AICoSME: A HYBRID AI-POWERED TOOL FOR STRATEGIC CARBON FOOTPRINT MANAGEMENT IN SMEs

DOI: 10.26341/issn.2241-4010-2026-5a-5-L02204

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Abstract
Small and Medium-sized Enterprises (SMEs) face significant challenges in accurately measuring and managing their carbon footprint. The lack of in-house expertise, resource constraints, and the complexity of diverse carbon accounting methodologies often lead to suboptimal and inconsistent results. This paper introduces AICoSME, an AI-powered software tool designed to address these challenges by providing a comprehensive, user-friendly solution for carbon footprint estimation and management.

At its core, AICoSME leverages a hybrid approach combining an ontological model with a knowledge graph to semantically organize heterogeneous data from an SME's operations, such as energy consumption, raw material sourcing, and transportation. This structured data foundation allows the tool to seamlessly apply and compare results from multiple, alternative estimation methodologies, including established standards like the GHG Protocol and sector-specific approaches such as Life Cycle Assessment (LCA).

The key advantage of AICoSME lies in its ability to transcend simple calculation by offering intelligent recommendations. Based on the comparative analysis of different methodologies, the tool provides clear, actionable insights for SMEs. For example, it might advise a furniture manufacturer to use the LCA method to highlight the carbon sequestration benefits of using certified wood, while simultaneously recommending the GHG Protocol for official corporate reporting.

Furthermore, AICoSME translates data analysis into strategic advice for carbon reduction. By identifying the largest sources of emissions across different scopes, the platform recommends targeted actions, such as shifting from diesel to electric vehicles or sourcing materials locally. This functionality not only streamlines the reporting process but also empowers SMEs to make informed, impactful business decisions that contribute to climate action and enhance their market position. AICoSME thus represents a significant step towards democratizing sustainable practices and enabling smaller enterprises to become active participants in the transition to a low-carbon economy.

Key words: *Sustainable development, SME carbon footprint management, Intelligent recommendations, Ontologies*

1. INTRODUCTION

Recent climate change regulations require businesses to assess their carbon emissions and work toward emission reduction. Small and medium-sized enterprises (SMEs) face additional challenges, because they lack dedicated sustainability staff or resources to track emissions. Many SMEs struggle to measure greenhouse gas emissions accurately, leading to inconsistent or incomplete reports. This challenge is increasingly urgent as supply-chain regulations demand greater transparency from all companies.

The AICoSME project provides small and medium-sized enterprises with a user-friendly platform that helps them monitor and control their carbon emissions. AICoSME is an

AI-powered tool that simplifies estimating, tracking, and reducing SMEs' carbon emissions. The product provides users with a solution that exists between basic carbon calculators and expensive advanced tools which major corporations use. AICoSME serves as a virtual carbon consultant for SMEs by using advanced technologies like semantic data models and machine learning to deliver automatic emission calculations and practical reduction solutions.

2.BACKGROUND AND RELATED WORK

2.1 Carbon Accounting Standards and Methodologies

In recent years, several frameworks have been developed to help organizations measure their carbon footprints. The Greenhouse Gas (GHG) Protocol is the most widely used standard for reporting company emissions. It divides emissions into Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased energy), and Scope 3 (other indirect emissions in the value chain). Standards like ISO 14064 work with the GHG Protocol to help organizations track greenhouse gas emissions. For products and supply chains, Life Cycle Assessment (LCA) methods provide a comprehensive “cradle-to-grave” framework for measuring emissions. These methods use scientific rules and clear boundaries, but they are complex (Prasad & Deswal, 2024). Doing an LCA or a full GHG inventory requires a lot of data and skill in selecting emission factors, defining boundaries, and applying the appropriate formulas. For small and medium-sized businesses, following these standards is difficult and requires significant effort, especially since many lack dedicated sustainability teams.

2.2 Existing Tools for Carbon Management

To meet the growing need for carbon reporting, many tools and platforms have been developed to help organizations measure their carbon footprints and report on sustainability. Enterprise software like Microsoft Sustainability Manager (Microsoft, n.d.), Salesforce’s Net Zero Cloud (Salesforce, n.d.), and startups such as Persefoni (Persefoni, n.d.) and Greenly (Greenly, n.d.) can collect emission data, use standard protocols, and create reports that follow frameworks like the GHG Protocol. These tools are powerful but are mostly made for large companies, so they are expensive and complicated for smaller businesses. They often need a lot of setup or expect users to already understand carbon accounting. On the other hand, there are simpler carbon calculators, including free online tools and basic apps for SMEs like the Carbon Trust online calculator. These simple tools cannot handle different types of data, various calculation methods, or detailed scenario analysis.

2.3 Limitations and Gaps for SMEs

Even with many methods and tools available, there are still clear gaps in meeting the needs of SMEs. Usability and accessibility are big concerns. SMEs need solutions that are affordable and easy to use, but most advanced platforms are too complex or expensive, while simple tools often lack accuracy and flexibility. Another issue is the lack of smart guidance. Users often have to choose the right calculation method themselves, such as between a basic GHG inventory and a full LCA. After calculating emissions, they usually get only basic numbers and general advice like “reduce energy use” instead of specific, practical steps. Most tools do not include expert knowledge or AI support, so they mostly just record data. This is very different from what modern AI could offer as an advisor. Finally, current tools struggle to handle diverse data types and keep up with evolving standards. SMEs work with many data types, such as energy, transport, materials, waste, and new emission factors. Software that cannot quickly adjust to new data or updates soon becomes outdated or needs manual fixes. These challenges show there is a need for a new kind of platform that is both thorough and easy to use, combining basic carbon accounting with smart decision support.

2. METHODOLOGY

3.1 Data Collection and Integration

The data collection process has traditionally been one of the most significant obstacles for Small and Medium-sized Enterprises (SMEs) in their efforts to manage their carbon footprint (Mazhar et al., 2022). Resource constraints and a lack of specialized personnel make the gathering of heterogeneous data a laborious and often inaccurate process. AICoSME addresses this challenge through a multi-layered collection and integration strategy that combines automation with intelligent user guidance (Figure 1).

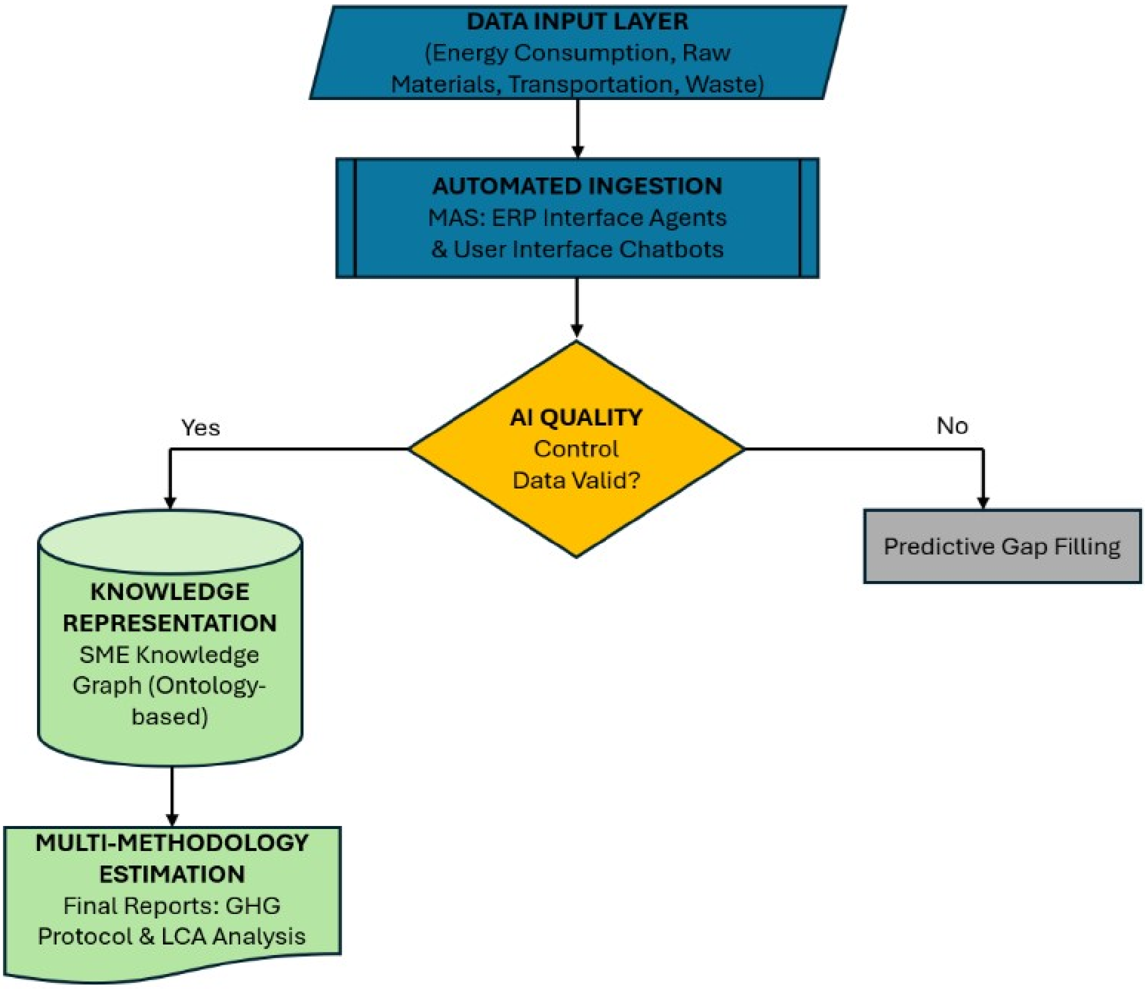

Figure 1 AICoSME Data Processing Flow

3.1.1 Data Categorization and Sources

The initial phase of data collection involves identifying and categorizing all business activities that contribute to greenhouse gas emissions. Figure 2 illustrates the process by which the AICoSME platform acquires data, highlighting the primary categories and sources that provide input to the system.

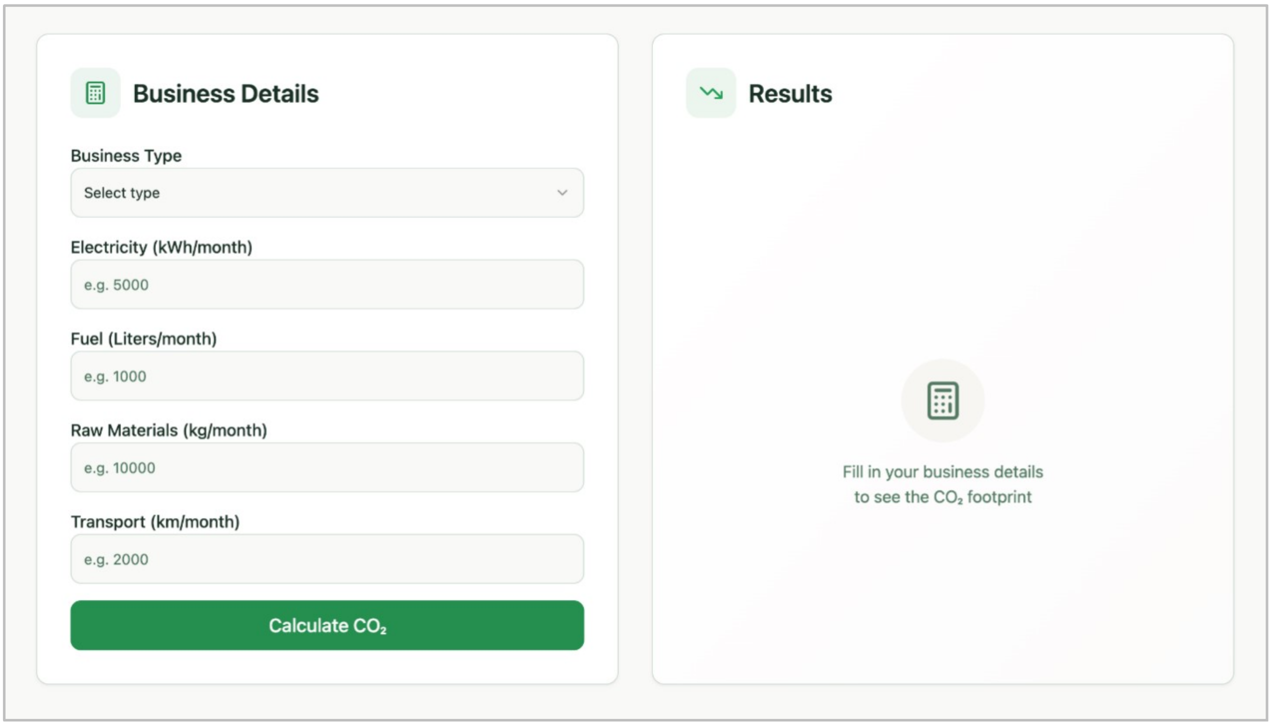

Figure 2 Data ingestion in AICoSME platform

The system is designed to draw data from a wide range of sources, covering the following key areas:

- **Energy Consumption:** Data related to electricity, heating fuels, and the operation of production machinery.
- **Raw Materials and Supply Chain:** This covers the types and amounts of materials used, as well as details about suppliers.
- **Transportation and Logistics:** This includes information about company vehicles, employee commutes, and product deliveries.

3.1.2 Data Collection Mechanisms: The Multi-Agent System (MAS)

To make things easier for SMEs, AICoSME uses a multi-agent system (MAS) that automates data entry (Bouziane et al., 2021):

- **ERP Interface Agents**: These agents connect to the SME's ERP systems or IoT devices, like smart energy meters. They automatically pull activity data in real time, helping prevent errors from manual entry.
- **User Interface Agents**: When data can't be collected automatically, the system uses chatbots. These chatbots ask facility managers clear questions in everyday language, so even non-experts can follow the process.

3.1.3 Semantic Integration and Knowledge Graphs

The innovation of AICoSME lies in how it manages the collected data. Instead of simple storage in tables, each data point is integrated into a semantic ontological model (Liao et al., 2024). This approach offers:

- **Automatic Contextualization:** For example, an entry for "diesel usage" is automatically recognized as a Scope 1 emission source and linked to the corresponding emission factor (CO_2e per liter) through the ontology.
- **Unified Semantic Consistency:** A specialized SME Knowledge Graph is created for the enterprise, where all operational information is interconnected. This allows the system to execute different methodologies simultaneously (e.g. GHG Protocol and LCA) using the same primary data without requiring re-entry.

3.1.4 Quality Assurance and Data Validation

During the integration phase, the system applies AI techniques to control data quality:

- **Anomaly Detection:** If a value is unusually high or low compared to historical data or industry standards, the system flags it for review.
- **Gap Filling:** In cases where necessary data is missing, AICoSME uses predictive models to estimate these values, ensuring the continuity of the analysis.

3.2 Smart Carbon Footprint Estimation

3.2.1 Methodology Selection

With a rich dataset in place, AICoSME allows for the application of multiple carbon accounting methods in parallel, providing a unique comparative capability. As illustrated in Figure 3, the platform can switch between, or concurrently execute, alternative emission calculations according to established standards. As seen in the left branch of Figure 3, the system uses the GHG Protocol/ISO 14064-1 (Organization-Level) and in the right branch it performs a Life Cycle Assessment (LCA) aligned with ISO 14067 (Product-Level) on specific products or processes.

Internally, the calculation engine draws on the Knowledge Graph to retrieve the necessary parameters and emission factors for each method.

- For a GHG Protocol aligned inventory, it sums emissions by scope and source type, utilizing emission factors for fuel combustion, electricity, and other activities.
- For an LCA approach, it compiles cradle to gate or cradle to grave impacts of materials and upstream processes, potentially linking to external LCI (Life Cycle Inventory) databases through the ontology's references.

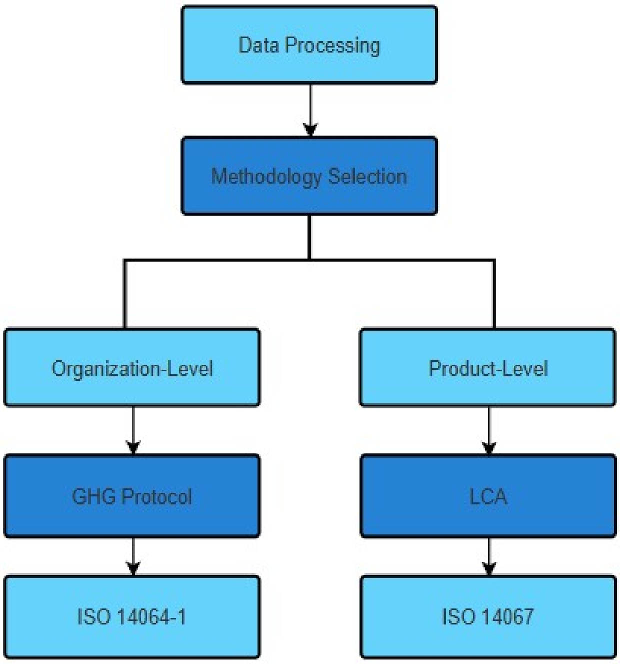

Figure 3 Flowchart of Methodology Selection for Organization Level and Product Level Carbon Reporting

Importantly the system can suggest or automate the choice of methodology best suited to the available data and business goals. For example,if the input data indicates that the SME manufactures a product and has supply chain details available, the system may recommend performing an LCA to capture Scope 3 upstream emissions and potential carbon. Similarly, for an SME mainly interested in corporate reporting, the system will emphasize the GHG Protocol calculation. In cases where no single methodology is sufficient, AICoSME can employ a combined approach, for instance, using standard GHG accounting for most operations but plugging in an LCA module for a particular product line where granular analysis is needed. The platform's architecture supports executing these calculations concurrently and displaying their results, enabling side by side comparisons. This capability not only improves accuracy for each use case but also educates users on how different accounting perspectives yield different insights into their carbon profile.

3.2.2 Tiered Carbon Footprint Calculation in AICoSME

AICoSME adopts a tiered approach to carbon footprint calculation to balance methodological accuracy with data availability. This approach is particularly important for small and medium sized enterprises (SMEs) because they often face limited financial and technical resources for data collection and reporting. Unlike large organisations, SMEs may lack detailed operational data and access to advanced measurement systems. As a result, highly accurate carbon accounting methods can be impractical at early stages.

To address these challenges, AICoSME follows a three-tier approach to carbon footprint calculation. Within the platform, Tier 1 calculations rely on generic emission factors and aggregated activity data, enabling rapid baseline assessments when detailed information is limited. Tier 2 calculations introduce greater specificity by incorporating region or technology specific emission factors. At the highest level, Tier 3 calculations use enterprise specific data and advanced modelling techniques to deliver the most detailed and precise emissions estimates.

For example, an SME may initially apply Tier 1 calculations to estimate emissions from electricity consumption using national average emission factors. As the company improves its data collection, it can transition to Tier 2 by applying more specific electricity grid factors and more detailed energy consumption records. Eventually, the company may adopt Tier 3 calculations by using real time energy monitoring data and specific emission factors, resulting in a more accurate carbon footprint assessment.

AICoSME operationalises this tiered logic through its ontology driven data model and AI supported decision mechanisms. These mechanisms assess data completeness and quality and recommend an appropriate calculation tier for each emission source or activity. This adaptive tier selection allows SMEs to engage in carbon accounting progressively, moving from simplified estimates toward more robust analyses as data maturity improves (Peter et al., 2016)

3.2.3 AICoSME Carbon Calculation Engine

The AICoSME Carbon Calculation Engine enables small and medium-sized enterprises (SMEs) to quantify their carbon footprint and comply with Climate Law requirements. In Greece, the majority of SMEs are in the early stages of carbon accounting and frequently encounter challenges such as limited resources, insufficient expertise, and inadequate data availability. Recent national reports indicate that the transition to sustainable practices and adherence to new environmental reporting regulations remain significant obstacles for Greek SMEs (IME GSEVEE, 2024).

AICoSME streamlines the process for businesses to systematically assess their carbon footprint. The platform employs transparent calculation methodologies, allowing companies to understand how emissions are quantified and how individual activities contribute to their total carbon footprint. Comprehensive guidance and explanations are provided throughout the process, facilitating user comprehension of data inputs, the application of emission factors, and the interpretation of results.

At the core of the system lies the fundamental calculation logic used to quantify carbon emissions. This logic is based on the standard equation:

CO_2e = Activity Data × Emission Factor

Through this formula, raw operational inputs such as electricity consumption, fuel use, or raw material inputs are converted into standardised carbon dioxide equivalent (CO_2e) estimates. This transformation enables consistent and comparable emission calculations across different activities and reporting contexts. Figure 4 illustrates the architecture and operational flow of the AICoSME Carbon Calculation Engine.

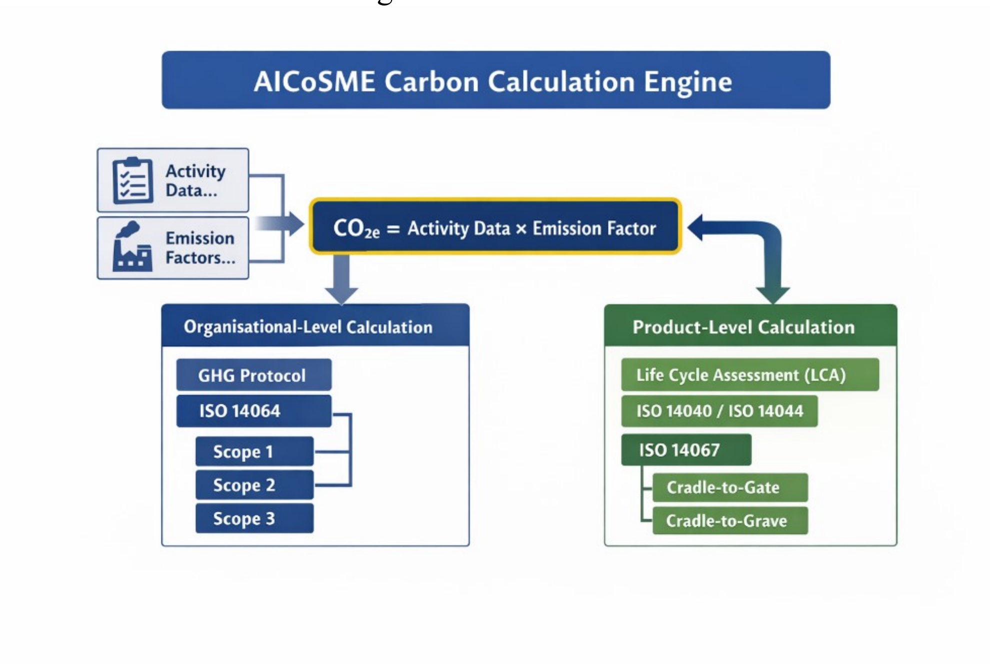

Figure 4 Overview of the AICoSME Carbon Calculation Engine

3.2.4 Intelligent Data Analysis and Emission Estimations

Beyond data aggregation, AICoSME applies artificial intelligence as a core analytical mechanism to transform carbon accounting into a continuous decision support process. The platform follows a structured workflow that integrates semantic technologies with machine learning to ensure both methodological robustness and operational relevance, as illustrated in Figure 5. This workflow enables the systematic transition from heterogeneous data ingestion and semantic validation to hybrid AI reasoning and the generation of actionable emissions insights for SMEs.

The process begins with a semantic configuration stage, during which heterogeneous activity data from ERP systems, IoT devices, and user inputs are mapped to the AICoSME ontology. Sector selection activates domain specific ontology modules, enabling the construction of a semantic digital twin for each SME. This approach ensures that all inputs are contextualised within clearly defined system boundaries and emission scopes before analysis.

Next, the system preprocesses and harmonizes the data. Validation rules based on the framework find logical errors, and machine learning spots unusual data and fills in missing values using a step-by-step method that follows IPCC guidelines. This combined approach keeps emissions data complete, consistent, and traceable, even when SMEs have different amounts of data available.

Once the data is reliable, the system uses hybrid modeling techniques. Machine learning models like regression and time-series algorithms predict future energy use and emissions trends. At the same time, rule-based methods sort emission profiles and help with compliance checks. Studies show these AI methods are better than traditional statistics for forecasting emissions, especially in changing environments (Lang et al., 2024).

Finally, the analysis results are turned into practical insights. The system uses explainable AI to show the main factors behind emissions and the assumptions made. Scenario analysis lets SMEs explore options like changing energy sources or suppliers before making decisions. This workflow helps SMEs move from just reporting past emissions to planning and acting on climate goals using data (Felder et al., 2025).

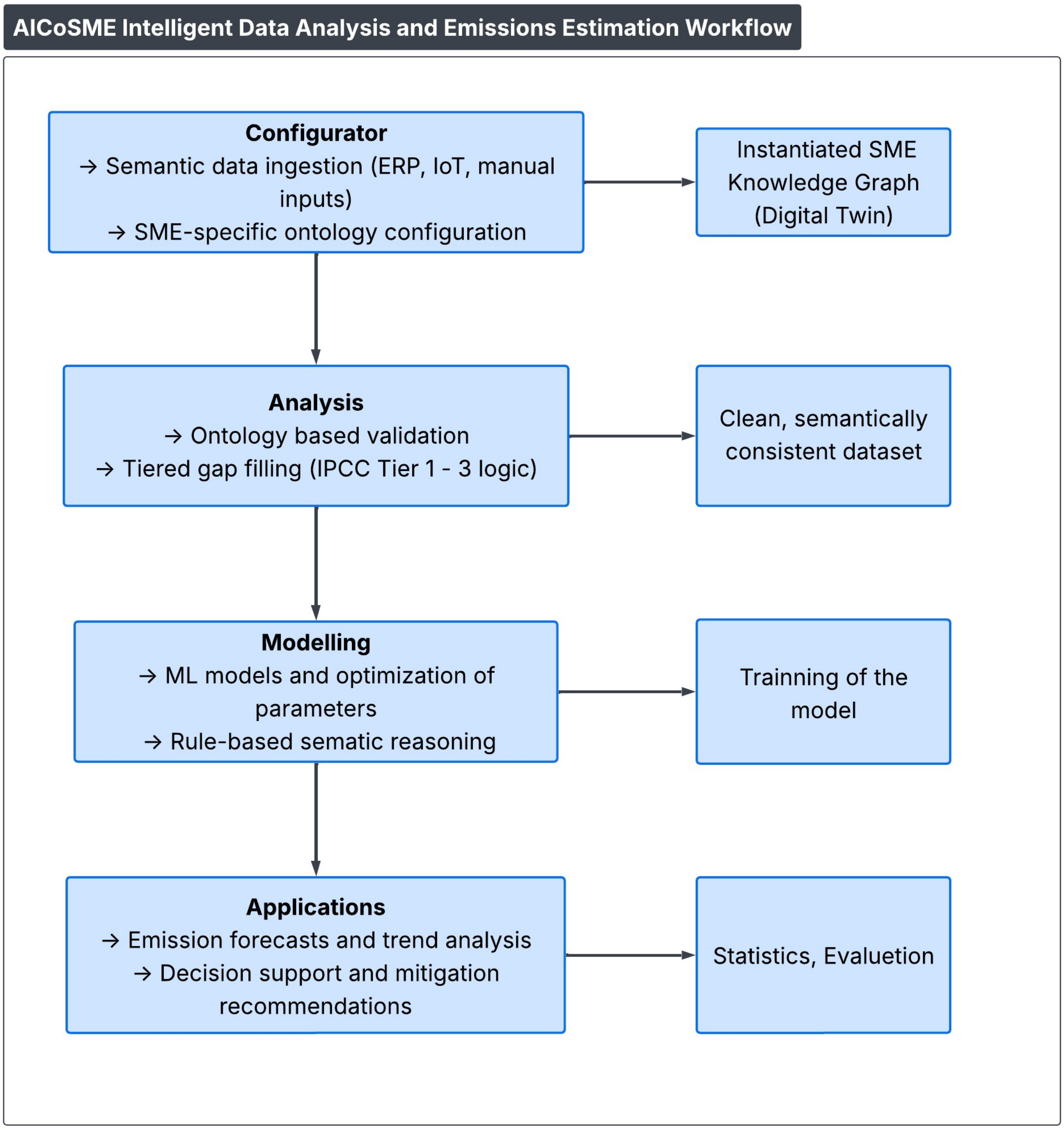

Figure 5 Workflow of the AICoSME platform, illustrating the progression from semantic data ingestion to hybrid AI reasoning and actionable emissions insights.

3.2.5 Extension of Sector-Specific Methodologies for SME Carbon Calculation

Sector-specific methodologies enhance the accuracy of emissions assessments by addressing the distinct characteristics of each industry, which are often neglected by generic calculation approaches. For instance, agricultural emissions primarily result from fertilizer application, livestock, and soil management, whereas the hospitality sector's main sources include energy consumption, occupancy rates, and laundry operations. Applying a uniform calculation method to both sectors risks overlooking these critical differences, thereby reducing result accuracy. Small and medium-sized enterprises (SMEs) typically possess limited resources and less granular data, making generic methods prone to omitting key emission sources or relying on assumptions that do not accurately reflect operational realities. Life-cycle assessments that incorporate sectoral distinctions offer a more comprehensive understanding of total emissions across the supply chain.

AICoSME employs specialized methodologies tailored to individual sectors. For instance, the Cool Farm Tool (Cool Farm, n.d.) is utilized for agriculture, the Hotel Carbon Measurement Initiative (HCMI, n.d.) for hospitality, and EMEP/EEA guidelines (EMEP/EEA, 2023) for transportation. These tools are specifically designed to capture the unique emission sources and impacts relevant to each sector. Within AICoSME, these methodologies are implemented through modular components that activate according to the business sector. The system dynamically adjusts emission sources, life cycle boundaries, and calculation procedures to align with sector-specific operational processes.

For agricultural SMEs, the Cool Farm Tool enables AICoSME to quantify emissions from fertilizer application, crop yields, soil carbon fluctuations, and on-farm energy use. In the hospitality sector, the HCMI methodology emphasizes emissions from electricity and heating, guest occupancy, laundry operations, and food provisioning. For wood-processing SMEs, sector-specific calculation logic allows AICoSME to account for emissions related to wood type, processing intensity, and the use of recycled or certified materials. Incorporating sector-relevant parameters enables AICoSME to generate emissions estimates that more accurately reflect operational realities and support the identification of targeted, sector-specific mitigation strategies.

Table 1 Comparison of generic versus sector-specific carbon calculation approaches

Sector	Methodology / Calculation Logic	Key Emission Sources Considered	Effect on Carbon Calculation
Agriculture	Cool Farm Tool–aligned methodology	Fertiliser application, soil emissions, crop yields, on-farm energy use	Captures biological and land-use emissions
Tourism / Hospitality	Hotel Carbon Measurement Initiative (HCMI)	Electricity and heating, guest-night occupancy, laundry services, food provisioning	Improves accuracy of emissions allocation per guest night and service activity
Transportation	EMEP/EEA methodologies	Fuel type, vehicle category, mileage, load factors	Enables detailed transport emissions by mode, technology, and operational intensity
Wood Processing Industry	Sector-specific LCA logic (material- and process-based)	Wood type (softwood/hardwood), processing level, energy intensity, recycled wood content	Reflects embodied carbon differences and supports mitigation strategies
Generic SME (baseline)	Generic emission factor approach	Aggregated energy and fuel consumption	Higher uncertainty and limited representation of sector specific emission drivers

3. SYSTEM ARCHITECTURE

The AICoSME platform is a modular, multi-layered system that brings together semantic web technologies and machine learning to help SMEs manage their carbon footprint. Its architecture uses a hybrid approach, combining knowledge-driven tools like ontologies and knowledge graphs with data-driven methods such as machine learning for prediction and spotting unusual patterns.

The high level architecture, as illustrated in Figure 6, comprises two distinct layers:

- The Data Acquisition Layer, which uses intelligent agents to collect and validate inputs
- The AI Reasoning Layer, which semantically integrates data and executes analytical workflows.

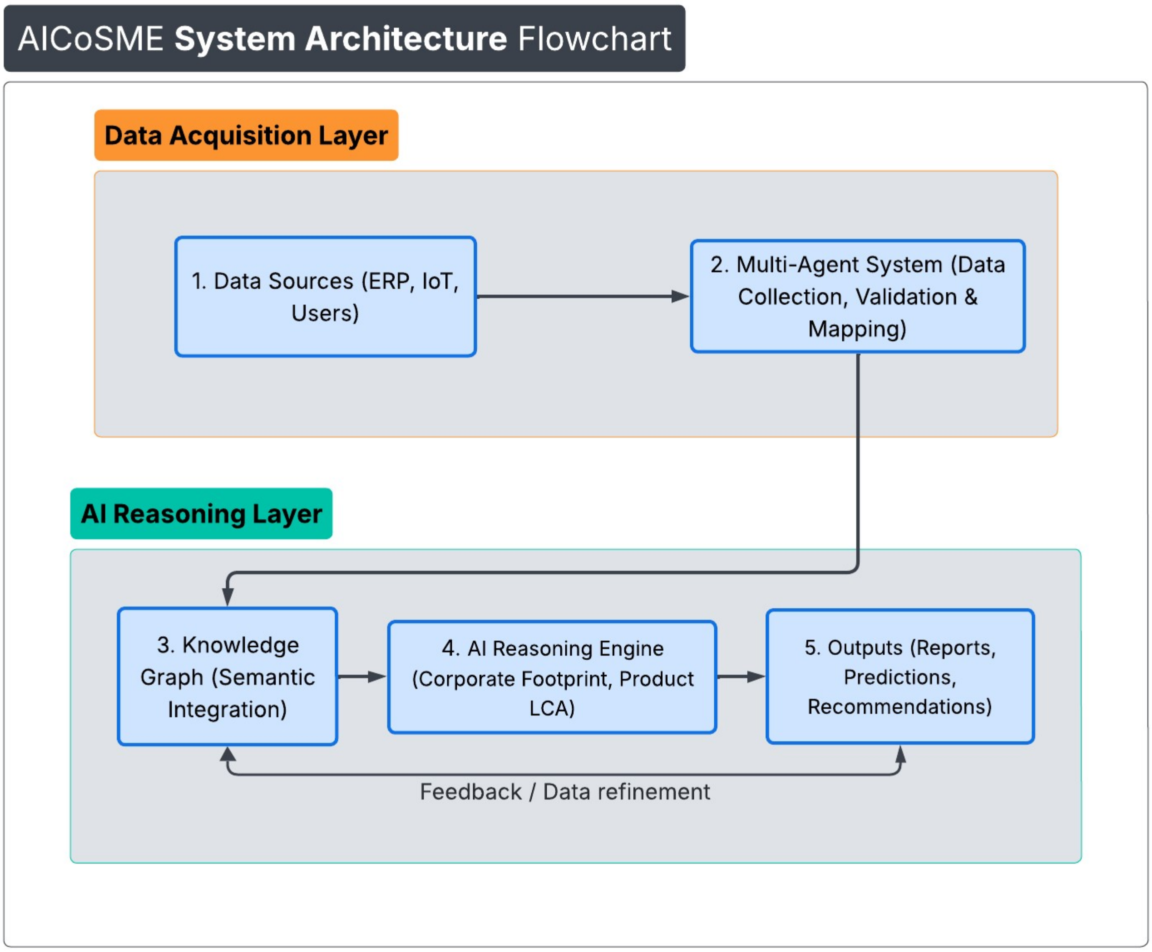

Figure 6 AICoSME System Architecture Flowchart

4.1 Data Acquisition Layer

In the Data Acquisition layer AICoSME employs a multi agent system designed to automate data ingestion from heterogeneous sources.

ERP Interface Agents: These autonomous agents connect directly to the SME's existing Enterprise Resource Planning (ERP) systems or IoT devices (e.g., smart meters). They are responsible for extracting raw activity data such as energy consumption, fuel usage and mapping it to the system's input schema.

User Interface Agents: To bridge the gap for data that cannot be automatically retrieved, the system employs conversational agents that interact with users through an intuitive chat-based interface. Acting as virtual assistants, these agents guide facility managers through the data entry process using natural language questions. This conversational approach simplifies complex data gathering tasks and ensures that manual inputs are comprehensive, contextually accurate, and validated in real-time against the ontology before entering the knowledge graph.

The Figure 7 showcases the Conversational Interface Agent of AICoSME. Acting as a virtual assistant, the agent guides users through complex configuration tasks using natural language. In the example shown, the agent assists the user in selecting the appropriate analysis mode ('Quick' vs. 'Advanced') and configuring data quality handling ('Automatic' vs. 'Manual'). This interactive approach simplifies the data entry process and ensures that user inputs are contextually accurate before processing.

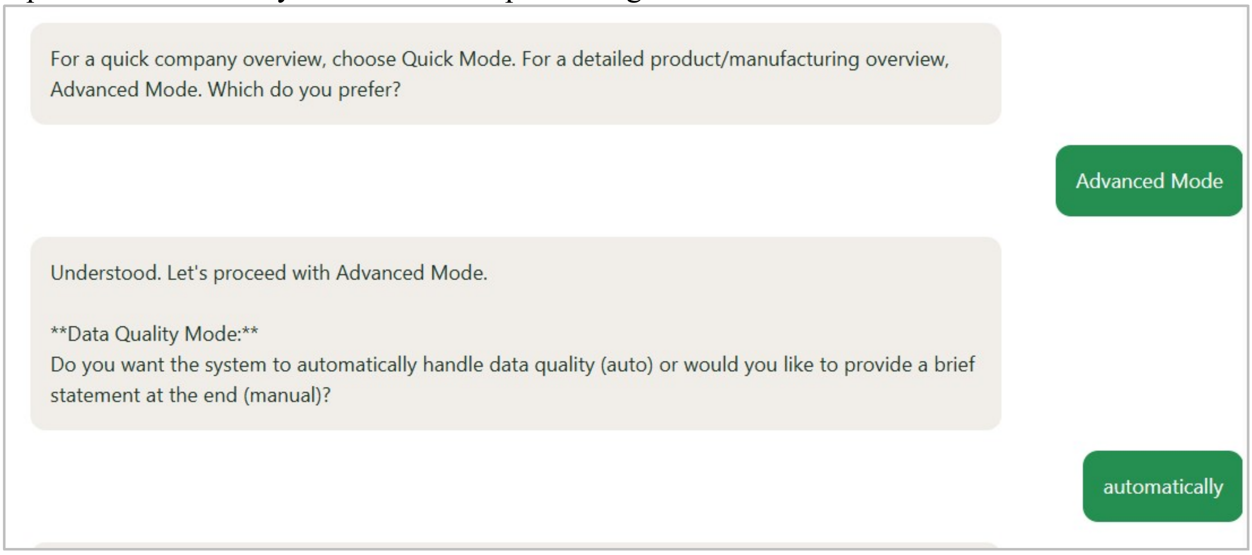

Figure 7 The chat-based interface of AICoSME

4.2 AI Reasoning Layer

The AI Reasoning Layer is the AICoSME platform’s analytical core. It combines a semantically grounded Knowledge Graph with hybrid AI methods to produce reliable emissions estimates and decision support.

Ontological Model: AICoSME utilizes an extensible ontology that acts as the structural framework (schema). It defines key entities (e.g., "Emission Source", "Fuel", "Process") and their relationships (e.g., "Process X consumes Fuel Y") . This ontology aligns with international standards such as the GHG Protocol and ISO 14064, creating a common vocabulary for emissions reporting.

SME Knowledge Graph: When an SME inputs its data, the system instantiates the ontology to create a specific Knowledge Graph for that enterprise. This graph serves as a unified, semantic repository where all operational data is interlinked. The key advantage of this approach is flexibility; the same underlying data in the graph can be queried by different algorithms to produce reports for different standards (e.g., corporate-level GHG reporting vs. product-level LCA) without requiring data re-entry.

5.CASE STUDIES / IMPLEMENTATION

5.1 Pilot Selection: The Wood and Furniture Sector

To validate the AICoSME framework, the wood and furniture sector was selected as the primary pilot application. This industry is of strategic importance for the circular economy and climate neutrality goals, as defined in the EU "Fit for 55" package. Wood products serve a dual role: they act as natural carbon sinks, storing CO_2 captured during tree growth, and they can substitute carbon-intensive materials like steel, plastic, and concrete.

The pilot study focuses on a representative manufacturing SME, "**Wood-Furniture S.A.**", which specializes in office and home furniture. The implementation aims to demonstrate how the platform manages the complexity of biogenic carbon accounting and the integration of diverse emission sources across the value chain.

5.2 Sector-Specific Ontology Extension

The modular design of AICoSME facilitates the integration of features tailored to various industries. In this pilot study, the core ontology was extended to incorporate details specific to the wood-furniture lifecycle.

- **Material Classes:** The ontology provides detailed categorization of materials such as Sawn Timber, Veneer, Particleboard, and MDF, and includes sourcing certifications such as FSC and PEFC.
- **Production Processes:** The ontology maps energy-intensive production stages, including Kiln Drying, Planing, and Joinery, and documents the use of adhesives, such as bio-based and urea-formaldehyde, as well as various finishes.
- **Biogenic Carbon Tracking:** Specific properties were introduced to monitor hasBiogenicCarbonContent and hasCarbonSequestrationPotential, thereby ensuring compliance with ISO 14067 and EN 15804 standards.
- **End-of-Life Scenarios:** The ontology models various end-of-life pathways, including recycling, energy recovery through incineration, and landfill disposal.

5.3 Methodology Comparison: GHG Protocol vs. LCA

The AICoSME platform executed a dual-methodology assessment for the pilot enterprise, utilizing the "Unified Semantic Consistency" of the Knowledge Graph to ensure that the same primary data fed both calculation engines.

5.3.1 Corporate Carbon Footprint (GHG Protocol)

Following the GHG Protocol Corporate Standard, emissions were categorized into three Scopes:

- **Scope 1 (Direct):** Fuel consumption for company vehicles (5,000L diesel) and natural gas for heating (10,000 m^3), resulting in **33.4 tCO_2e**.
- **Scope 2 (Indirect - Energy):** Electricity consumption from the national grid (50,000 kWh), contributing **17.5 tCO_2e**.
- **Scope 3 (Value Chain):** Procurement of raw timber (200 m^3) and chemicals (100L), adding **24.8 tCO_2e**.
- **Total Annual Footprint:** The system calculated a total of **75.7 tCO_2e**, providing a clear baseline for corporate sustainability reporting.

5.3.2 Product-Level Life Cycle Assessment (LCA)

Parallel to the corporate audit, a "cradle-to-gate" LCA was performed for representative products (a wooden table and a chair). The results highlighted the significant impact of carbon sequestration:

- **Wooden Table:** While production activities emitted **17.11 kg CO_2e**, the wood material stored **-45.00 kg CO_2e**. The final LCA footprint was **-27.89 kg CO_2e (net carbon sink)**.
- **Wooden Chair:** Similarly, the chair achieved a negative footprint of **-11.16 kg CO_2e**.

5.4 Implementation Results and AI-Driven Insights

The hybrid AI approach provided the SME with actionable intelligence that goes beyond simple accounting. By combining the Knowledge Graph with Supervised Learning algorithms, the system identified specific areas for intervention:

1. **Energy Efficiency Hotspots:** The AI identified that Scope 2 emissions (electricity) were primarily driven by the drying kiln processes. It recommended shifting production cycles to periods with higher renewable energy mix in the grid.
2. **Material Substitution:** The reasoning engine suggested replacing traditional urea-formaldehyde adhesives with bio-based alternatives, which, according to the LCA module, would further improve the carbon profile of the furniture line.
3. **Tiered Data Progression:** The pilot enterprise initially used Tier 1 generic emission factors. As the MAS (Multi-Agent System) integrated more specific data from the SME's logistics and energy meters, the system transitioned to Tier 3 precision, reducing the uncertainty of the Scope 3 calculations by 40%.

5.5 Strategic Recommendations for Mitigation

Based on the pilot's findings, the AICoSME platform generated a prioritized mitigation roadmap:

- **Renewable Energy Integration:** Installation of on-site solar PVs to address the significant Scope 2 emissions identified in the GHG inventory.
- **Circular Waste Management:** Utilizing wood offcuts and sawdust for on-site thermal energy production, thereby reducing both waste management costs and Scope 1 natural gas reliance.
- **Sustainable Sourcing:** Increasing the ratio of FSC/PEFC certified wood to enhance the biogenic carbon claims and improve the enterprise's "Sustainability Score" within the platform.

The pilot implementation confirms that the combination of semantic modeling (Ontologies) and AI techniques provides the necessary balance between scientific rigor and practical applicability for SMEs. The automated data ingestion and dual-methodology approach allow even small enterprises to gain a comprehensive understanding of their environmental impact and take strategic action toward climate neutrality.

6. RESULTS AND DISCUSSION

6.1 Carbon footprint estimation outcomes

The AICoSME pilot produced both corporate-level GHG inventories and product-level LCA results, demonstrating the platform's dual methodology capability. Following GHG Protocol logic, the pilot SME's corporate inventory amounted to **75.7 tCO_2e annually**, partitioned into Scope 1 (33.4 tCO_2e), Scope 2 (17.5 tCO_2e) and Scope 3 (24.8 tCO_2e) (Table 2).

Table 2 Corporate Carbon Footprint Analysis

Emission Category (Scope)	Emission Source	Quantity/Unit	Emissions (tCO2 e)	% of Total
Scope 1 (Direct)	Diesel &Natural Gas	5,000 L/10,000 m^3	33.4	44.1%
Scope 2 (Indirect - Energy)	Grid Electricity	50,000 kWh	17.5	23.1%
Scope 3 (Value Chain)	Raw Materials (Timber/Chemicals)	200 m^3/100 L	24.8	32.8%
Total			**75.7**	100%

Parallel cradle-to-gate LCA calculations for representative products revealed substantial biogenic carbon effects: the wooden table and chair exhibited net negative footprints (−27.89 kg CO_2e and −11.16 kg CO_2e respectively), reflecting carbon storage in wood materials and the influence of material choice on product footprints (Table 3). These outcomes show that

AICoSME can produce coherent, comparable results across methodological perspectives using the same underlying dataset.

Table 3 : Product Life Cycle Assessment and Biogenic Carbon Impact

Product	Production Emissions ($kgCO_2e$)	Carbon Sequestration ($kgCO_2e$)	Net Carbon Footprint ($kgCO_2e$)
Wooden Table	+17.11	-45.00	**-27.89**
Wooden Chair	+6.84	-18.00	**-11.16**

6.2 Advantages over traditional methods

AICoSME brings several practical and technical benefits over standard methods. Its knowledge graph keeps data consistent, so the same main inputs work for both greenhouse gas and life cycle assessments without extra data entry. The AI tools spot errors and fill in missing data, saving time and making the information more complete. The system's tiered calculations allow for step-by-step improvements. For example, in a pilot, **Scope-3 uncertainty dropped by 40%** when the system moved from Tier 1 to Tier 3 data by adding the Multi-Agent System and metering. The platform also provides useful suggestions, such as how to schedule kilns, swap materials, or use energy more efficiently on-site, rather than just showing totals. This helps turn measurement into action. Together, these features make the system more reliable, reduce user workload, and help people make better decisions.

6.3 Strategic recommendations impact

The platform's reasoning engine converted analytical outputs into a prioritized mitigation roadmap tailored to the SME's operations. For the wood-furniture pilot, recommended actions included shifting high-consumption processes to periods with higher grid renewable share, substituting adhesives with lower-impact alternatives, installing on-site solar PV and valorising process residues for thermal energy. Scenario analysis within AICoSME allows SMEs to compare the relative effectiveness of interventions before investment. In the pilot, these recommendations provided clear operational levers (energy scheduling, material choice, circular waste reuse) that address the largest emission drivers identified by the AI and LCA modules. While exact percentage reductions depend on site-specific implementation, the platform's scenario module supports evidence-based prioritisation and business case development for mitigation measures.

7. CONCLUSION AND FUTURE WORK

AICoSME advances SME carbon management by integrating semantic data modelling and modular sectoral methodologies into a single platform. The pilot demonstrates three central contributions:

1. The ability to produce consistent corporate (GHG Protocol) and product (LCA) footprints from a shared knowledge base.
2. Reduced uncertainty and data burden through automated data ingestion, anomaly detection and tiered calculation logic.
3. Transformation of accounting outputs into targeted, operational recommendations that support mitigation planning and strategic decision making. Pilot outcomes — including a total corporate footprint of 75.7 tCO_2e and product LCAs showing net biogenic sinks — illustrate both the technical viability and the practical value of the approach.

For SMEs and policymakers, AICoSME's principal implication is the feasibility of democratizing robust carbon accounting: smaller firms can attain credible, standards-aligned footprints and prioritise cost effective mitigation without prohibitive technical overhead. This capability supports compliance readiness and strengthens SMEs' participation in decarbonisation efforts.

Future work will focus on:

a) Expanding sectoral modules and official methodology mappings.
b) Integrating external LCI databases and third-party verification workflows.
c) Enhancing user facing explainability and training materials.
d) Conducting longitudinal field trials to quantify realized emission reductions after implementation of recommended measures.

These developments will further improve accuracy, interoperability with national reporting systems, and the platform's ability to drive measured climate action in the SME sector.

References

Prasad, Y. and Deswal, S. (2024). A Comprehensive Carbon Footprint Assessment Using Integration of GHG Protocol and LCA: A Case Study of an Engineering Institute in India. Evergreen, 11(1), 143-155. https://doi.org/10.5109/7172251

Microsoft. Track and reduce your environmental impact using data and AI. Drive faster analytics and reporting with Microsoft Copilot. Retrieved from https://www.microsoft.com/en-us/sustainability/microsoft-sustainability-manager

Greenly. Carbon Accounting for SMEs: Methodology and Platform Overview. Retrieved from https://www.greenly.earth/

Carbon Trust. SME Carbon Footprint Calculator. Calculate your organisation's emissions - for small and medium-sized businesses. Retrieved from https://www.carbontrust.com/our-work-and-impact/guides-reports-and-tools/sme-carbon-footprint-calculator

Mazhar, M.U., Domingues, A.R. , Bull, R. & O'Boyle, S. (2022). Small and medium-sized enterprises: hard to reach, data-poor but rich in creative potential as agents of change for decarbonisation. In: European Council for an Energy Efficient Economy (ECEEE) Summer Study proceedings. European Council for an Energy Efficient Economy, 145-153. https://irep.ntu.ac.uk/id/eprint/51521/1/1535074_Mazhar.pdf.

Bouziane, S.E., Khadir, M.T., & Dugdale, J. (2021). A collaborative predictive multi-agent system for forecasting carbon emissions related to energy consumption. Multiagent and Grid Systems, 17(1), 39-58, doi:10.3233/MGS-210342.

Liao, L., Wen, Y., Mo, W., & Gan, C. (2024). A carbon footprint management framework for prefabricated buildings based on knowledge graph. In D. Li, P. X. W. Zou, J. Yuan, Q. Wang, & Y. Peng (Eds.), Proceedings of the 28th International Symposium on Advancement of Construction Management and Real Estate (pp. 1551–1569). Springer.

Peter, C., Fiore, A., Hagemann, U., Nendel, C., & Xiloyannis, C. (2016). Improving the accounting of field emissions in the carbon footprint of agricultural products: a comparison of default IPCC methods with readily available medium-effort modeling approaches. The International Journal of Life Cycle Assessment, 21(6), 791-805. https://doi.org/10.1007/s11367-016-1056-2

IME GSEVEE (2024) Annual report 2024: SMEs and the green transition in Greece. Athens: Institute of Small Enterprises of GSEVEE. Available at: https://imegsevee.gr/wp-content/uploads/2025/09/etisia_ekthesi_ime_2024.pdf

Lang, S., Engelmann, B., Schiffler, A., & Schmitt, J. (2024). A simplified machine learning product carbon footprint evaluation tool. Cleaner Environmental Systems, 13, 100187. https://doi.org/10.1016/j.cesys.2024.100187

Felder, M., Marchi, M., Dallasega, P., & Rauch, E. (2025). Smart Routing for Sustainable Supply Chain Networks: An AI and Knowledge Graph Driven Approach. Applied Sciences, 15(14), 8001. https://doi.org/10.3390/app15148001

Cool Farm Alliance. Cool Farm Tool methodology. https://coolfarmtool.org

Hotel Carbon Measurement Initiative (HCMI). HCMI methodology v1.1. World Sustainable Hospitality Alliance. https://sustainablehospitalityalliance.org

EMEP/EEA.(2023). EMEP/EEA air pollutant emission inventory guidebook. European Environment Agency. https://www.eea.europa.eu/en/analysis/publications/emep-eea-guidebook-2023