A Generalized Primary Data Share Method for Life Cycle Assessment Including Activity Data

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Abstract: - The Primary Data Share (PDS) is increasingly used as a quality indicator in Life Cycle Assessment (LCA). Existing PDS approaches typically recognize only fully primary emission data, or require both activity and emission data to be entirely primary to achieve a PDS of 100%. As a result, improvements in foreground system modeling, particularly in activity data, are not adequately reflected. This study proposes a generalized PDS method that allows for variable contributions of primary activity and emission data. The method does not aim to replace existing approaches, but to complement them by better capturing modeling effort and data provenance. The proposed method quantifies the proportion of an LCA result that is based on primary data—defined as data directly collected from the studied system—relative to secondary data from background databases. Primariness is defined at the level of the calculation structure, explicitly incorporating both activity data and emission data into the PDS formulation. The resulting model-structural PDS is particularly suited for hybrid LCA systems combining foreground and background data and supports more transparent reporting of data origin and quality.

Key-Words: - data transparency, life cycle assessment, matrix, primary activity data, primary emission data, primary data share

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1 Introduction

Generally, the so-called primary data share (PDS) is getting more attention in life cycle assessment (LCA) studies [1], [2], [3], [4], [5], [6], [7], [8]. The PDS is an important indicator in data models and for quality checks of LCAs [9]. The current most accepted definition is that PDS is "the proportion of the total environmental impact that is derived from processes for which emission data are used" [10], [11].

This means that if emission factors (EFs) are secondary, PDS will be zero, even if the Bill of Materials (BoM) data are fully primary and the system structure is known in detail [10], [11]. Hence, two LCA studies can get the same PDS even if one uses crude foreground but primary EFs and the other detailed foreground but secondary EFs. Generally, foreground modelling needs more attention [12]. Moreover, supplier-network detail and emission-intensity sources affect Scope 3 results [13]. Furthermore, a PDS value alone cannot establish whether an LCA can be independently reproduced [14]. Additionally primary-data-based social LCA is an emerging research area [15], [16]. Secondary EFs are common, for instance, in the automotive industry [17] and mining [18]. Moreover, the primary data status cannot alone explain the uncertainty of LCA scores [19].

The problem addressed is that supply-chain modeling effort is ignored by emission-only PDS metrics. Existing PDS metrics measure data reliability, while the proposed PDS approach measures modeling data completeness. The essential difference is that the proposed approach measures the share of the result that is based on primary data, whereas counting data elements only measures the share of the inputs that are primary. The proposed approach is useful for LCI data exchange standards because it provides a result-referenced, continuous, and model-agnostic way to signal how much of an LCI-based PCF is grounded in primary data—without forcing partners to disclose the data itself.

2 Problem Formulation

The main question: Can a PDS model be developed that quantifies the share of system contributions based on primary data by explicitly integrating both activity data and environmental data into the calculation? The present research defines PDS as the share of the total Product Carbon Footprint (PCF) greenhouse gas emissions that is calculated using primary data, as opposed to secondary (average or generic) data. In other words, PDS quantifies how much of a PCF result is based on supply-chain-

specific primary data rather than background database data. The main PDS models differ in logic according to Table 1.

For the comparison in Table 1, let $A_{prim,i}$ denote the primary-data status of activity data for contribution i and $B_{prim,i}$ the primary-data status of emission data, with 1 = primary and 0 = secondary. The corresponding process-level primary-data indicators are $B_{prim,i}$ (Holzapfel), $A_{prim,i}B_{prim,i}$ (Catena-X), and $\frac{A_{prim,i}+B_{prim,i}}{2}$ (proposed approach).

Table 1. Primary logic and normalization for PDS methods

Method for PDS	Process-level indicator	**Normalization**
Catena-X [10], [11]	$A_{prim},i \times B_{prim},i$	Absolute
Holzapfel [1]	B_{prim},i	Absolute
Proposed approach	$\frac{A_{prim},i + B_{prim},i}{2}$	Absolute

Source: created by the authors.

At the moment, two studies with identical PCF results but radically different foreground knowledge can receive the same PDS.

3 Problem Solution

The solution is to set up a mathematical specification for previous and proposed PDS models and evaluate the PDS for some case studies.

Figure 1 shows the conceptual calculation flow in which the primary-data status is resolved for activity and emission data at the contribution level; the resulting indicator is then weighted by the absolute environmental contribution to obtain product-level PDS.

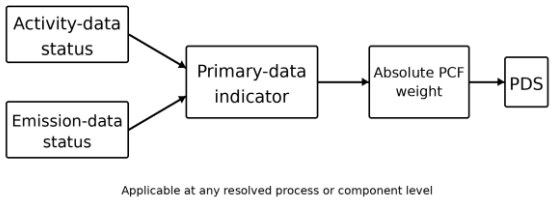

Fig. 1: Conceptual calculation flow.
Source: created by the authors.

3.1 Primary Data Share – Mathematical Specification

3.1.1 Technology System (Activity Levels)

The technology system is represented by a square matrix describing interdependencies between processes.

$$A \in R^{n \times n} \quad (1)$$

A is the technology matrix, where each element represents required inputs per unit output.

$$\alpha \in R^{n} \quad (2)$$

α is the functional unit vector defining the demanded product system output. Typically α is zero everywhere except for the final product index.

$$p \in R^{n} \quad (3)$$

p is the activity level vector representing required process outputs.

$$A\,p = \alpha \quad (4)$$

This linear system determines the required activity levels to satisfy the functional unit.

$$p = \arg\min_{x} |Ax - \alpha|_2 \quad (5)$$

In general, p is obtained via least-squares minimization.

$$p = A^{-1}\alpha \quad \text{(if A nonsingular)} \quad (6)$$

If A is invertible, the solution equals the matrix inverse formulation.

3.1.2 Process Environmental Contributions

Environmental intensities are assigned to each process and multiplied by activity levels.

$$B \in R^{n} \quad (7)$$

B is the environmental intensity vector for one impact category.

$$\beta_i = p_i B_i \quad (8)$$

β_i denotes the impact contribution of process i.

$$\beta = p \odot B \quad (9)$$

Element-wise multiplication produces the full contribution vector.

3.1.3 Total Impact (Signed)

$$\beta_{total} = \sum_{i=1}^{n} \beta_i \quad (10)$$

The total system impact is the signed sum of all process contributions.

3.1.4 Absolute Normalization

Absolute normalization ensures weighting remains valid even if negative contributions occur.

$$|\beta_i| \quad (11)$$

Absolute value of individual contributions.

$$\beta_{abs} = \sum_{i=1}^{n} |\beta_i| \quad (12)$$

Total magnitude of impact contributions.

$$w_i = \frac{|\beta_i|}{\sum_{k=1}^{n} |\beta_k|} \quad (13)$$

w_i represents the normalized absolute weight of process *i*. Properties: $w_i \geq 0, \sum_i w_i = 1$

3.1.5 Primary Data Indicators

Primary data flags classify activity and emission data as primary (1) or secondary (0).

$$A_{prim,i} \in \{0,1\} \quad (14)$$

Binary flag indicating primary activity data.

$$B_{prim,i} \in \{0,1\} \quad (15)$$

Binary flag indicating primary emission data.

3.1.5.1 Holzapfel Indicator

$$\phi_i^H = B_{prim,i} \quad (16)$$

Primary status depends solely on emission data.

3.1.5.2 Catena-X Indicator

$$\phi_i^{CX} = A_{prim,i} B_{prim,i} \quad (17)$$

Primary status requires both activity and emission data to be primary.

3.1.5.3 Proposed Indicator

$$\phi_i^A = \frac{A_{prim,i} + B_{prim,i}}{2} \quad (19)$$

Provides partial credit if either activity or emission data are primary.

3.1.6 Primary Data Share (Absolute Weighted)

$$PDS = \frac{\sum_{i=1}^{n} |\beta_i| \phi_i}{\sum_{i=1}^{n} |\beta_i|} \quad (20)$$

PDS represents the absolute-impact-weighted share of processes classified as primary.

3.1.7 Expanded Forms by Method

3.1.7.1 Holzapfel

$$PDS_H = \frac{\sum_{i=1}^{n} |\beta_i| B_{prim,i}}{\sum_{i=1}^{n} |\beta_i|} \quad (21)$$

3.1.7.2 Catena-X

$$PDS_{CX} = \frac{\sum_{i=1}^{n} |\beta_i| A_{prim,i} B_{prim,i}}{\sum_{i=1}^{n} |\beta_i|} \quad (22)$$

3.1.7.3 Proposed

$$PDS_A = \frac{\sum_{i=1}^{n} |\beta_i| \left(\frac{A_{prim,i} + B_{prim,i}}{2}\right)}{\sum_{i=1}^{n} |\beta_i|} \quad (23)$$

3.1.8 Functional Unit Definition

$$\alpha_j = \begin{cases} 1 \; if \; j = \; final \; product \\ 0 \; otherwise \end{cases} \quad (24)$$

Defines the demanded reference product. The functional unit vector α equals 1 at the index corresponding to the final product.

3.1.9 Domain and Bounds

$$0 \leq \phi_i \leq 1 \quad (25)$$

$$w_i \geq 0, \quad \sum_i w_i = 1$$

$$0 \; \leq PDS \; \leq 1$$

These properties guarantee bounded and interpretable results.

3.1.10 Multiple Impact Categories for analyses beyond PCF

$$\beta_i^{(j)} = p_i B_i^{(j)} \quad (26)$$

$$PDS^{(j)} = \frac{\Sigma_i \left|\beta_i^{(j)}\right| \phi_i}{\Sigma_i \left|\beta_i^{(j)}\right|} \quad (27)$$

PDS can be computed independently for each impact category j.

3.1.11 Computational implementation

The numerical implementation follows directly from the mathematical specification above. The calculation can be reproduced using the following algorithmic sequence:

Algorithm 1. Calculation of PDS for one impact category

1. Define the technology matrix A and functional-unit vector α.
2. Solve $A\ p\ =\ \alpha$; if an exact solution is unavailable, obtain the least-squares solution.
3. Define the environmental intensity vector B and calculate the contribution vector $\beta\ =\ p\ \odot\ B$.
4. Assign $A_{prim,i}$ and $B_{prim,i}$ to each resolved contribution i.
5. Calculate the selected primary-data indicator for each i.
6. Calculate absolute contribution weights w_i according to Equation 13.
7. Sum the weighted indicators to obtain PDS according to Equation 20.
8. Repeat for additional impact categories or primary-data scenarios.

Once the environmental contributions of the individual processes have been calculated, the additional computation required for PDS is limited to assigning the primary-data indicators, calculating the absolute contribution weights, and aggregating the weighted indicators. The main computational effort therefore remains the calculation of the underlying LCA system, while the PDS calculation itself adds only a limited computational step.

3.2 Results

3.2.1 Results for Example 1

Example 1 is obtained from [20]. Table 2 shows inputs and A/B assumptions for Example 1.

Table 2. Example 1 inputs and primary-data scenarios

Process/input	B x input = impact	A/B: Original | New | Random
P1 / 5	0.02 x 5 = 0.10	1/1 | 1/1 | 0/1
P2 / 2	0.30 x 2 = 0.60	1/1 | 1/1 | 1/0
P3 / 3	0.50 x 3 = 1.50	1/1 | 1/1 | 0/1
P4 / 10	12 x 10 = 120	0/0 | 1/0 | 0/1
P5 / 0.05	1300 x 0.05 = 65	0/0 | 1/0 | 1/0
FINAL / 1	0 x 1 = 0	0/0 | 1/0 | 0/1

Source: created by the authors.

A/B denotes primary activity-data / emission-data status (1 = primary; 0 = secondary).

Table 3 shows results for Example 1.

Table 3. Example 1 outputs (total impact = 187.2000)

Scenario	Proposed	Holzapfel	Catena-X
Original	1.18%	1.18%	1.18%
New	50.59%	1.18%	1.18%
Random Mixed	50.00%	64.96%	0.00%
All Primary	100.00%	100.00%	100.00%

Source: created by the authors.

As shown in the Random Mixed Case, Holzapfel PDS (HPDS) will be higher than the proposed PDS (PPDS) whenever enough of the total (absolute) impact is carried by processes with secondary activity data and primary emission data. HPDS gives full credit to process 4 which is 120 of 187.2, while PPDS gives 50% credit to process 4. On the other hand, PPDS gives 50% credit to process 5, which contributes 65, and HPDS gives zero.

3.2.2 Results for Example 2

Example 2 uses the 46-process smartphone LCA calculation structure and default environmental data represented in the GNU Octave result-generation example of Annex I-I of [21]. The technology matrix, process quantities, environmental intensities, and the 99% manufacturing-yield adjustment are taken from that example. The primary-data classifications are analytical assumptions introduced in the present study for the purpose of comparing the three PDS methods; they are not requirements of [21]. The complete model contains 46 processes, including the final Smartphone process. Table 4 shows the Annex

I-I processes and the assumed activity-data/emission-data primary status used in the PDS experiment. A/B denotes primary activity-data / emission-data status (1 = primary; 0 = secondary).

Table 4. Example 2 process groups and assumed primary-data status

EN 304 132 process group	Processes	Assumed A/B status
Cameras	CAMERA 1.8	1/0
	CAMERA 2.1, 2.4, 2, 4	1/1
Components	PCB Rigid	0/1
	CHARGER, PCB Flexible, Battery, Display Flexible OLED	1/1
Raw materials	Polycarbonate	0/1
	Steel	1/0
	ABS, Al, Co, Cu, Au, In, Pt, Ag, Stainless Steel, Ta, Sn	1/1
ICs	All 9 IC processes	1/1
Packaging	Paperboard, Wood Pallet	1/0
	LDPE film	0/1
	Corrugated Cardboard, PET, LLPDE stretch film	1/1
Assembly/processing	Final Assembly, Scour Al	0/0
Distribution	Trp Leg1–3	0/0
Use	Use	1/0
End-of-life/final	End-of-life, Smartphone	0/0

Source: created by the authors.

Table 5 shows Example 2 results.

Table 5. Example 2 total outputs and PDS results

Example 2 total outputs and PDS results
GWP100 total = 72.8651 kg CO2e; Proposed = 81.79%; Holzapfel = 75.65%; Catena-X = 73.86%
ADP total = 7.18025E-4 kg Sb-eq; Proposed = 64.45%; Holzapfel = 64.31%; Catena-X = 64.26%

Source: created by the authors.

Using the EN 304 132 Annex I-I model [21] and its 99% yield correction gives total outputs of 72.8651 kg CO2e for GWP100 and 7.18025E-4 kg Sb-eq for ADP. Under the primary-data status assumptions of Table 5, the proposed PDS is 81.79% for GWP100 and 64.45% for ADP. The corresponding Holzapfel values are 75.65% and 64.31%, while the Catena-X values are 73.86% and 64.26%, respectively.

3.2.3 Sensitivity to the activity-data weight

The 50/50 split in the proposed indicator is a symmetric and transparent convention rather than a claim that activity data and emission data always have identical uncertainty or decision importance. Its sensitivity can be represented by the generalized indicator $I_{i(w)} = w\,A_{prim,i} + (1-w)B_{prim,i}, 0 \leq w \leq 1$. The proposed indicator corresponds to $w = 0.5$. Because the product PDS is a weighted sum of $I_{i(w)}$, PDS varies linearly with w when the underlying contribution weights and primary-data classifications are fixed. Figure 2 shows the sensitivity of the PDS for Example 1 to the weight of the activity data.

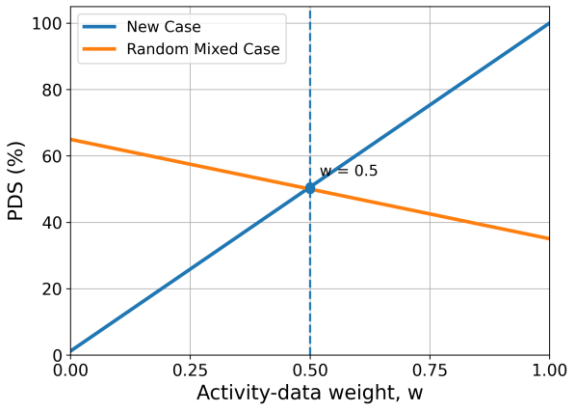

Fig. 2: Sensitivity of Example 1 PDS to the activity-data weight w.
Source: created by the authors.

The New Case increases from 1.18% at w = 0 to 100% at w = 1 and equals 50.59% at $w = 0.5$. The Random Mixed Case decreases from 64.96% to 35.04% and equals 50.00% at w = 0.5.

4 Discussion

The proposed PDS definition adopts the Catena-X approach of absolute normalization to ensure bounded and robust results, particularly in the presence of negative contributions, which are common for certain impact categories such as abiotic depletion potential (ADP) in end-of-life treatments.
The proposed PDS explicitly avoids penalizing suppliers that provide high-quality primary foreground data while still relying on generic emission factors. This is particularly relevant in

early-stage supply chains and for emerging materials, where primary activity data often become available before primary emission data.

Existing PDS approaches, such as Catena-X and Holzapfel, effectively address the question: "What share of the final PCF result is calculated using primary environmental data?" In contrast, the proposed generalized PDS addresses the question: "What share of the system contribution is based on primary data, considering both activity data and environmental data?" Table 6 shows an overview of principal differences between PDS methods.

Table 6. Overview of principal differences between PDS methods

Aspect	**CATENA-X**	**Holzapfel**	**Present approach**
Role of $A_{prim,i}$ (activity-data status)	Not counted in PDS	Not counted in PDS	Explicitly counted
Case $A_{prim,i}$ = 1, $B_{prim,i}$ = 0	$Indicator = 0$	$Indicator = 0$	$Indicator = 0.5$
Rationale	Traceable, auditable supply-chain accountability. Footprint data fully owned and controlled by the reporting actor.	PDS reflects emissions credibility and data quality	PDS reflects model specificity

Source: created by the authors.

In the Original Case (Example 1), the majority of the environmental impact is driven by processes 4 and 5, for which data are not primary. Consequently, the PDS is very low (1.18%), consistent with existing approaches [1], [7], [11]. Using the proposed method, activity data are primary across all processes, while only a subset of emission data are primary, resulting in a moderate PDS (~50.6%). In the All Primary Case, all data are primary, yielding a PDS of 100%.

Example 2 demonstrates the method on a standardized smartphone LCA structure [21] rather than on an arbitrary synthetic model [20]. The underlying 46-process system, environmental intensities, and manufacturing-yield treatment are taken from Annex I-I of [21], whereas the primary-data flags are scenario assumptions introduced here. The differences between PDS methods are larger for GWP100 than for ADP because the environmental contribution weighting interacts differently with the locations of the assumed mixed primary/secondary data.

LCI and PCF data exchange standards—such as Catena-X—must balance several requirements: confidentiality (avoiding disclosure of raw LCI data), comparability (ensuring consistent interpretation of results), machine readability, and low implementation burden for suppliers. As a result, such standards cannot rely on full foreground model exchange, uncertainty distributions, sensitivity matrices, or expert interpretation. Instead, they must rely on scalar indicators with stable semantics. In this context, it is sufficient to exchange the PCF value, the PDS value, and a clear definition of primariness, without exposing underlying model details. The proposed PDS formulation supports interoperability across tools and systems under these constraints.

While sector-specific standardization improves comparability, significant differences in data sources and modeling approaches remain [22]. The proposed PDS complements such standardization efforts by explicitly quantifying the share of primary data in the result.

The proposed PDS model reflects the relative importance of processes through contribution-based weighting, while simplifying the intra-process treatment of activity and emission data by assigning equal weights. The 50/50 choice is adopted as a symmetric reference convention: in the multiplicative PCF relation, activity and emission factors enter jointly, but the convention is not intended to imply equal empirical uncertainty, data quality, or decision importance.

The sensitivity analysis in Figure 2 shows explicitly how alternative weighting choices affect PDS. The dependence is linear for fixed process contributions and primary-data classifications, so the effect of departing from the 50/50 convention is transparent and bounded between the activity-only and emission-only endpoints. The equal weighting therefore provides a stable and implementation-friendly reference case while keeping alternative policy or sector-specific weights possible.

Future work may explore uncertainty-based or sector-specific weighting schemes and their empirical calibration, while preserving the

transparent contribution-weighted structure of the present formulation.

5 Conclusion

A model-structural PDS formulation is proposed in which the role of activity data is explicitly incorporated into the calculation. The PDS is computed from a normalized contribution vector derived from the underlying matrix system, where both the activity structure and the environmental intensities determine primariness.

In contrast to existing approaches, primariness is defined at the level of the calculation structure rather than solely at the level of output data. This allows partial attribution when only activity or emission data are primary, resulting in a continuous and more informative PDS metric.

The proposed approach better reflects model specificity and foreground modeling effort, while remaining compatible with the requirements of data exchange standards, including robustness, comparability, and low data disclosure.

In addition, the proposed PDS formulation is specified as a transparent computational sequence, enabling traceability of the calculation without depending on a particular software implementation. By linking the mathematical formulation to explicit algorithmic steps, the approach supports reproducibility and facilitates implementation across tools and organizations.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

[1] P. Holzapfel, V. Bach, F.A. Jaeger, M. Finkbeiner. The primary data share indicator for supply chain specificity in product carbon footprinting. Ecological Indicators, Vol. 166, 2024, 112435. doi: https://doi.org/10.1016/j.ecolind.2024.112435

[2] P. Holzapfel, D. Blizniukova, V. Bach, M. Finkbeiner. Chain of custody modelling in carbon footprinting and life cycle assessment. The International Journal of Life Cycle Assessment, Vol. 30, No. 5, 2025, 980-993. doi: https://doi.org/10.1007/s11367-025-02452-9

[3] P. Holzapfel. Towards supply chain specific life cycle assessment: Challenges and solutions. 2025, URL: api-depositonce.tu-berlin.de/server/api/core/bitstreams/7b7d9ac9-1a75-4e14-9b36-6ae907f32779/content

[4] L. Roche, P. Holzapfel, M. Finkbeiner. Primary data share indicator for social life cycle assessment. Journal of Cleaner Production, Vol. 497, 2025, 145051. doi: https://doi.org/10.1016/j.jclepro.2025.145051

[5] World Business Council for Sustainable Development. PACT Methodology: Methodology for Calculating and Exchanging Cradle-to-Gate Product Carbon Footprints (PCFs), v3.0, 2025. URL: https://docs.carbon-transparency.org/ref/methodology/pact-methodology-v3.0.pdf

[6] Together for Sustainability. The Product Carbon Footprint Guideline for the Chemical Industry, v3.0, 2024. URL: https://www.tfs-initiative.com/app/uploads/2024/12/TfS-PCF-Guidelines-2024.pdf

[7] World Business Council for Sustainable Development. Technical Specifications for PCF Data Exchange, v3.0.3, 2025. URL: https://docs.carbon-transparency.org/tr/data-exchange-protocol/latest/

[8] International Organization for Standardization. ISO 20915:2026, Life cycle inventory calculation methodology for steel products. ISO, 2026. URL: https://www.iso.org/standard/89957.html

[9] Y. Liang, J.M. Mogollón, S. Cunha, F. Donati, C. Li, B. Mintjes, R. Kleijn, D. Monfort Climent, R. Wang, S. Muller, A. Mas-Fons, B. Miranda Xicotencatl, R. Istrate. Emerging digital product passport initiatives require improved data structuring to support life cycle assessment. Journal of Industrial Ecology, Vol. 30, 2026, 2131-2139. doi: https://doi.org/10.1007/s44498-026-00144-7

[10] Catena-X. Catena-X Automotive Network: Catena-X Product Carbon Footprint Rulebook" v2.0, 2022. URL: https://catena-x.net/fileadmin/user_upload/Vereinsdokumente/Geschaeftsstelle_Dateien_Ablage/CX-0029-ProductCarbonFootprintRulebook-v2.0.0.pdf

[11] Catena-X. Catena-X Automotive Network: Catena-X Product Carbon Footprint Rulebook, v4.0, 2025. URL: https://catena-x.net/wp-content/uploads/2025/10/Catena-X-Product-Carbon-Footprint-Rulebook_v4-with-line-numbers.pdf

[12] W. Liu, L. Wang, F. Li, L. Kong, X. Xiao, Y. Wang, Y. Cui, B. Wang, L. Li. A graph-based C-BOM framework integrating multi-view xBOM data for efficient product carbon footprint assessment. Journal of Cleaner Production, Vol. 569, 2026, 148709. doi: https://doi.org/10.1016/j.jclepro.2026.148709

[13] Z. Wang, K. Hubacek, F. Ruzzenenti. Systematic bias in Scope 3 emissions accounting: evidence from firm-level supply networks. npj Environmental Social Sciences, Vol. 1, 2026, 17. doi: https://doi.org/10.1038/s44432-026-00017-1

[14] A.K. Kamali, A. Koyamparambath, B. Laratte, G. Sonnemann. Reproducibility as a missing scientific criterion in life cycle assessment: a reporting framework. The International Journal of Life Cycle Assessment, Vol. 31, 2026, 135. doi: https://doi.org/10.1007/s11367-026-02708-y

[15] L. Roche, I. Wolf, V. Coroamă, M. Finkbeiner. Advancing primary data-based social life cycle assessment: Methodological challenges and potential solutions. Sustainable Production and Consumption, Vol. 63, 2026, 167-190. doi: https://doi.org/10.1016/j.spc.2026.01.001

[16] L. Roche, V.C. Coroamă, M. Finkbeiner. Towards more focused methodological development: An action plan for primary data-based social life cycle assessment. The International Journal of Life Cycle Assessment, Vol. 31, 2026, 93. doi: https://doi.org/10.1007/s11367-026-02663-8

[17] S. Reichelstein. Carbon emission statements: Balance sheets and flow statements. ZEW-Centre for European Economic Research Discussion Paper, 2023, (23-065). URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4672099

[18] M. Berger. (2026). Harmonized calculations methods for product carbon footprints and life cycle assessments in the mining and metals industry. The International Journal of Life Cycle Assessment, Vol. 31, No. 1, 2026, p. 28. doi: https://doi.org/10.1007/s11367-026-02596-2

[19] A. Ciroth, S. Muller, B.P. Weidema, P. Lesage. Empirically based uncertainty factors for the pedigree matrix in ecoinvent. The International Journal of Life Cycle Assessment, Vol. 21, No. 9, 2016, 1338-1348. doi: https://doi.org/10.1007/s11367-013-0670-5

[20] European Telecommunications Standards Institute. ETSI TS 104 134. 2025, URL: https://www.etsi.org/deliver/etsi_ts/104100_104199/104134/01.01.01_60/ts_104134v010101p.pdf

[21] European Telecommunications Standards Institute. ETSI EN 304 132 V1.1.1:2026, Environmental Engineering (EE); Mobile ICT devices (M-ICT); Product Specific Requirements for Life Cycle Assessment (LCA) of Smartphones. ETSI, 2026. URL: https://www.etsi.org/deliver/etsi_en/304100_304199/304132/01.01.01_60/en_304132v010101p.pdf

[22] A.S.G. Andrae, M.S. Vaija. To which degree does sector specific standardization make life cycle assessments comparable?—the case of global warming potential of smartphones. Challenges, Vol. 5, No. 2, 2014, 409-429. doi: https://doi.org/10.3390/challe5020409

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