International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 11 | Nov - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Development of a Supplier Data Quality and Engagement Framework for Scope 3 Greenhouse Gas Accounting in Industrial Supply Chains

Chinmaya Bhat
Independent Researcher, India
chinmayapaaras@gmail.com

Abstract— Scope 3 emissions dominate the greenhouse gas inventories of industrial firms, yet their calculation depends on supplier information that varies widely in completeness, specificity and method. Reporting standards prescribe how categories should be calculated but offer no operational mechanism for judging whether the underlying supplier data are good enough, or for deciding which suppliers to engage first. This paper develops a five-stage Supplier Data Quality and Engagement Framework that closes that gap. A Supplier Data Quality Index combines a five-dimension pedigree assessment, the share of primary activity data and an emission-factor quality grade into a single bounded score. Scores are mapped to category uncertainties, propagated to inventory level by quadrature, and converted into an Engagement Priority Index that weights each category by its emissions share, its uncertainty and the reporting firm's contractual leverage. The framework is applied to the FY2024-25 and FY2025-26 disclosures of five large Indian industrial companies. Only one firm publishes a category-level Scope 3 breakdown; on that inventory of 19.55 Mt CO_2 the framework returns an inventory uncertainty of 45.7 per cent, concentrated almost entirely in two categories that together carry 99.1 per cent of emissions. Upgrading only those two to primary-data quality reduces inventory uncertainty to 18.2 per cent, a 60 per cent improvement from two engagement programmes rather than fifteen. A Monte Carlo analysis over the weighting scheme confirms the top three priorities are stable. The framework is reproducible from public disclosure alone.

Keywords: data quality, emission factors, GHG Protocol, Scope 3 emissions, supplier engagement, uncertainty propagation

I. INTRODUCTION

For most industrial organisations the emissions that matter least to their own operations matter most to their inventory. Scope 1 and Scope 2 emissions arise inside the fence line and are metered, audited and, increasingly, externally assured. Scope 3 emissions arise in the value chain, are calculated rather than measured, and routinely account for the larger share of the total [1], [2]. The arithmetic of corporate decarbonisation therefore rests on information that the reporting company does not generate and cannot directly verify.

The Corporate Value Chain (Scope 3) Accounting and Reporting Standard resolves the definitional problem well. It partitions the value chain into fifteen categories, specifies boundary rules, and sets out calculation methods ranging from supplier-specific measurement to spend-based estimation using environmentally extended input-output factors [1]; the organisation-level specification in ISO 14064-1 imposes comparable requirements [3]. What it does not supply is an operational test of sufficiency. A company may apply the Standard faithfully, calculate every applicable category, and still produce an inventory in which a single spend-based line item carries several million tonnes of CO_2 on an emission factor derived from sectoral averages rather than from any supplier in its actual network.

This creates a practical difficulty that is not primarily methodological but managerial. Supplier engagement is expensive. Collecting primary activity data requires onboarding, template design, capability building, verification and recurring maintenance, and industrial firms routinely transact with thousands of suppliers. A rational programme must therefore target the suppliers and categories where better data would most improve the reliability of the reported figure. Making that judgment requires three things the Standard does not provide: a quantitative measure of how good each category's data currently is, a translation of that measure into inventory uncertainty, and a prioritisation rule that combines data weakness with materiality and with the reporting firm's actual ability to influence the data holder.

This paper develops such a framework and tests it against the published disclosures of five large Indian industrial companies for the financial years 2024-25 and 2025-26. The empirical setting is deliberate. Indian listed entities now report under the Business Responsibility and Sustainability Reporting regime, whose Core indicators attract mandatory reasonable assurance [4], [5], and the sample therefore represents disclosure prepared under regulatory scrutiny rather than voluntary reporting. The paper pursues six objectives: to identify supplier-level data requirements for the major Scope 3 categories; to develop a supplier data-quality scoring system; to evaluate primary and secondary data availability; to identify high-emission and high-uncertainty categories requiring engagement; to develop prioritisation criteria; and to test the framework using industrial-company disclosures.

One point about the unit of analysis must be made at the outset, because it conditions everything that follows. The scoring instrument developed here is specified for supplier data, and objective one is met at supplier level: Table I states what each category requires from each named class of data holder. Objectives two, four and five, however, are operationalised at the level of the Scope 3 category rather than the individual supplier. The reason is evidentiary. No company in the sample publishes a supplier-level emission figure, a supplier-level data-quality record, or any allocation of a category total across named suppliers; coverage is reported only as an aggregate proportion of the value chain. A supplier-level demonstration would therefore require the author to construct a supplier register that no disclosure supports. The category is used instead as the scoring unit, each category standing for the

population of suppliers that holds its data and sharing the calculation method, the emission-factor grade and the contractual relationship that the scoring rubrics actually discriminate on. Every element of the framework applies unchanged at supplier level inside a firm that holds a supplier register, and Section V returns to what is lost by the aggregation.

The contribution is a reproducible scoring and prioritisation model that operates entirely on information a company already possesses or publishes, and that converts qualitative data-quality judgments into a quantity a decision maker can act on: the expected reduction in inventory uncertainty per engagement programme.

II. LITERATURE REVIEW

A. Scope 3 accounting and its boundary problem

The importance of value-chain emissions to the industrial carbon footprint is well established. Hertwich and Wood show that upstream and downstream emissions exceed direct emissions for most industrial sectors, and that the ratio has grown as production has become more fragmented [2]. Matthews and colleagues demonstrated earlier that carbon footprints calculated at different boundaries diverge substantially, and that direct emissions alone are a poor proxy for total impact [6]. The implication is that boundary choices and calculation conventions, rather than physical performance, often drive reported differences between firms.

Empirical work on disclosure quality supports that concern. Downie and Stubbs, examining Australian corporate assessments, found wide variation in which categories firms chose to calculate and in the rigour applied to each [7]. Blanco and co-authors, analysing CDP responses from United States firms, documented inconsistent category coverage and methods across firms nominally reporting under the same standard [8]. Klaaßen and Stoll, working with a large cross-country sample, showed that reported corporate carbon footprints are not directly comparable without substantial harmonisation, with Scope 3 the principal source of divergence [9]. Busch and colleagues reach a similar conclusion for carbon performance data generally, noting that data providers disagree materially on the same firms [10].

Patchell takes the argument further, questioning whether the Standard's ambitions can be operationalised at all given the governance distance between a reporting firm and its lower-tier suppliers [11]. Huang, Weber and Matthews offered an early practical response, proposing that firms screen categories by contribution and concentrate effort where the footprint actually sits [12]. That screening logic is the starting point for the present framework, but screening by magnitude alone is insufficient: a large category calculated well needs less attention than a mid-sized category calculated from a sectoral average.

B. Data quality assessment in inventory work

Life cycle inventory research has a mature apparatus for exactly this problem. Weidema and Wesnæs introduced the pedigree matrix, scoring each data point on independent qualitative dimensions — reliability, completeness, and temporal, geographical and technological correlation — on an ordinal scale [13]. The approach was embedded in the ecoinvent database and subsequently calibrated: Ciroth and colleagues derived empirically grounded uncertainty factors for each pedigree level, converting qualitative scores into variance contributions [14], [15]. The 2006 IPCC Guidelines provide the complementary aggregation machinery, setting out error propagation rules for combining category-level uncertainties into an inventory total [16].

These two literatures have remained largely separate. Pedigree scoring is standard practice in life cycle assessment but is rarely applied to corporate Scope 3 inventories, and corporate Scope 3 research rarely quantifies uncertainty at all. The present paper joins them, and adds the element neither supplies: a leverage term reflecting that a reporting firm's ability to obtain better data differs sharply across categories.

C. Identified gaps

Six gaps follow from the review. First, Scope 3 standards provide calculation methods but not a comprehensive supplier-readiness scoring model. Second, existing studies concentrate on emission calculation rather than on the governance of supplier data. Third, little empirical work simultaneously evaluates completeness, primary-data share, supplier maturity, emission-factor quality and uncertainty. Fourth, supplier criticality and Scope 3 data-quality prioritisation are seldom integrated. Fifth, the improvement obtainable by replacing secondary factors with supplier-specific primary data is rarely quantified. Sixth, no supplier-level data-quality and engagement framework exists that an industrial firm could apply directly.

III. METHODOLOGY

A. Framework architecture

The Supplier Data Quality and Engagement Framework (SDQEF) proceeds in five stages, shown in Fig. 1. Stage 1 screens categories by emissions contribution. Stage 2 maps the supplier-level data each material category requires. Stage 3 scores the quality of the data actually held. Stage 4 propagates category uncertainty to inventory level. Stage 5 converts the results into an engagement priority ordering and an expected-improvement roadmap. Primary data obtained through engagement re-enters Stage 2, making the framework a repeating cycle rather than a one-off assessment.

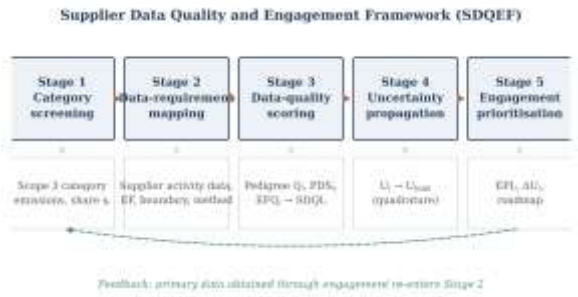


Fig. 1. Architecture of the Supplier Data Quality and Engagement Framework

B. Stage 1: category screening

For a Scope 3 inventory of n applicable categories with emissions E_i, the contribution share of category i is given by (1).

$$s_i = E_i / \Sigma_j E_j , \quad i = 1 \ldots n \qquad (1)$$

where E_i is the reported emission of category i in t CO_2e and s_i is its dimensionless share of the total inventory.

C. Stage 2: supplier data requirements

Each category imposes a distinct data demand on suppliers. Table I sets out the minimum supplier-level data elements

required for the categories most material to industrial firms, together with the holder of that data and the calculation method the element supports. The table is the operational translation of objective one and defines what "complete" means for each category in the scoring that follows.

TABLE I. SUPPLIER-LEVEL DATA REQUIREMENTS BY SCOPE 3 CATEGORY

Category	Minimum supplier data element	Data holder	Method enabled
Cat 1 Purchased goods and services	Product mass, cradle-to-gate factor, route, allocation	Tier 1 supplier	Supplier-specific
Cat 2 Capital goods	Asset mass by material, manufacturing energy	Equipment vendor	Average-data
Cat 3 Fuel and energy-related	Fuel volumes, grid mix, upstream factor	Reporting firm, utility	Average-data
Cat 4 Upstream transport	Tonne-kilometres by mode, load factor, fuel type	Logistics provider	Distance-based
Cat 5 Waste in operations	Waste mass by stream, treatment route	Waste contractor	Waste-type-specific
Cat 6 Business travel	Passenger-kilometres by mode and cabin class	Travel agency	Distance-based
Cat 7 Employee commuting	Mode split, distance, occupancy, headcount	Reporting firm	Average-data
Cat 8 Upstream leased assets	Floor area or energy metered, allocation key	Lessor	Asset-specific
Cat 9 Downstream transport	Tonne-kilometres beyond point of sale	Distributor	Distance-based
Cat 11 Use of sold products	Lifetime, usage intensity, in-use efficiency	Reporting firm, user	Direct use-phase
Cat 14 Franchises	Franchisee Scope 1 and 2, outlet count, extrapolation	Franchisee	Franchise-specific

D. Stage 3: the Supplier Data Quality Index

Data quality is assessed on three independent constructs. The first is a pedigree score following Weidema and Wesnæs [13], adapted to the corporate inventory setting. Five dimensions are rated on an ordinal scale from 1 (weakest) to 5 (strongest) using the rubric in Table II, and combined by (2).

$$Q_i = \Sigma_k \, w_k \cdot q_{ik} \,, \quad \Sigma_k \, w_k = 1 \qquad (2)$$

where q_{ik} is the score of category i on dimension k and w_k is the weight of that dimension. Technological representativeness and completeness carry 0.25 each, reliability 0.20, and temporal and geographical representativeness 0.15 each. The allocation is an author judgment rather than an empirical calibration: it places method specificity and coverage ahead of currency and location, on the reasoning that a corporate inventory is compiled on a fixed annual cycle from a largely domestic supply base, so that the temporal and geographical dimensions vary less across categories than the method does.

TABLE II. PEDIGREE SCORING RUBRIC FOR SUPPLIER DATA

Score	Technological	Completeness	Reliability	Temporal	Geographical
5	Supplier-specific, exact product	All suppliers covered	Verified or assured	Reporting period itself	Same site or facility
4	Supplier-specific, similar product	Representative majority	Attested, internally checked	Within one year	Same country
3	Industry average, same route	Partial, extrapolated	Unverified submission	Within three years	Same region
2	Proxy or sectoral average	Material exclusions known	Modelled from proxy	Within six years	Other region, similar
1	Unrelated proxy process	Coverage unknown	Non-qualified estimate	Older or unknown	Global or unknown

The column headings of Table II abbreviate technological, temporal and geographical representativeness. The five dimensions and their ordinal anchors follow the pedigree matrix of Weidema and Wesnæs [13]; the wording of each cell has been adapted to the corporate Scope 3 setting, where the data point scored is a category calculation rather than a unit process. Temporal scores refer to the vintage of the activity data and emission factor relative to the reporting period, and geographical scores to the match between the factor's origin and the location of the activity.

The pedigree score is rescaled to the unit interval by (3) so that it can be combined with two proportional measures.

$$\hat{Q}_i = (Q_i - 1)/4 \qquad (3)$$

The second construct is the primary data share, the proportion of a category's emissions calculated from activity data originating with the entity that caused the emission, as in (4).

$$PDS_i = E_i^p / E_i \,, \quad 0 \le PDS_i \le 1 \qquad (4)$$

where E_i^p is that part of category i calculated from primary supplier activity data. The third construct, EFQ_i, grades the emission factor on a four-point scale: 1.00 for supplier-measured factors, 0.75 for regional industry-average factors, 0.50 for national average factors and 0.25 for spend-based input-output factors.

The three constructs combine into the Supplier Data Quality Index of (5).

$$SDQI_i = \alpha \cdot \hat{Q}_i + \beta \cdot PDS_i + \gamma \cdot EFQ_i \,, \quad \alpha + \beta + \gamma = 1 \qquad (5)$$

with $\alpha = 0.50$, $\beta = 0.30$ and $\gamma = 0.20$ in the base case. SDQI is bounded on [0, 1]. The weighting is tested by Monte Carlo simulation in Section IV-E.

E. Stage 4: uncertainty propagation

Qualitative quality must become quantitative uncertainty before it can be aggregated. Following the calibration logic of Ciroth and colleagues [14], SDQI is mapped linearly onto a relative uncertainty band by (6).

$$U_i = U_{max} - (U_{max} - U_{min}) \cdot SDQI_i \qquad (6)$$

where $U_{min} = 0.10$ and $U_{max} = 1.00$ are the relative standard uncertainties assigned to fully supplier-specific and to spend-based estimates respectively. These anchors reflect the Standard's own characterisation of spend-based estimation as the least specific method available [1].

Category uncertainties are combined into an inventory-level figure using the error propagation rule of the 2006 IPCC

Guidelines for uncorrelated quantities summed in quadrature [16], giving (7).

$$U_{total} = \sqrt{(\Sigma_i (U_i \cdot E_i)^2)} / \Sigma_i E_i \quad (7)$$

Equation (7) has a consequence central to this paper: because each term enters as the square of an absolute uncertainty, inventory uncertainty is governed almost entirely by large categories with weak data. Small categories cannot move it regardless of how poorly they are calculated.

F. Stage 5: engagement prioritisation

Priority must reflect materiality, data weakness and the reporting firm's ability to act. The Engagement Priority Index of (8) multiplies the three.

$$EPI_i = (s_i \cdot U_i \cdot I_i) / \Sigma_j (s_j \cdot U_j \cdot I_j) \quad (8)$$

where $I_i \in (0, 1]$ is a leverage coefficient expressing the reporting firm's contractual and commercial influence over the entity that holds category i's data.

The leverage coefficient is the one term in the framework with no precedent in the data quality literature, so its definition is set out explicitly. I_i is assigned on four anchors reflecting the instrument through which the reporting firm could compel or purchase the data. A value of 0.90 applies where the data holder is a counterparty the firm already pays under a contract whose terms it sets, so that a data clause can be added at renewal: Tier 1 goods suppliers and contracted travel providers. Values of 0.70 to 0.80 apply where a contract exists but data provision would be a new request outside its present scope: waste contractors, franchisees, lessors and utilities. A value of 0.60 applies where the data are held inside the firm but depend on voluntary individual response, as in commuting surveys. A value of 0.30 applies where the holder has no contractual relationship with the firm at the time the emission occurs, as with the users of sold products. The coefficient is a category-level proxy for the supplier criticality that a firm applying the framework internally would measure directly from spend, substitutability and supply risk; the values used for each category are reported in Table V so that every figure in the results can be recomputed.

The practical value of a prioritisation is the improvement it buys. Equation (9) gives the reduction in inventory uncertainty obtained by raising category i to a target data quality, holding all other categories constant.

$$\Delta U_i = U_{total} - U_{total} \mid U_i \rightarrow U^* \quad (9)$$

where U* is the uncertainty corresponding to the target SDQI, set at 0.85 here, representing supplier-specific data of attested reliability covering the majority of the category.

G. Data and sample

The framework was applied to the integrated annual reports and BRSR disclosures of five large Indian industrial companies for FY2024-25 and FY2025-26: JSW Steel, Reliance Industries, UltraTech Cement, Tata Motors (commercial vehicles) and Tata Motors Passenger Vehicles. These span steel, refining and petrochemicals, cement and automotive manufacturing. All emissions, procurement and value-chain figures used below are as published by the companies [17], [18], [19], [20], [21], [22]. Pedigree scores, primary-data shares, emission-factor grades and leverage coefficients are the author's assessments obtained by applying the rubrics of Table I and Table II to the calculation methods each company discloses; they are not company disclosures, and the sensitivity of conclusions to them is tested in Section IV-E.

IV. RESULTS

A. Scope 3 disclosure in the sample

The first finding concerns the raw material available to any such framework. Of the five companies, only Tata Motors Passenger Vehicles publishes a category-level Scope 3 breakdown. JSW Steel and UltraTech Cement report a single consolidated Scope 3 total; Tata Motors (commercial vehicles) describes its Scope 3 trajectory narratively without an absolute figure; and for Reliance Industries the Scope 3 table was not retrieved from the sections of the BRSR examined for this study, so no inference about what that company discloses can be drawn here. Table III sets out the position, and Fig. 2 shows it graphically against the fifteen categories the Standard defines.

TABLE III. SCOPE 3 DISCLOSURE GRANULARITY IN THE SAMPLE, FY2025-26

Company	Scope 3 total	Categories shown	Assurance of Scope 3
Tata Motors Passenger Vehicles	19.55 Mt CO_2	8 of 15	Assured-indicator list not published
UltraTech Cement	12.83 Mt CO_2	0 (total only)	Provider named; level not retrieved
JSW Steel	8.95 Mt CO_2	0 (total only)	Note states assured
Tata Motors (commercial vehicles)	Not disclosed	0	Assured-indicator list not published
Reliance Industries	Not retrieved	Not retrieved	Not in listed assured indicators

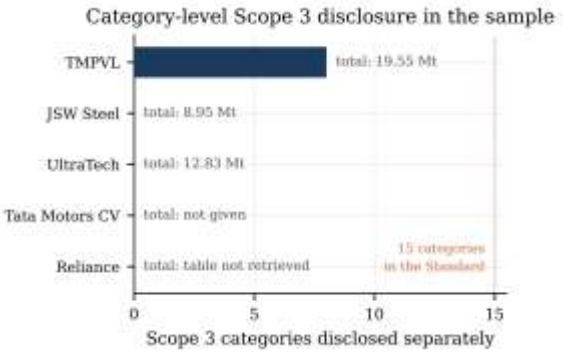


Fig. 2. Category-level Scope 3 disclosure across the sample

Three further observations follow. No company in the sample publishes a data-quality score, an uncertainty estimate, or a primary-versus-secondary data split for any Scope 3 category. No company publishes a supplier-level emissions figure or a supplier-level data-quality record, and only UltraTech Cement publishes an absolute count of suppliers, identifying 128 critical suppliers within a Tier 1 base it describes as numbering over a thousand [19]; the other companies report value-chain engagement only as a proportion. And no figure for Category 4 or Category 9 transport emissions appears anywhere in the sample, although JSW Steel names both as applicable to its business. Where methodological transparency does exist, it is at the level of a footnote: Tata Motors Passenger Vehicles labels its Category 1 calculation a "Spend based method", records that its commuting figure covers only company-contracted buses, and states that its franchise figure rests on

data from 404 dealer partners extrapolated across the network [17].

A further comparability problem appears within a single reporting entity. JSW Steel's BRSR reports Scope 3 of 8,693,479 t CO_2 for FY2024-25 [18], while its integrated report for that year describes net Scope 3 of 8.3 million tonnes after a credit of 5.5 million t CO_2 for avoided emissions calculated under worldsteel guidance [22], [23]. Both figures are defensible under their respective conventions, but a reader cannot reconcile them without the footnotes, and an uncertainty framework must treat convention choice as a distinct source of divergence from measurement error.

B. Category concentration

Applying (1) to the disclosed inventory of 19,549,732 t CO_2 produces extreme concentration. Use of sold products accounts for 72.7 per cent and purchased goods and services for 26.4 per cent; together they carry 99.1 per cent of the inventory. The remaining six disclosed categories sum to 0.9 per cent. Fig. 3 shows the distribution and its cumulative curve.

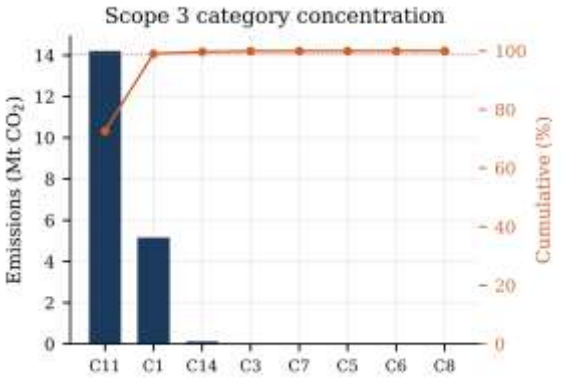


Fig. 3. Scope 3 category concentration, Tata Motors Passenger Vehicles FY2025-26

C. Data quality scores

Table IV reports the pedigree, primary-data and emission-factor components, the resulting SDQI, and the mapped uncertainty for each category. The pattern is the one the framework is designed to expose. Category 1, the second largest, has the weakest score in the inventory (SDQI 0.294), because a spend-based calculation scores low on technological representativeness, carries no primary supplier data and uses an input-output factor. Category 14, by contrast, is small but well calculated (SDQI 0.696), resting on primary Scope 1 and Scope 2 returns from named dealer partners. Category 11, the largest, sits in between at 0.479: the modelling convention is standard and the coverage complete, but the underlying usage assumptions are not supplier-specific and are not independently verified.

TABLE IV. DATA QUALITY SCORING AND MAPPED UNCERTAINTY BY CATEGORY

Cat	Share (%)	Q	PDS	EF Q	SDQI	U (%)
C1	26.37	2.95	0.00	0.25	0.294	73.6
C3	0.25	4.15	0.80	0.75	0.784	29.5
C5	0.02	3.70	0.60	0.50	0.618	44.4
C6	0.02	3.30	0.70	0.50	0.598	46.2
C7	0.03	3.20	0.40	0.50	0.495	55.5
C8	0.01	3.30	0.50	0.50	0.537	51.6
C11	72.71	3.55	0.20	0.50	0.479	56.9
C14	0.59	4.05	0.55	0.75	0.696	37.3

Fig. 4 plots materiality against data quality. The upper-left region, containing categories that are both large and weakly evidenced, is where engagement effort belongs; the lower-right region requires only maintenance. The two categories in the upper-left quadrant are precisely the two that dominate the inventory.

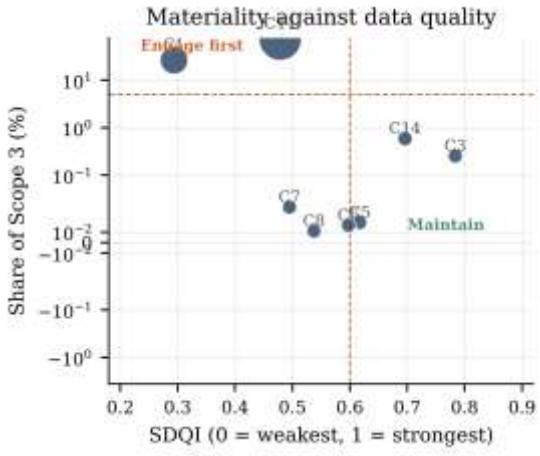


Fig. 4. Category materiality plotted against Supplier Data Quality Index

D. Inventory uncertainty and engagement priority

Propagating the category uncertainties through (7) gives an inventory-level relative uncertainty of 45.7 per cent. Table V reports the Engagement Priority Index from (8) and the marginal uncertainty reduction from (9). The ranking is dominated by the two material categories, but their order differs from their emissions order: Category 1 ranks first on EPI despite being smaller than Category 11, because its data are weaker and because contractual leverage over Tier 1 suppliers is far greater than over vehicle users.

TABLE V. ENGAGEMENT PRIORITY AND MARGINAL UNCERTAINTY REDUCTION

Cat	Share (%)	U (%)	Leverage I	EPI	Rank	ΔU (pp)
C1	26.37	73.6	0.90	0.5794	1	3.86
C11	72.71	56.9	0.30	0.4120	2	19.85
C14	0.59	37.3	0.80	0.0059	3	0.00
C3	0.25	29.5	0.70	0.0017	4	0.00
C7	0.03	55.5	0.60	0.0004	5	0.00
C5	0.02	44.4	0.80	0.0002	6	0.00
C6	0.02	46.2	0.90	0.0002	7	0.00
C8	0.01	51.6	0.70	0.0001	8	0.00

The practical result is in Fig. 5, which applies (9) sequentially in EPI rank order. Upgrading Category 1 alone reduces inventory uncertainty from 45.7 per cent to 41.8 per cent. Adding Category 11 brings it to 18.2 per cent. The remaining six categories, upgraded in full, change the total by less than 0.05 percentage points. Two engagement programmes therefore deliver a 60 per cent reduction in inventory

uncertainty, and the other six are not worth funding for inventory-quality reasons alone.

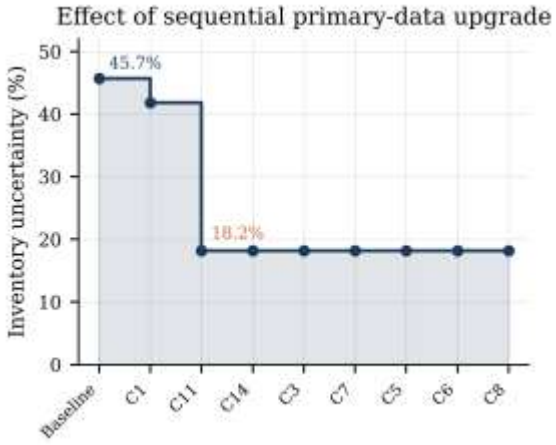


Fig. 5. Inventory uncertainty under sequential primary-data upgrade in priority order

E. Sensitivity to the weighting scheme

The weights α, β and γ in (5) are judgments, so their influence was tested by Monte Carlo simulation. Five thousand weight vectors were drawn from a Dirichlet distribution centred on the base case, the full scoring and prioritisation recomputed for each, and the rank of every category recorded. Categories 1, 11 and 14 occupy the top three positions in 100 per cent of draws, and Category 1 is ranked first in every draw. No category outside the top three enters it under any weighting tested. The ordering that drives the engagement decision is therefore robust to the weighting scheme, which matters because the weights are the most contestable element of the framework.

F. Disclosed evidence bearing on data quality

The scores in Table IV are not free assessments: each rests on a disclosed statement about how the category was calculated. Table VI records that evidence category by category, so that a reader can see which disclosure supports which score and recompute any of them. Only two kinds of statement appear in the sample: a named calculation method, and an admitted boundary restriction. Neither is accompanied anywhere by a quantitative quality or uncertainty measure, which is the gap the index in (5) is built to fill.

TABLE VI. PER-CATEGORY EVIDENCE BEARING ON DATA QUALITY, AS DISCLOSED

Scope 3 category	Disclosed evidence	Consequence for scoring
Cat 1 Purchased goods and services	Calculation labelled a "spend based method"; procurement disclosed only as MSME and local-sourcing percentages, with no absolute spend	Input-output factor grade, EFQ 0.25; no primary supplier data, PDS 0
Cat 3 Fuel and energy-related activities	Derived from the firm's own metered fuel and purchased-electricity consumption	Mostly primary activity data; published upstream factors
Cat 5 Waste generated in operations	Waste volumes by stream combined with average treatment factors	Partial primary data; average-factor grade
Cat 6 Business travel	Travel records with average factors by mode	Primary activity data; average-factor grade
Cat 7 Employee commuting	Stated to cover only commuting by company buses contracted through third parties	Admitted material exclusion; completeness scored 2 of 5
Cat 8 Upstream leased assets	Shared-office utilities allocated between group entities; allocation key not stated	Reliability unverified; allocation not reproducible
Cat 11 Use of sold products	Modelled lifetime fuel use of vehicles sold in the year	Estimation-dependent; neither supplier-specific nor verified
Cat 14 Franchises	Primary Scope 1 and Scope 2 returns from 404 dealer partners, extrapolated across outlet categories	Highest primary-data share and factor grade in the inventory

One company-level disclosure also bears directly on the primary-data share of (4). Reliance Industries does not report its value chain under a single coverage figure. It separates the counterparties whose data it has examined directly from those it has reviewed at one remove, and from those about which it holds nothing beyond what is public [20]. The three tiers are a disclosed gradient of evidence strength, which is precisely the quantity PDS in (4) is built to capture, and no other company in the sample publishes anything equivalent.

V. DISCUSSION

The results carry a counter-intuitive implication for supplier engagement strategy. Programmes are commonly organised around breadth, measured by the proportion of suppliers surveyed or onboarded to a reporting platform. The quadrature rule of (7) shows that breadth is close to irrelevant for inventory reliability. Because absolute uncertainties combine as squares, a programme that improves data for ninety per cent of suppliers accounting for one per cent of emissions will not move the reported figure, while one that improves a single category carrying a quarter of the inventory will move it substantially. Engagement breadth and inventory quality are different objectives and should be budgeted separately.

The leverage term in (8) explains a pattern visible in the sample. Category 11 is the largest emissions block in the automotive inventory but ranks second on priority, because the reporting firm cannot compel vehicle users to supply usage data. Improvement there comes through product design and more defensible modelling assumptions, not supplier engagement. Conversely, Category 14 is trivially small yet is the best-evidenced category in the inventory, because the franchise relationship makes primary data collection straightforward. Firms tend to collect the data they can rather than the data that matters, and an explicit leverage coefficient makes that tendency visible and correctable.

For assurance providers the findings suggest a sharper line of enquiry, but the position on assurance of Scope 3 differs across the sample and the three cases should not be conflated. In one case the exclusion is confirmed: Reliance Industries publishes an appendix listing every assured indicator, and Scope 3 is not among them [20]. In one case the evidence conflicts: JSW

Steel carries an indicator-level note stating that its Scope 3 table is assured by its assurance provider, while the engagement's own scope statement describes reasonable assurance of BRSR Core indicators, of which Scope 3 is not one [18]. In the remaining cases the question is indeterminate rather than settled. Both Tata Motors entities obtain reasonable assurance on BRSR Core and limited assurance on indicators described only as "select", without publishing the list, so whether Scope 3 falls inside the limited-assurance scope cannot be established from the disclosure [17], [21]; and for UltraTech Cement the assurance statement was not retrieved from the sections examined, so neither the level nor the indicator scope is known [19]. The distinction matters for the argument that follows: a confirmed exclusion is a finding about assurance practice, whereas an unpublished indicator list is a finding about disclosure of assurance scope. If assurance is to extend to Scope 3, a reproducible data-quality metric is a precondition, since reasonable assurance over a spend-based estimate with an undisclosed uncertainty band is not a meaningful proposition. SDQI offers one such metric computable from information a company already holds.

Four limitations bound these conclusions. The framework was applied in full to one inventory, because only one company in the sample discloses categories separately; the quantitative results are therefore a demonstration of the method rather than a cross-sectional finding. The scoring unit is the category, not the supplier, for the evidentiary reason given in Section I, and this leaves one of the gaps identified in Section II-C only partly closed: the integration of supplier criticality with data-quality prioritisation is achieved here through a category-level leverage coefficient rather than through a criticality measure computed for each supplier. Within a category the framework cannot distinguish a critical sole-source supplier from a readily substitutable one, and the only disclosure in the sample that would support such a distinction is UltraTech Cement's count of 128 critical suppliers, published without the emissions or data-quality attributes that would make it usable. The pedigree, primary-data and leverage parameters are author assessments of disclosed methods, not company data, and a firm applying the framework internally would populate them from its own records with far greater accuracy. The linear mapping in (6) is a calibration choice; the empirically derived uncertainty factors of Ciroth and colleagues [14] would give a non-linear alternative, and the Monte Carlo analysis tested the weights rather than the mapping form. None of the three affects the ordinal conclusion, which is driven by the quadratic structure of (7) and the extreme concentration of the inventory.

VI. CONCLUSION

This paper set out to convert Scope 3 supplier data quality from a qualitative concern into a quantity that supports resource allocation. The Supplier Data Quality and Engagement Framework scores each category on pedigree, primary-data share and emission-factor quality, maps the composite to an uncertainty band, propagates it to inventory level, and ranks categories by emissions share, data weakness and contractual leverage.

Applied to the only category-level Scope 3 inventory published in a sample of five large Indian industrial companies, the framework returns an inventory uncertainty of 45.7 per cent and identifies two categories, carrying 99.1 per cent of emissions, whose upgrading to primary-data quality would reduce that figure to 18.2 per cent. The priority ordering is stable across five thousand weighting draws. The wider empirical finding is one of absence: no company in the sample publishes a data-quality score, an uncertainty estimate or a primary-data share for any Scope 3 category; only one publishes an absolute supplier count, and that without emissions or data-quality attributes; three of the five publish no Scope 3 category detail at all, and for a fourth the category table was not retrieved from the sections examined. Supplier engagement is extensively described in qualitative terms and nowhere connected to the reliability of the reported inventory.

Three directions follow. The uncertainty mapping of (6) should be calibrated against observed variance from firms that have replaced spend-based factors with supplier-specific data, allowing the anchors to be estimated rather than assumed. The framework should be applied at supplier rather than category level once disclosure or internal data permits, which would make the leverage coefficient an observable procurement variable and would allow the marginal uncertainty reduction of (9) to be divided by the cost of the engagement programme that delivers it, the criterion a firm with a binding budget actually needs. And the regulatory implication deserves testing: requiring disclosure of primary-data share by category would cost reporters little, since they must already know it to perform the calculation, and would make Scope 3 inventories comparable in a way that totals alone can never be.

VII. DECLARATION ON THE USE OF ARTIFICIAL INTELLIGENCE

Preparation of this manuscript involved an artificial intelligence assistant (Anthropic Claude). Its role was confined to three tasks: reading the quantitative disclosures out of the corporate reports cited here, writing the Python that implements the pedigree scoring, the quadrature propagation and the Dirichlet weight simulation set out in Section III, and drawing the figures from the output of that code. It also assisted with language editing. The research question, the five-stage framework, every parameter and anchor value, and every conclusion drawn from the results are the author's. Each extracted figure was checked back against the source document before use. The author has reviewed the whole manuscript and is responsible for it.

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