Toward Artificial Intelligence and Blockchain-Enabled Frameworks to Improve Critical Review Control and EPD Verification Process

Javier Martin Echazarreta and Claudia Peña

Abstract This paper explores the adoption of new technologies to improve consistent and reliable verification of environmental performance indicators of products and services. Life Cycle Assessment (LCA) Critical Review (CR) for Environmental Product Declaration (EPD) verification aimed at providing reliable information on environmental performance of products and services. There is a need to improve accuracy, facilitating comparability of results between EPDs, as well as ensure impartiality and transparency of the process. Using Artificial Intelligence (AI) and Machine Learning (ML) for auditing EPD verification processes can establish an effective framework for EPD Program Operators (POs) to validate the work of verifiers, improve the quality of EPDs, and promote continuous improvement and timesaving in the new era of massive EPD publication. AI and ML tools offer the ability to leverage vast datasets and address complex, multidimensional issues in LCA projects. These technologies can validate Life Cycle Inventory (LCI) data by identifying, isolating, and rectifying errors, inconsistencies, and outliers, as demonstrated in numerous case studies. Algorithms can also support the auditing of the CR process, correcting mistakes and preventing distortions by minimizing the risk of human error. The ML framework, aligned with ISO 14071 and ISO 17029 standards, enhances direct and efficient oversight of verifiers, maintaining the impartiality of the process and further reducing the potential for human mistakes. This integration not only improves accuracy but also streamlines the verification process, offering a more reliable and objective assessment of environmental performance. Furthermore, the paper emphasizes the necessity for POs to integrate these new tools to keep pace with emerging trends and future challenges, making EPDs remain effective and relevant.

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1 Introduction

An Environmental Product Declaration (EPD) is a standardized document that shows the environmental performance, e.g., emissions to the end user. An EPD shall be verified by third-party verifier in compliance with the ISO 14025 standard, General Programme Instructions (GPI), and a Product Category Rule (PCR) specified and published by an EPD Programme Operator (PO). In most cases, the EPDs are a pdf file; however, some operators modify the pdf file through an online platform. EPDs are published and registered on the website of the Programme Operator, who sets the rules for the verification and publication of EPDs (ISO 2006).

EPDs are critical instruments used to communicate a product's environmental impacts transparently. Traditionally static PDF documents, their verification requires compliance with international standards (e.g., ISO 14025), GPI, guided by Product Category Rules. However, the exponential growth in data and increasing demand for transparency have rendered manual verification processes inefficient and vulnerable to errors.

EPDs are required in the construction sector for certifying buildings, and as described by Brisson et al., they are recognized around the world as a means of assessing the environmental performance of buildings and facilitating product comparisons. The importance of using EPDs is therefore increasing (Stapel et al. 2024).

The digitization of the EPD format not only improves the effectiveness of EPDs, but also brings significant benefits in terms of accessibility, integrity, interoperability, standardization, and data exchange. It makes it possible to display them in a simple electronic format, the process launched in 2020 leading Eco-Portal displaying all digitized EPDs. The ILCD (International Life Cycle Data) + EPD format developed by the Indata network was considered the most suitable for digitization and included all the information contained in an EPD. Digital transformation—through standardized formats like ILCD + EPD and platforms like ECO Platform—has provided interoperability and data harmonization. Yet, challenges remain in ensuring consistent, high-quality, and scalable verification practices. Artificial Intelligence (AI), machine learning (ML), and blockchain offer a pathway to reimagine EPD verification, ensuring accuracy, transparency, and trust (Pannuti 2023).

Accompanying digitalization, Blanco et al. consider that ML will also tend to drive results toward expected values or ranges that are largely based on past data. Further, digitization is an essential step in the application of AI and ML to a life cycle assessment (LCA) project or verification process (Blanco et al. 2024).

In addition, the manual extraction of data from PDF format requires a resource-intensive task with the risk of introducing human error, confusion, and loss of environmental performance data. To avoid this, most of the EPD programme operators are contributing to a database such as ECO Platform and InData Network to drive digital transformation, reducing costs and human risk of data manipulation (Stapel et al. 2022).

One of the difficulties of digitalization is the different electronics formats no standardized, thus the ECO Platform has developed a web application programming interface (API) where each PO can upload the different results from each EPD to have the data harmonized and available for consultation in the same format. Anyone, who wishes to obtain information from the EPDs and work with the data, should download them from the Eco Platform website (Stapel et al. 2022).

While digitization alone is not enough to improve data quality, digitizing EPDs can help to improve data quality through AI in conjunction with the verification process. Furthermore, machine learning is a subset of AI and involves different mathematical and statistical algorithms linked with an existing data set, the statistical algorithms include, e.g., linear regression, cluster, and principal component as part of the analysis to help the verification process. Therefore, machine learning can be used not only in the LCA project as many papers described, but also it will be used in the critical reviews (Koyamparambath et al. 2022; Rao et al. 2017).

As Ibn-Mohamed et al. contemplated, the complex relationship between environmental factors, emissions, and impact categories, including global warming potential (GWP), acidification potential, eutrophication potential, and human toxicity, can be considered by AI in the environmental impact assessment. As Ibn-Mohammed et al. describe the integration of AI techniques into LCA can support data collection, modeling, analysis, monitoring, and presentation in the stages of a product's life cycle assessment (Ibn Mohammed et al. 2023). In addition, the new techniques can help identify potential errors and deviations in the LCA that may not have been previously identified by the verifier in the first step of the verification procedure.

As Pannuti (2023) considers, the environmental performance of building and infrastructure design can benefit from the EPD digitization process. However, the digitization process is necessary to start using AI in the EPD databases to support the verification process and transform it from a human activity into a hybrid process where human activities may be complemented by AI to improve the quality of data.

As Bogani et al. consider the Artificial Intelligence encompass in most aspect of our lives, however, ethical legal and safety and morals concerns should be integrated with our lives to improve the human productivity and the quality of the works (Bogani et al. 2022).

In addition to improving the quality of EPDs, Gailhofer et al. suggest that AI could be used to improve the detection of fraudulent ecolabels and product declarations. Such use would require third-party certified ecolabeling to start using AI in their procedures for tracking labeled products (Gailhofer et al. 2021).

The important role of AI in the sustainability approach could help address global environmental challenges. However, it will raise unique ethical, legal, and philosophical challenges that need to be addressed (Yigitcanlar 2021).

As Bogani et al. consider AI encompasses in most aspects of our lives, however, ethical legal and safety and morals concerns should be integrated with our lives to improve human productivity and the quality of the verification process. This working paper proposes a framework for the EPD PO to adopt, incorporating new technologies to ensure consistent and reliable product and service assessments. The hybrid verification process will ensure comparability and impartiality of results, reducing the time taken and improving the reliability of EPDs.

2 Methodological Framework

A hybrid framework integrates artificial intelligence, machine learning, and blockchain technologies to modernize and improve the EPD verification process, replacing the current human verification into a hybrid verification process.

The articles identified through Google Scholar were tracked and cited. Those published since 2014 that applied AI to LCA studies and the verification process were identified and screened based on their abstracts and full texts. The current EPD verification process of the International EPD System (IES) was selected as an example module to expand the hybrid process into a real process, based on GPI 5.0.1.

The studies from the LCA and AI perspectives were finally thoroughly evaluated, including those from the ML perspective. The study particularly examines the use of generative and discriminative AI to improve data quality, reduce human error, and strengthen auditability within the context of ISO 14025, ISO 14071, and ISO 17029 standards. It also addresses challenges in ML model development, data bias and proposes a robust methodology for deployment, governance, and sustainability. A deeper focus is given to the contextual variability in EPD results, the attributional nature of LCA models, and limitations to collaborate with the verification process to hybrid framework to reduce the human errors.

2.1 Scope and Design

The research adopts a mixed-method approach integrating:

- Literature review on AI/ML in LCA/EPD contexts from the last 10 years: a comprehensive literature survey of peer-reviewed articles was conducted to assess the current state of machine learning applications in life cycle assessment and their integration in EPD workflows, focusing on automation, accuracy, and standardization.
- Gap analysis of current EPD verification and the hybrid verification process against ISO frameworks: verification processes were benchmarked against ISO 14025, 14071, and 17029 to identify bottlenecks, human limitations, and areas where AI could enhance impartiality, reproducibility, and data transparency.

The focus of this paper is to derive the potential inclusion of AI in the current verification process through the development of a hybrid verification process to improve the current methodologies used by different operators such as IES.

2.2 Workflow Components

The different workflow components not only incorporate AI, but also include blockchain architecture for verification event logging: a blockchain-based system is proposed to capture every step in the EPD verification process, ensuring data provenance, immutability, and third-party validation compliance.

The principal workflow components are:

- The AI/ML model development life cycle should include the data acquisition from existing EPDs, training the model, and it should be validated from the same PCR and complementary Product Category Rule (c-PCR).
- Blockchain architecture for verification event logging.
- Validation frameworks for EPD databases include contextual harmonization methods.

3 Challenges in ML Model Development for EPD Verification

3.1 Data Quality and Annotation Bias

AI model performance in EPD verification is critically dependent on the accuracy and representativeness of the data used for model training. LCA and EPD datasets often originate from diverse and heterogeneous sources, such as regional databases, company-specific inventories, and industry-average data. This heterogeneity may lead to varying levels of granularity, conflicting assumptions, and divergent system boundaries.

The representation of the results from the AI will depend on the:

(1) Heterogeneous sources (e.g., national databases, industry reports): these introduce inconsistencies in functional units, time periods, and background data assumptions, making harmonized training difficult.
(2) Missing metadata or inconsistent units: gaps in metadata or poorly documented data quality indicators hinder effective normalization and model generalization across EPDs.
(3) Annotation bias, due to subjective human interpretation of product systems: This occurs when different practitioners interpret or define product systems differently, impacting the consistency of supervised learning outcomes.
(4) Compliance of the EPD with the GPI, PCR, and c-PCR, because it tends to harmonize the results of the data.
(5) Anomalies or outliers in data that are inconsistent with other data from the same product performed by the same GPI, PCR, or c-PCR.

Despite harmonized Product Category Rules (PCRs), EPDs show contextual differences rooted in regional practices, supply chain configurations, and local LCI datasets. These nuances highlight the critical role of domain-specific human oversight, as automation alone may not adequately reflect the real-world variability or the nuanced boundaries of attributional LCA, and the EPDs may show results aggregated (Köck et al. 2023; Parvatker and Eckelman 2019).

Elouariaghli et al. believe that deep learning and machine learning will be able to improve current databases and generate others for more or less direct use. Thus, improving the quality of databases through better Critical review (CR) is likely to improve EPDs (Elouariaghli et al. 2022).

The algorithms are designed to explicitly isolate anomalies rather than profile normal instances. Two quantitative properties are used: (i) they are in the minority and consist of a smaller number of cases, and (ii) they have attribute values that are very different from those of normal instances (Liu et al. 2008).

As most program operators have a large database where they can search for anomalies in new records or draft EPDs, when AI checks and compares them with the database, the results will be accepted or rejected if an anomaly appears. According to Samariya et al., an outlier is a data point that does not match the rest of the data. One option is to use anomaly detection algorithms based on isolation, such as the isolation forest algorithm (Samariya and Thakkar 2023).

3.2 Algorithm Selection

Choosing the appropriate machine learning algorithm is highly dependent on the type of data, the verification task at hand, and the stage within the EPD lifecycle being addressed. Different ML methods serve distinct roles and some of them in supporting the verification process, from anomaly detection and impact assessment validation to textual analysis of verifier comments. The following algorithms are among the most commonly used, with the following applications:

- Random Forests and SVMs perform well in structured tabular data (e.g., impact indicators): These algorithms are ideal for tasks such as classification of environmental performance levels or detection of outliers in GWP or energy use metrics, where input features are well-structured and labeled.
- Isolation Forest (iForest) can be applied to LCA databases, particularly for anomaly detection, such as identifying outlier processes, suspicious inventory data, or inconsistent environmental impact values.
- Neural networks (CNNs, LSTMs) are suitable for unstructured texts (e.g., reviewer comments): These models help in interpreting textual data from CR reports, enabling automated flagging of inconsistencies or omitted assumptions.
- Generative models (LLMs, GANs) can simulate missing data, reconstruct incomplete EPDs, and generate counterfactuals for review: Such models are especially useful when input data is sparse or when scenario testing is required to estimate ranges of impact.

However, as Neupane et al. (2025) conclude, the algorithm efficacy depends on the life cycle stage being analyzed (e.g., inventory vs. impact assessment) and contextual validity must always be preserved: Algorithms must be chosen to suit the data phase—e.g., inventory generation versus final indicator aggregation and must undergo strict contextual calibration to ensure methodological appropriateness; based on use-case (Neupane et al. 2025).

Meanwhile, Martínez et al. believe that machine learning models can efficiently handle large datasets and complex systems with rigorous model equations. iForest is distinguished from existing model-based distance-based and density-based methods in the following ways; (i) the isolation nature of iForest allows them to build partial models and exploit subsampling to an extent not possible with existing methods; (ii) iForest utilizes no distance or density measures to detect anomalies; (iii) iForest has a linear time complexity with a low constant and a low memory requirement; and (iv) iForest has the ability to scale up to handle extremely large amounts of data and high dimensional problems with a large number of irrelevant attributes (Martínez-Ramón et al. 2024; Liu et al. 2008).

4 Role of Generative AI in Verification Process

The verification process, defined by ISO 14025, has specific requirements to ensure the credibility and transparency of the environmental performance presented in an EPD. These requirements are essential to establish that the environmental information on a product is accurate, reliable, and compliant with the standard.

4.1 Traditional Framework—IES Current Verification Process (Human)

Here's a breakdown of the key requirements for the verification process in a traditional verification according to ISO 14025, 14071, and GPI 5.0.1 from IES:

(1) Considerations from the independence of the Verifier

Third-party verification: The verifier shall be an independent third party with no direct involvement in the development of the LCA project or the preparation of the EPD and no conflict of interest with the organization submitting the LCA project & EPD for verification. The verifier shall act with impartiality and objectivity to ensure that the environmental claims are verified fairly and accurately in accordance with the principles of GPI 5.0.0 Sect. 8.

(2) Competence of the Verifier

According to GPI 5.0.0 Sect. 5.10.1, verifiers must be independent and demonstrate a broad set of competencies. They should have general knowledge of environmental issues relevant to industry and products, along with specific process and product expertise, including familiarity with applicable standards in their verification sector. They must be well-versed in LCA and relevant standards, including ISO 14040, 14044, ISO 14020, ISO 14025, ISO 14071, and EN 15804. Additionally, they need knowledge of the International EPD System, its GPI, and any national or regional licensees involved. Practical experience in reviewing LCAs or verifying EPDs, or similar work, is essential. Finally, verifiers must be proficient in English to comprehend relevant documentation and to produce verification reports. There are also further requirements specific to the type of third-party verifier: individual verifiers and Accredited Certification Bodies.

(3) Review of the Environmental Product Declaration and the methodology used

According to the main objectives of verification described in the GPI 5.0.1 Sect. 8.2.1. The EPD owner uploads the EPD and Excel file of the LCA results (if a machine-readable format is opted for) to the EPD Portal of the PO. The verifier shall do a verification of the accuracy of the life cycle data used to assess the environmental impacts (e.g., energy consumption, emissions, resource use) for both mandatory and optional indicators. The correct application of LCA methodology and calculations, ensuring that the LCA has been carried out in accordance with ISO 14040 and 14044, GPI, PCR, and c-PCR. The transparency of the EPD, ensuring that all data sources are clearly identified and that any assumptions or limitations in the data are disclosed, as well as compliance with environmental standards. In addition to the methodology, the verification includes checking that the company has used consistent functional units and appropriate impact categories (e.g., climate change, resource depletion, etc.), and the system boundaries of the product (what is included in the LCA) should be clearly defined.

(4) Confirmation of Data Quality

The verifier shall assess the quality of the data used in the EPD, ensuring that the data are relevant to the product and system boundary. Reliable and obtained from trusted sources (e.g., peer-reviewed databases or industry-specific data). Any exclusions should be justified, and the verifiers should review the plausibility and accuracy of both the LCA and EPD by assessing precision, completeness, consistency, reproducibility, sources, and uncertainty of the presented information and data. The verifier should also confirm that the EPD owner has established internal follow-up procedures for EPD updates during its validity period, to reflect current environmental conditions and practices. The verifier should also check that the assumptions, estimates, or proxies used in the assessment are reasonable and adequately documented, including geographical coverage, period, and technology coverage.

(5) Adequacy of Environmental Claims

The verifier shall ensure that all environmental claims made in the declaration are truthful, based on accurate data, do not mislead the public, and meet the requirements in ISO 14021 and national legislation.

(6) Transparency and Clarity

The EPD needs to be written and presented in a way which is clear and understandable to all stakeholders (consumers, regulators, etc.).

(7) EPD verification report

The verifier shall complete and upload the EPD verification report based on the EPD verification report template published by the PO. For construction products, the EPD verification report template is mandatory to use as it complies with ECO Platform verification checklist. Additionally, the dialogue between the verifier and EPD owner (or LCA practitioner) from the verification procedure, regarding, e.g., discrepancies or non-conformities discovered during the verification, shall be documented and included in the verification report.

The verifier shall upload the completed EPD verification report to the EPD Portal in the verification process.

A schema describes the sequence of the current verification in Fig. 1.

Besides the previous description of a traditional and current CR, the new framework is fully compliant with ISO standards and GPI of IES; however, it will improve and ensure the process by incorporating the tools of AI at different points transform traditional verification into hybrid verification process. Below we describe the AI tools to be applied in each of them.

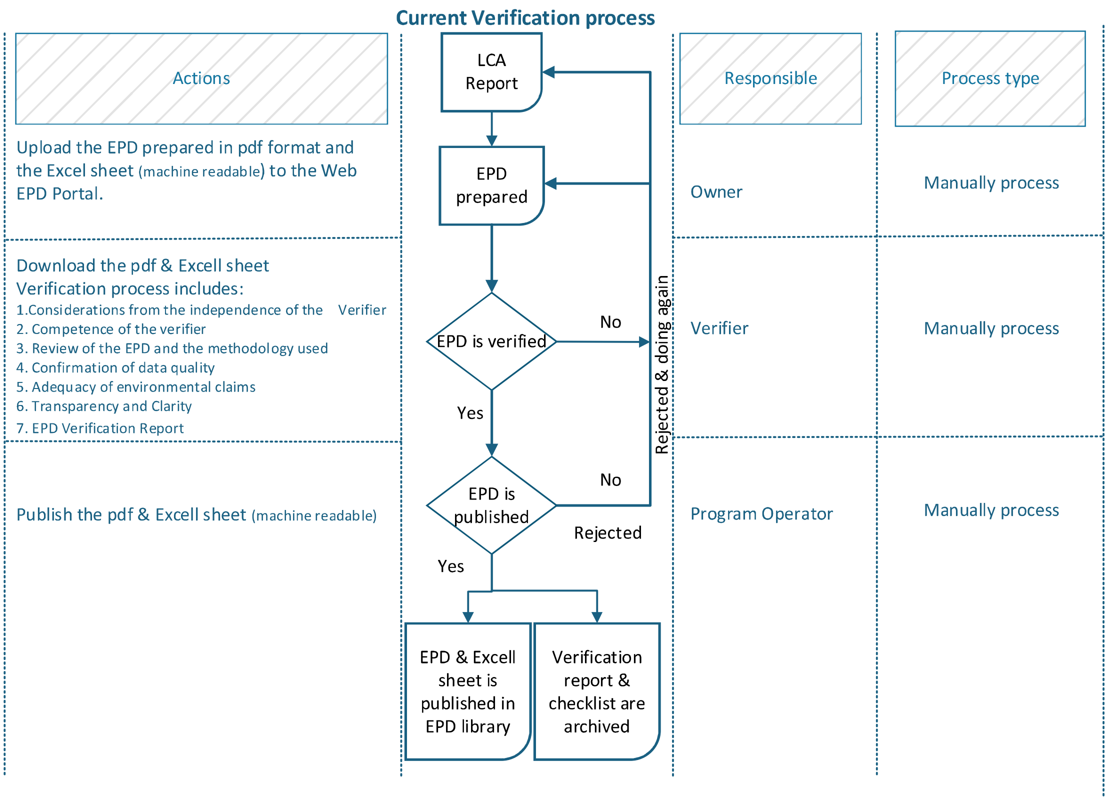

Fig. 1 Flowchart from current verification process

4.2 New Framework—Hybrid Verification Process

To adopt a hybrid process, the system shall be modified in the next steps of the verification process:

(1) The review process of Confirmation of Data Quality, the Review of the EPD, the methodology used, and the Adequacy of Environmental Claims

The verification including the confirmation, accuracy of the life cycle data used to assess the environmental impacts, and the adequacy of Environmental claims shall be done by the Verifier and the AI separately. The tool suggested to make a verification of accuracy of the life cycle data from the EPD, according to the bibliography, could be Isolation Forest to detect anomalies in the new EPD, and the results shall be incorporated as an AI Control Report, which the Verifier could access to validate it with the manual verification report. If a potential deviation is also called an anomaly detected, the Verifier rejects the EPD and asks EPD owner to adjust it and replace the wrong data or confirm it, justifying the deviation with documents to the verifier.

(2) Verification Checklist, Verification Report, and AI Control Report

Finally, the verification checklist shall be filled by the Verifier and the AI application separately; therefore, the PO shall control any potential deviation between the Verifier's report and the AI control report. Finally, if no differences are found between them, the EPD will be published. If some differences are detected, the EPD will be rejected in order to solve any potential deviations.

However, for any reason there is a potential deviation from the existing information in the different databases, and it was checked. The operator and verifier shall be notified by the Owner and justified in the EPD to be published. To safeguard the immutability of the information the AI Report and each step shall be registered in the Blockchain.

A schema describes the sequence of the hybrid verification process (See Fig. 2).

Thus, AI should support the identification of anomalies and data gaps, suggest likely corrections, and summarize documentation, while human experts must verify the alignment of LCA model structures with PCRs, validate regional assumptions, and ensure methodological appropriateness.

All the steps by a PO to adapt AI and ML to modify the current verification process to a hybrid verification process. For example, a flowchart adapted from Elsaid et al. has been designed to use the Isolation Forest for the hybrid verification process. It shows how a PO could use AI—ML to detect anomalies in the EPDs before they are published (Elsaid and Binbusayyis 2024) (See Fig. 3).

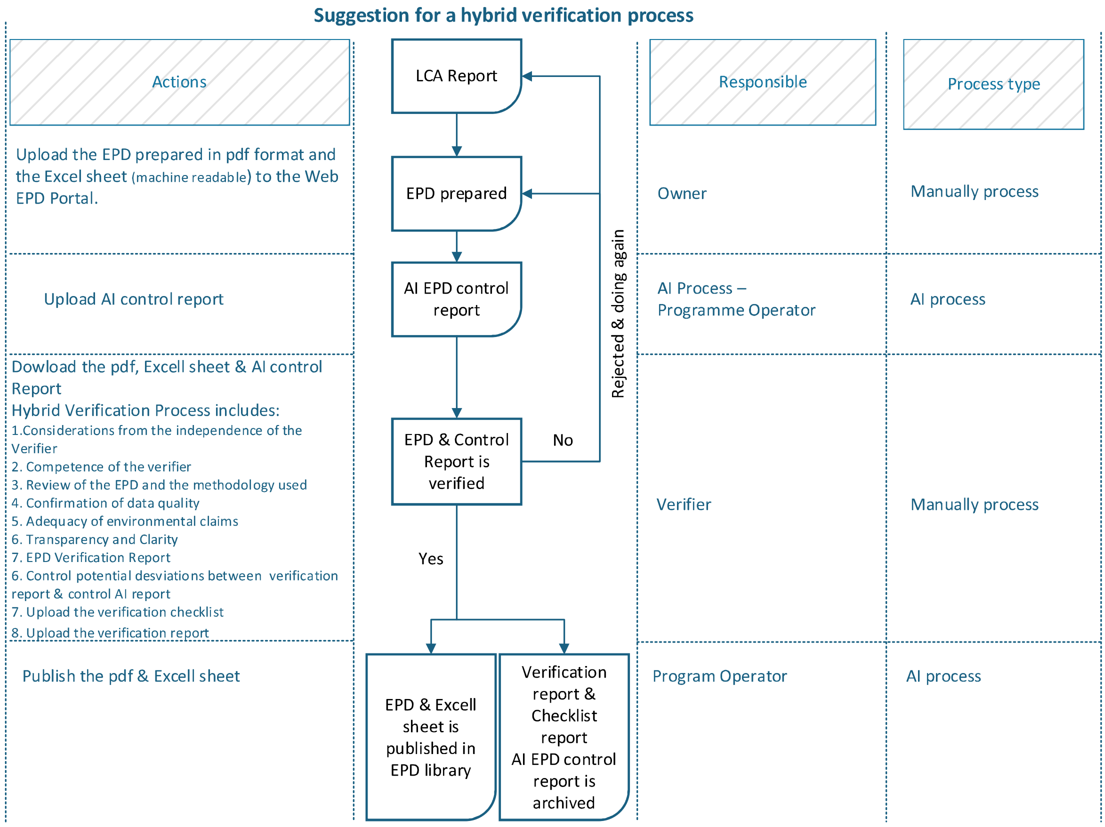

Fig. 2 Flowchart from current verification process

5 Discussion

The integration of artificial intelligence with Isolation Forest and blockchain technologies into the EPD verification process presents a transformative opportunity to improve transparency, reliability, and scalability, characteristics from blockchain described by Olanrewaju et al. AI can mitigate human error through rule-based automation and ML-driven logic checks, reducing the cognitive burden on critical reviewers and minimizing inconsistencies in assessments and detecting anomalies. This is especially critical when reviewing large-scale databases where manual validation is impractical (Olanrewaju et al. 2022).

Anomaly detection is another key benefit, as fairness-conscious algorithms can be trained on diverse, multi-source LCA datasets to identify anomalies and limit systemic bias introduced by regionally or sectorally biased data. However, these benefits are dependent on properly curated training data and robust oversight of the machine learning models applied.

In terms of scalability, AI facilitates automated parsing, normalization, and cross-verification of EPDs, even across different operators and geographies. This capability is essential for platforms such as InData and ECO Platform, which host thousands of digital EPDs and require consistent quality control to maintain public confidence. As a large database is required to use iForest, a PO, e.g., International EPD System

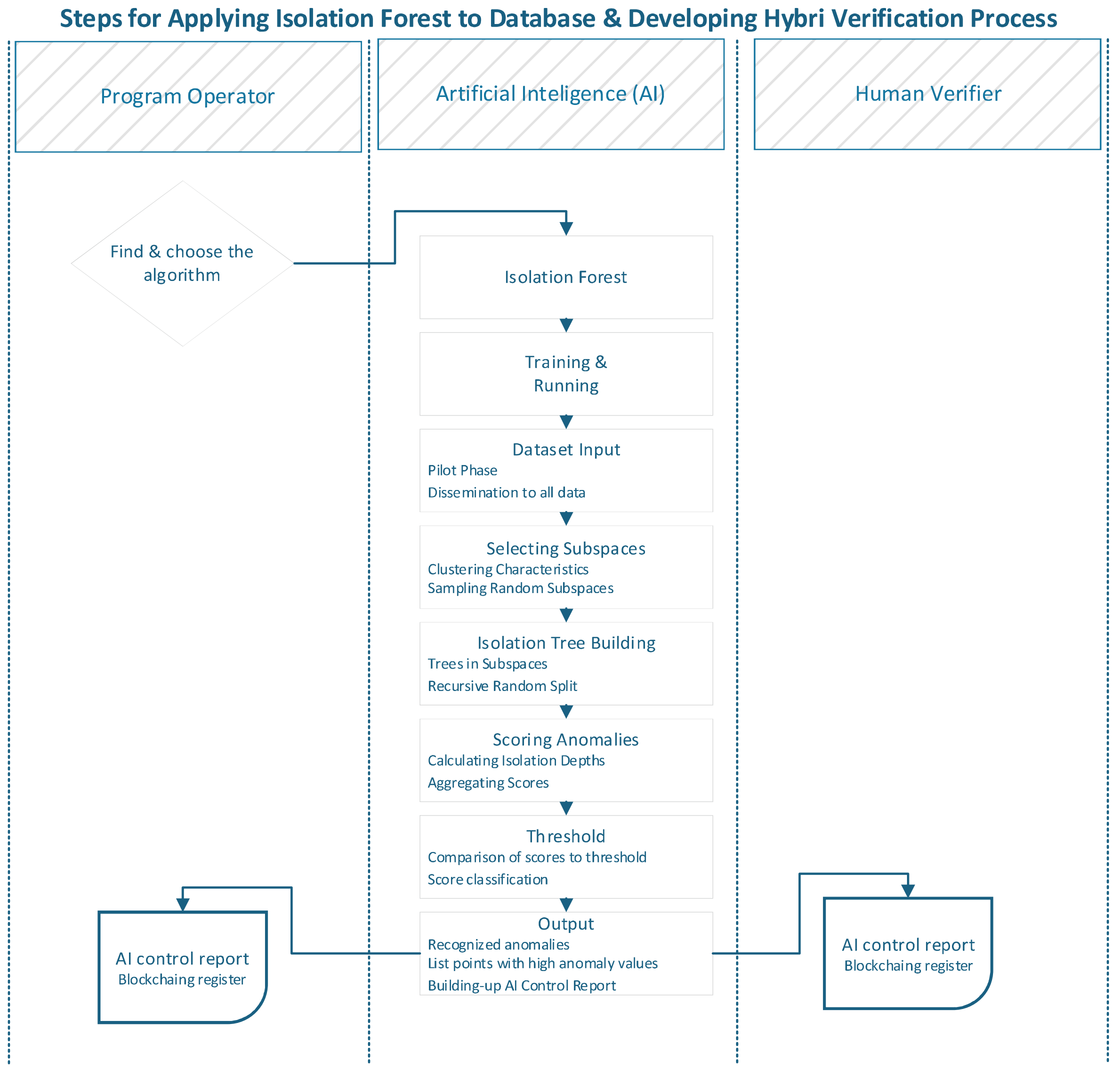

Fig. 3 Flowchart adapted from Elsaid et al. to isolating fores applied to hybrid verification process

with thousands of published EPDs, can use iForest to become an ongoing verification process in a hybrid verification process.

Blockchain complements these capabilities by embedding trust directly into the system architecture. Immutably logging verification events, smart contract execution, and verifier interventions, blockchain provides an auditable, tamper-proof ledger of the verification process. This reinforces impartiality and reproducibility, key tenets of ISO 17029 and ISO 14071 (ISO 17029, 2019; ISO 14071, 2014).

However, full automation is neither feasible nor advisable for all EPD verification tasks. As highlighted by Ghoroghi et al. (2022) and Romeiko et al. (2024), attributional LCAs often involve methodological judgements about system boundaries, attribution rules, and data quality—tasks that require human contextual interpretation and ethical reasoning. AI lacks semantic and domain-specific awareness to resolve these complexities with full autonomy. The verification process should be a hybrid activity to increase productivity and quality of the process (Ghoroghi et al. 2022; Romeiko et al. 2024).

Therefore, the optimal configuration is a hybrid framework where AI supports and augments expert reviewers without replacing the critical role of the human eye. Human reviewers must remain responsible for tasks involving subjective decisions, such as interpreting GPI, PCR, c-PCR, and specific requirements, or evaluating methodological assumptions in different regional contexts. AI, on the other hand, can be entrusted with repetitive, structured tasks such as data quality checks and anomaly detection.

In summary, while AI technologies such as IForest and blockchain greatly enhance the efficiency and auditability of EPD verification, the human element remains indispensable for ensuring contextual accuracy and upholding ethical standards.

6 Conclusions

A hybrid verification associated with the use of a blockchain framework that integrates AI with traditional verification processes can indeed strengthen the integrity and reliability of EPDs. Some of the benefits of using the new framework are: (i) Increased accuracy: AI-ML tools quickly analyze large datasets and identify potential anomalies or inconsistencies in the data reported in EPDs; (ii) When an anomaly is detected, the verifier can focus on more complex assessments or conduct an analysis of the cause of the anomaly; (iii) ML algorithms can quickly identify patterns and trends in environmental impacts that may not be visible through human analysis; (iv) as the demand for EPDs and the number of verifiers increases, AI can collaborate to provide more homogeneous verification and reduce the discrepancy between verifications of the same product EPDs by different experts, tending to harmonize the results from different verifications.

Combining AI with established verification practices, a hybrid model can enhance the overall credibility of EPDs, ultimately supporting sustainability efforts and informed decision-making to consumers and businesses like ensuring the impartiality from the process and improving the quality of data.

Incorporating new technologies (AI and blockchain) into the verification process, working together to ensure the accuracy, efficiency, and credibility of critical reviews in accordance with ISO 17029, 14071, and 14025 standards.

Integrating AI and blockchain technologies is not merely an upgrade but a paradigm shift in how environmental declarations are reviewed and trusted across supply chains. However, domain-specific human expertise, contextual analysis, and ethical governance must remain central to EPD verification.

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