It also promises to reshape LCA work practices by shifting effort away from manual data handling toward supervision, validation, and interpretation of AI-generated results. However, this study shows that AI integration in LCA currently remains limited and uneven. Uptake by the community is concentrated in general public generative AI tools, used at least occasionally by 70% of surveyed practitioners largely for auxiliary tasks such as literature review and report writing, while 62% never use other forms of machine learning. Most existing AI-LCA applications are narrowly focused on estimating missing inventory data and predicting impact scores, while critical steps such as methodological framing, interpretation, review, and decision support, as well as subjective ISO compliance requirements including functional unit, system boundaries, and allocations, are poorly explored.

The critical analysis indicates that most applications are still at proof-of-concept or early deployment stages, with weak integration into established LCA workflows, despite the emergence of AI-powered LCA software. Commercial tools are the exception in terms of maturity, being largely production ready. Although efficiency gains are frequently claimed, they are rarely supported by empirical evidence of improved output quality, robustness, or representativeness. This finding suggests that current AI-LCA applications tend to prioritize efficiency over effectiveness, creating a risk that AI may erode scientific integrity if not carefully governed. Operational barriers, including limited accessibility, high technical skill requirements, and the prevalence of proprietary AI-LCA commercial tools, further constrain the adoption of AI in LCA. Extending the critical analysis toward a more multi-dimensional mapping across the LCA workflow steps, including the level of automation (rule-based, human-in-command, or full automation), would improve the understanding of the maturity of AI-LCA applications in terms of degree of automation, and enable more relevant interpretation of the state-of-art.

From an ethical perspective, AI-LCA applications show high risks related to fairness, transparency, accountability, and sustainability. These AI risks directly threaten all core LCA values, especially transparency and scientific integrity, as identified by the community survey as both the most important and the most vulnerable to AI use. The opaque nature of many AI models, the potential for bias in training data, the weak accountability frameworks and the use of energy-intensive AI models could undermine trust in LCA results if left unaddressed. As 88% of the reviewed applications originate from academia, these trends predominantly

reflect academic practice; industrial tools diverge in showing higher risks for sustainability, transparency, and safety and security. Additionally, the risk of the AI divide exacerbates regional disparities, particularly for practitioners in the Global South, where access to AI tools, data, and expertise remains limited.

Introducing AI into LCA workflows brings with it potential real-world exposure to novel forms of risk relating to data protection, security and other risks (Sect. 3.3). For example, new risks for data protection and accountability include liability for the use of copyright data in the training phase for new models or the risk of inadvertent disclosure of confidential data in the use phase of AI systems. Transparency and human validation remain important to ensure trust and prevent against bias in LCA results, especially given the models largely operate as black-box engines and responsibility is shared among stakeholders, including in the case of autonomous systems. Where sensitive personal or demographic information is present, particularly in S-LCA domains, paying attention to privacy-preserving mechanisms that prevent disclosing or training on sensitive information is an important concern to fairness and privacy. These risks are significant but *are* manageable with sufficient attention. At the organizational level, concrete but demonstrative examples of technical measures include hardening systems against AI-specific threats such as prompt injection and model poisoning. Non-technical measures, such as human validation of AI outputs and human-in-command not only offer the advantage of helping to increase trust and minimize errors but could also for instance help manage costs, find hidden errors, and avoid wasted tokens on poor quality outputs.

The path forward must prioritize responsible AI integration in LCA, where efficiency gains are harmonized with ethical principles and organizational readiness, by developing responsible guidelines for the use of AI in LCA and implementing robust governance mechanisms. As stakeholders are interdependent, such guidelines cannot be developed in isolation: they require coordinated commitments across the community. Developers of AI-LCA tools and methods should favour accessible implementations with publicly available documentation, or source code, to maximise transparency. To improve accuracy and fairness stakeholders should tackle representation bias in training data, report their validation procedures, and evaluate applications against standardized benchmarks. Evaluation may include comparison of output quality with current practice and should provide explicit protocols for uncertainty quantification and reporting. To promote sustainability, users of AI-LCA applications, primarily practitioners, should adopt a need-based approach that reserves AI for tasks where it demonstrably improves practice and prefers rule-based automation where it suffices, maintain human validation for value-laden choices such as goal and scope definition, and document where and how AI was used in a study. Governance bodies, including standardization organizations, regulators, and coordinating initiatives such as the Life Cycle Initiative, ACLCA, and ISO, can help consolidate these practices into ethical guidelines and accountability frameworks that clarify liability attribution, support reviewers in developing competencies for validating AI-assisted studies, and foster global collaboration and investment in local data generation to counter unequal access to AI tools, data, and expertise. Machine-readable formats and shared interfaces, possibly mandated by standardization or regulatory bodies, can help ensure that AI systems handle data and understand context, ensuring quality at scale. Through such coordinated commitments, the LCA community can harness AI's potential while safeguarding its foundational values and ensuring that environmental decisions remain grounded in verifiable data. Ultimately, the goal is not merely to adopt AI for its technical capabilities but also to do so in a way that strengthens LCA's role as a trusted tool for sustainability decision-making.

As AI continues to evolve, ongoing dialogue, empirical testing, and adaptive governance will be essential to navigate the complexities of this transformation. More systematic evaluations of LLMs and emerging AI systems such as agentic workflows and RAG will be needed to clarify their appropriate and credible roles in LCA, and to adapt the responsible guidelines as new capabilities and new risks emerge. The insights from this study provide a foundation for future guidance, supporting the LCA community in shaping a roadmap for effective, inclusive, and responsible AI use – one that aligns with global sustainability objectives and upholds the integrity of LCA practice. Collaborative efforts to develop transparent and accessible standardized metrics, frameworks for mandatory disclosure, adoption of sustainable and frugal AI practices would significantly aid in mitigating potential life cycle impacts of using AI (UNEP 2024; Chien et al. 2026).

In addition to overcoming the discussed challenges for an effective integration and adoption of AI in LCA, future work must continue to extend the current discussion to complementary LCA approaches such as consequential LCA, prospective LCA, S-LCA, absolute environmental sustainability assessment (AESA), and life cycle sustainability assessment (LCSA). Although interest in this direction is already emerging, e.g., ensuring reproducibility in industrial ecology (Rankin et al. 2026), and adopting AI for prospective LCA (Preuss and You 2026), additional efforts will uncover further opportunities and challenges.

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