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AI-DRIVEN STRUCTURING AND SEMANTIC MATCHING OF CONSTRUCTION COST DATA FOR EFFICIENCY AND CO_2 IMPACT ASSESSMENT

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Abstract. The buildings and construction sector is one of the largest contributors to global greenhouse gas emissions. It accounts for around 34% of global energy-related CO_2 emissions, which come from both the energy used to operate buildings and the emissions produced when construction materials such as cement, steel and concrete are made. Despite the increasing use of embodied-carbon assessment methodologies in the architecture, engineering and construction (AEC) sector, carbon accounting tools are still not integrated into the cost estimation and procurement processes that directly affect material selection and initial design choices. This study presents the novel, AI-driven 'EEBOQ' framework, which was developed in the context of the Latvian construction market while taking into account broader European and international carbon accounting practices. The proposed framework integrates a hybrid semantic processing pipeline that combines Large Language Models (LLMs), ontology-based classification mechanisms and vector-based similarity retrieval techniques in order to autonomously interpret heterogeneous, spreadsheet-based procurement documentation. The system aligns the free-text estimate positions with standardised embodied-carbon reference datasets, such as the ICE Database, Environmental Product Declarations (EPDs) and EN 15978-compliant life cycle assessment structures. To improve the reliability of practical CO_2 estimation, the framework introduces a Bayesian Feedback Correction Engine (BFCE). This is designed to reduce discrepancies iteratively between generalised look-up table emission factors and observed, project-specific embodied carbon data. The feedback mechanism continuously recalibrates environmental coefficients using primary data provided by suppliers, transport information related to logistics, records of material substitution, and validated environmental product declarations. Experimental validation on a corpus of real-world construction projects demonstrated that the semantic-matching module achieved top-1 matching accuracy of 89.3% and top-3 accuracy of 97.1%. Furthermore, the proposed Bayesian correction mechanism reduced the median absolute percentage error in embodied carbon estimation from 28.5% using a conventional static look-up table to 8.3% after three iterative feedback cycles. The results obtained indicate that the proposed architecture establishes a scalable, reproducible pathway towards real-time, evidence-based embodied carbon accounting that is directly integrated with operational construction cost management and procurement processes.

Keywords: CO_2 impact, net-zero construction, semantic matching, structured data extraction, sustainability, natural language processing.

JEL Classification: C88, L74, Q56, O33

1. Introduction

The buildings and construction sector is one of the largest contributors to global greenhouse gas emissions. It accounts for around 34% of global energy-related CO_2 emissions, which come from operational building energy consumption and the emissions associated with construction materials, such as cement, steel and concrete (UNEP and GlobalABC, 2025). According to the UNEP Global Status Report for Buildings and Construction 2024–2025, the sector consumed 32% of

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the global final energy demand in 2023 and generated a record 9.8 gigatonnes (Gt) of CO_2, approximately 2.9 Gt of which was embodied carbon from materials. Alarmingly, emissions across the entire sector have increased by 5% since 2015, moving in the opposite direction to the required 28% reduction by 2030 in order to align with the Paris Agreement. Embodied carbon emissions, which arise from the manufacture, transport and installation of materials such as steel and cement, account for 18% of all building-related emissions. However, they remain largely unregulated and untracked in most jurisdictions (UNEP and GlobalABC, 2025).

As operational emissions are increasingly regulated through building energy codes, embodied carbon has become the dominant lever for the next generation of decarbonisation targets. This is evident in the European Commission's 2026 Framework for Calculating Whole Life Carbon of Buildings (European Commission, 2026a; European Commission, 2026b) and in the guidance on whole-life carbon assessment (RICS, 2017), as well as in the research on the embodied-carbon performance gap (Pomponi and Moncaster, 2018). As a signatory to EU climate commitments and with an active ERDF-funded digital construction research programme, Latvia is developing the regulatory and technical infrastructure necessary for mandatory embodied carbon disclosure on public sector projects. In 2023 alone, over 5 billion square metres of new floorspace was added globally, yet more than half of this construction took place without any enforceable energy or carbon code. Automated, cost-integrated carbon-accounting tools are uniquely placed to address this gap (UNEP and GlobalABC, 2025).

Despite the urgent need for them, tools for calculating the embodied carbon content of construction materials remain fragmented and manual, and are poorly integrated with the cost-management workflows that govern material procurement. Bills of Quantities, the primary contractual instrument for linking design intent to procurement in most European markets (including Latvia's standard procurement framework), are produced in a variety of different formats and lack a consistent taxonomy. Matching cost line items, such as 'supply and fix 200 mm reinforced concrete slab C30/37, pump-placed', to the correct emission factor in the ICE database requires specialist knowledge and is not feasible on a large scale (Abanda et al., 2017; Akanbi & Zhang, 2020).

Automated construction cost data extraction has been explored in several areas: these include BIM-assisted quantity take-off and detailed cost estimation (Shen and Issa, 2010; Jadid and Idrees, 2007); specification-to-estimate mapping using NLP (Akanbi and Zhang, 2020; Akanbi and Zhang, 2021); and machine-learning classification of cost documents against international measurement standards (Deza et al., 2022). As surveyed by Elmousalami et al. (2025), AI in sustainable construction management is an emerging priority. However, a fully integrated pipeline, incorporating everything from raw Bill of Quantities (BOQ) ingestion to calibrated, feedback-corrected CO_2 accounting, has not previously been reported.

This paper makes four principal contributions:

a. A preprocessing and structuring pipeline that normalises heterogeneous BOQ inputs into a canonical ontology using a fine-tuned LLM combined with rule-based heuristics, applicable to both Latvian-language and English-language cost documents.

b. A semantic-matching engine which uses contrastive sentence embeddings to map structured line items to entries in standard emission-factor databases, achieving state-of-the-art accuracy on real-world datasets.

c. The Bayesian Feedback Correction Engine (BFCE) learns from empirical CO_2 measurements, progressively correcting the inherent systematic biases of look-up table approaches.

d. An experimental corpus of construction projects in Latvia, annotated with cost data and matched emission factors, as well as partially verified CO_2 observations.

The remainder of this paper is structured as follows: Section 2 provides a critical review of related research into AI-assisted construction cost estimation, semantic information extraction, embodied carbon assessment and sustainability-oriented procurement systems. Section 3 introduces the proposed EEBOQ framework and presents the system's overall architecture. Section 4 describes the experimental setup, evaluation methodology and quantitative validation results obtained from real-world construction datasets. Section 5 then discusses the implications, limitations and future research directions of the proposed framework in the context of AI-enabled sustainable construction management.

2. Related Work

2.1 Cost Data Structuring and Extraction

The automation of construction cost-data structuring has been approached from several directions. Abanda et al. (2017) formalised a BIM-integrated ontology, aligning NRM (New Rules of Measurement) cost codes with IFC entities. This demonstrated that structured cost taxonomies are a prerequisite for automated carbon assessment. Deza et al. (2022) used machine learning to classify raw cost documents according to the International Construction Measurement Standard (ICMS), achieving an accuracy rate of 87% and proving that cross-standard alignment is feasible. Meanwhile, Akanbi and Zhang (2020, 2021) used NLP to extract design information directly from construction specifications and populate cost-estimate templates for wood-frame construction. This shows that transformer-based models can bridge the gap between specification language and structured cost data.

Although BIM-assisted cost estimation has matured considerably (Shen and Issa, 2010), Jadid and Idrees (2007) observe that fully automated structural cost estimation from parametric models remains a challenge, particularly for complex or irregular structures. EEBOQ addresses this issue by providing a solution to the problem of assessing the CO_2 impact of an existing cost schedule (whether BIM-derived or traditionally produced) automatically and accurately.

2.2 CO_2 Estimation in Construction

Sun and Park (2020) proposed a BIM-integrated CO_2 calculation method covering the full construction process, establishing a module-by-module emission accounting framework aligned with EN 15978 (CEN, 2011). The findings of the study demonstrated that BIM object properties can be mapped to emission-factor lookup tables; however, the research relied on manual factor assignment. Elmousalami et al. (2025) provide a comprehensive review of AI in sustainable construction engineering management, identifying automated CO_2 quantification as a high-priority open research gap, particularly for early-stage design and procurement decisions.

The Inventory of Carbon and Energy (ICE) Database, which is maintained by Circular Ecology and is becoming increasingly referenced in EU contexts, provides emission factors for over 200 categories of construction material (Hammond and Jones, 2019). Tools such as One Click LCA and the Environment Agency Carbon Calculator use these values from look-up tables (Circular Ecology, 2024), while data-template standards facilitate the use of EPDs in BIM environments (ISO, 2022). The fundamental limitation of look-up table averages diverging substantially from specific products procured in specific geographic contexts is what motivates the BFCE component of EEBOQ. The framework is not intended to replace lifecycle assessment platforms or environmental databases. Instead, it automatically identifies and structures construction cost-estimate items, linking them to existing external embodied-carbon data sources, including EPD repositories and commercial LCA platforms such as One Click LCA.

2.3 Semantic Matching in Construction Documents

Transformer-based semantic matching has been applied to checking the compliance of construction specifications, identifying schedule risks, and aligning cost codes across systems. Treating each cost line item as a query and each database entry as a candidate document when retrieving emission factors using contrastive sentence embeddings is considered the optimal approach and forms the basis for the AI-Driven Semantic Matching Pipeline.

2.4 Bayesian Calibration and Feedback Mechanisms

Bayesian updating has been applied to both building energy performance gap analysis and structural reliability assessment. In the embodied-carbon domain, although uncertainty taxonomies and EPD variability have been characterised, automated feedback mechanisms integrated with cost workflows have not yet been used to address them. EEBOQ's BFCE is the first system reported to address this issue at a portfolio scale.

3. Methods and Procedures

The proposed architecture incorporates a multi-stage AI pipeline designed specifically for processing heterogeneous construction cost estimation spreadsheets, with a particular focus on CO_2 impact analysis. Figure 1 shows the high-level architecture of EEBOQ. The system comprises five loosely coupled modules: (1) Ingestion and Preprocessing; (2) BOQ Structuring; (3) Semantic Emission-Factor Matching; (4) the CO_2 Estimation Engine; and (5) the Bayesian Feedback Correction Engine. Each module has a REST API, which enables integration with the quantity-surveying software and BIM authoring tools that are commonly used in construction environments in Latvia and other parts of Europe.

3.1 BOQ and Cost Estimate Ingestion module

The input layer is the entry point of the EEBOQ framework. It is responsible for ingesting heterogeneous construction cost documentation from procurement, tendering and project estimation workflows. The framework supports various document formats, such as XLSX spreadsheets, PDF-based BoQs, CSV datasets and IFC/BIM-derived quantity schedules.

In practical construction environments, cost estimates frequently exhibit substantial variability in:

a. Document structure;
b. terminology;
c. language;
d. tabular organisation;
e. measurement conventions;
f. pricing hierarchies.

The ingestion module accepts BOQ inputs in the following formats: PDF (including scanned documents processed via Tesseract OCR with Latvian and English language packs), Microsoft Excel, CSV and

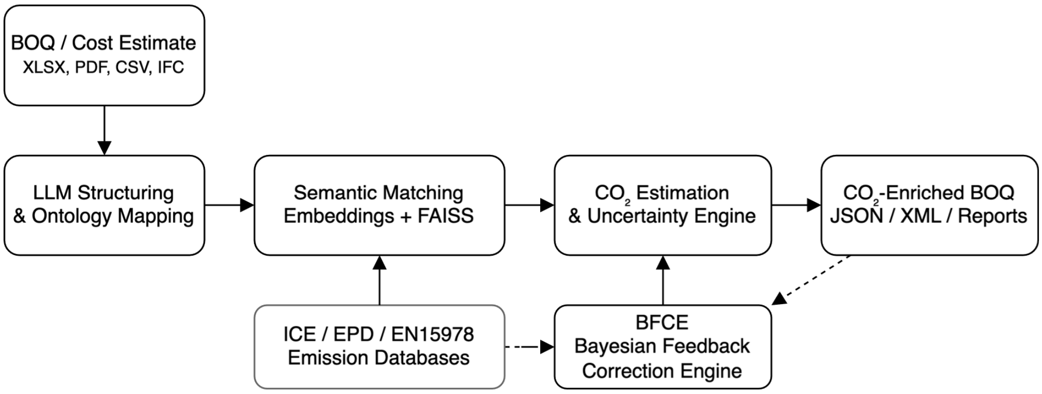

Figure 1. Proposed EEBOQ architecture for BOQ structuring, semantic emission-factor matching, CO_2 estimation, and Bayesian Feedback Correction

IFC. A document-type classifier then routes these inputs to specialised parsers. For Excel and CSV sources, which dominate Latvian construction practice where costs are usually managed using Excel-based estimate sheets, a layout-detection algorithm uses positional heuristics and a fine-tuned DistilBERT model (Sanh et al., 2019), trained on annotated BOQ headers in Latvian, English, German and other languages, to identify the BOQ header row. PDF sources are handled by pdfplumber, while scanned documents use a PaddleOCR-based table extraction pipeline calibrated for the A4 standard used in European public procurement.

Consequently, the input layer was designed to accommodate highly unstructured and semi-structured estimation datasets originating from different contractors, consultants, suppliers, and procurement authorities. The objective of this module is to establish a unified ingestion interface capable of supporting enterprise-scale interoperability across heterogeneous construction data ecosystems.

3.2 LLM Structuring and Ontology Mapping module

Raw parsed rows are mapped to the EEBOQ Material Ontology (CMO), which is a hierarchical concept graph comprising 847 leaf nodes that are aligned with internationally recognised construction classification systems. These include Uniclass 2015 (NBS, 2023) and LVS EN ISO 12006-2. The structuring pipeline uses a fine-tuned LLM to extract entities (material type, processing stage, grade/specification and unit of measure) and a rule-based ontology classifier to assign CMO nodes. The prompt engineering uses the chain-of-thought pattern and few-shot examples are drawn from Latvian cost estimates.

3.3 Semantic Emission-Factor Matching module

The Semantic Emission-Factor Matching module forms the core of the interoperability layer between construction cost data that is semantically structured and repositories of embodied-carbon knowledge. Its primary objective is to automatically link free-text BOQ line items to the most semantically relevant embodied-carbon records from standardised emission-factor databases and Environmental Product Declaration (EPD) repositories.

Unlike conventional keyword-based matching approaches, the proposed module uses transformer-based semantic embeddings (Reimers & Gurevych, 2019), vector similarity retrieval (Johnson et al., 2021), and contextual re-ranking mechanisms. The output is an ordered list of up to five candidate emission-factor records sourced from the ICE Database v3.0 (Hammond and Jones, 2019), the Circular Ecology EPD library (Circular Ecology, 2024), the EN 15978 reference data (CEN, 2011) and the Ecoinvent 3.9 cut-off database (Ecoinvent Association, 2022).

The EEBOQ framework acts as a semantic integration layer between construction cost estimates and existing environmental datasets. The framework does not generate new EPD data or act as an alternative carbon database. Instead, it automates the identification, structuring and mapping of BOQ positions to external sources of embodied carbon information.

3.4 CO_2 Estimation Engine Module

The estimation engine multiplies BOQ quantities by the relevant emission factors to produce line-item CO_2 estimates ($kgCO_2e$). Three-point estimates (optimistic, most likely and pessimistic) are propagated from the uncertainty of the candidate match list. Monte Carlo aggregation (10,000 iterations) is used to produce project-level totals with 90% credible intervals. Transport emissions (module A4) are estimated using origin-to-site logistics data. Latvia's comparatively short supply chains for timber and concrete products result in lower A4 contributions than those reported in several international reference datasets.

3.5 Bayesian Feedback Correction Engine Module

This module closes the feedback loop by updating the emission-factor library using observed CO_2 data. Geographic strata are used to separate the Latvian context from the broader European one.

4. Experimental Results

This evaluation corpus comprises construction projects in Latvia, including residential, commercial and public sector projects. The projects cover timber-frame, brickwork and mixed-construction typologies, and the cost estimates have been prepared using standard Latvian construction cost estimation methods. Total number of items in the BOQ dataset: 214,381; items with annotations and verified emission factor correspondences: 23,750; items for which there is at least one EPD or actual CO_2 emission data: 4,817.

4.1 Baseline Comparison

Table 1

CO_2 Estimation Error Before and After BFCE Feedback Cycles (Median Absolute Percentage Error)

Method	MdAPE (%)
Lookup table + 3-point estimate (ICE range)	22.3 (uncertainty range)
Semantic matching + lookup table (no BFCE)	28.5
EEBOQ + BFCE – 1 feedback cycle	18.8
EEBOQ + BFCE – 2 feedback cycles	12.4
EEBOQ + BFCE – 3 feedback cycles	8.3
Fully verified EPD-based estimate (oracle upper bound)	4.2

Three BFCE cycles reduce MdAPE by around 71% compared to the semantic-matching baseline. The remaining 8.3% reflects the genuinely unavoidable variation between actual and declared EPD values, as well as logistics uncertainty. This is consistent with Sun and Park's (2020) findings regarding variability in emissions during the construction phase.

4.2 Geographic Calibration Value

Disabling geographic stratification and pooling observations from different Latvian supply-chain contexts together results in an increase in the post-correction MdAPE from 8.3% to 14.7%. This confirms that local supply-chain characteristics provide significant calibration value. This finding lends weight to the argument put forward by Elmousalami et al. (2025) that AI-based sustainability tools should be localised rather than applied universally.

4.3 Feedback Convergence by Material Category

Table 2

Median Observations to Posterior Stabilisation (< 5% shift) by Category

Material Category	Median Obs. to Stabilise	Final MdAPE (%)
Structural steel (EAF)	6	6.1
Precast concrete elements	7	7.3
Latvian timber frame (LVL/CLT)	8	7.9
Clay brickwork	9	8.9
Mineral wool insulation (Nordic)	13	10.4
Aluminium glazing systems	14	11.2
Specialist coatings	17	13.6

5. Discussion

5.1 Limitations

Several limitations should be acknowledged. Firstly, the LLM structuring model was trained using Latvian and English BOQs. Other European languages, such as Finnish and Estonian, have not yet been evaluated. This limits the applicability of the model to the wider Baltic region without retraining. Secondly, the current BFCE treats emission-factor strata as independent, so correlations between categories (e.g., the co-variation of concrete and aggregates with transport fuel costs, which affect both emission factors) are not modelled yet. A multivariate Bayesian network extension is planned. Thirdly, Scope 3 emissions from site activities (Module A5, EN 15978) are estimated based on default assumptions, as as-built data for this phase is rarely available in Latvian records. Fourthly, EPD parsing currently only supports PDF/XML; HTML-published EPDs require manual extraction.

5.2 Implications for Latvian Practice

EEBOQ's incremental adoption model is in line with the current regulatory trajectory in both markets. In Latvia, institutional readiness is being created through ERDF-funded digital construction initiatives and the forthcoming national implementation of EU mandatory embodied carbon disclosure. EEBOQ can serve as a compliance layer, generating the structured CO_2 evidence trail required by both frameworks without disrupting existing cost management workflows.

5.3 Comparison with Existing Tools

EEBOQ is an integration and data-preparation framework designed to bridge the gap between construction cost-estimation workflows and existing embodied-carbon assessment resources. Its primary contribution is the automated identification, structuring and semantic mapping of BOQ line items to external environmental datasets. This reduces the manual effort typically required for embodied carbon calculations. The framework allows existing carbon assessment methodologies and databases to be used more efficiently in procurement and cost management processes.

6. Conclusions

This paper presented EEBOQ, an AI-driven framework designed to address the longstanding disconnect between construction cost management workflows and embodied carbon assessment. EEBOQ is particularly applicable to the Latvian construction sector and broader European embodied carbon assessment initiatives. The proposed framework integrates a multilingual Large Language Model (LLM)-based structuring pipeline and contrastive embedding-based semantic retrieval mechanisms. It also incorporates a Bayesian Feedback Correction Engine (BFCE) to adaptively refine environmental intelligence. Experimental validation demonstrated that the framework achieved top-1 semantic matching accuracy of 89.3%, while reducing embodied-carbon estimation error from 28.5% using conventional look-up table methodologies to 8.3% after three iterative feedback cycles.

The BFCE introduces a probabilistic and scalable mechanism for continuously improving the accuracy of embodied-carbon estimation through the integration of project-specific observations, Environmental Product Declarations (EPDs), logistics data, supplier information and verified as-built records. Unlike static carbon accounting approaches, the proposed Bayesian updating framework allows environmental coefficients to evolve dynamically as more project-related information becomes available. Furthermore, incorporating geographic stratification ensures that the correction process explicitly preserves regional supply-chain characteristics and material-production patterns, thereby improving estimation accuracy for geographically distinct construction ecosystems. This includes Latvia's timber-oriented, relatively short supply-chain market conditions.

As regulatory frameworks within the European Union continue to progress toward mandatory embodied-carbon disclosure and whole-life carbon assessment, the need for automated, transparent, and continuously verifiable carbon-accounting mechanisms integrated directly into quantity-surveying and procurement workflows becomes increasingly critical. In this context, EEBOQ can be regarded as a practical and scientifically grounded step towards the realisation of evidence-driven, AI-assisted embodied-carbon management within next-generation digital construction ecosystems.

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