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ARTIFICIAL INTELLIGENCE (AI)-AUGMENTED CARBON ACCOUNTING WITH ECOSCOPEAI: STRENGTHENING SDG 12 AND SDG 13 THROUGH CSRD AND CBAM INTEGRATION

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ABSTRACT

PURPOSE: This research paper describes EcoScopeAI, an AI-powered carbon accounting prototype to assist small and medium-sized enterprises (SMEs) in meeting the requirements of two new EU regulations: the Corporate Sustainability Reporting Directive (CSRD) and the Carbon Border Adjustment Mechanism (CBAM). These regulations are designed to drive greater accuracy, automation and transparency in sustainability reporting in line with SDG 12 and SDG 13. The UK's Department for Environment, Food and Rural Affairs (DEFRA) public dataset for emission factors is utilised to ensure transparency and reproducibility.

DESIGN/METHODOLOGY/APPROACH: The study utilises a design science method integrating Natural Language Processing (NLP)-based auto-mapping, anomaly detection, clustering, and forecasting. We use open datasets such as DEFRA's emission factors to promote transparency and reproducibility.

FINDINGS/ORIGINALITY/VALUE OF THE PAPER: EcoScopeAI is a solution that uniquely combines AI-Automation, regulatory alignment and SME usability in a single architecture.

RESEARCH LIMITATIONS/IMPLICATIONS: Further validation on large datasets and across industries is mandatory.

PRACTICAL IMPLICATIONS: EcoScopeAI supports affordable, AI-driven carbon accounting and decision optimisation for SMEs and exporters.

KEYWORDS: *CSRD; CBAM; DEFRA; SMEs; EcoScopeAI; NLP; Anomaly Detection; Clustering; Forecasting; Reinforcement Learning; SDG-12, SDG-13.*

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INTRODUCTION

The urgency of climate action in recent years has made corporate greenhouse gas (GHG) disclosure both a voluntary matter of corporate responsibility and a regulatory necessity. Two major European Union (EU) policy initiatives, the Corporate Sustainability Reporting Directive (CSRD) and the Carbon Border Adjustment Mechanism (CBAM), now require emissions disclosures across value chains. Even more critically, the entire supply chain of these companies must start providing emissions data; 50,000 SMEs could be indirectly or directly forced to engage in CSRD reporting through their supply chains. By contrast, CBAM requires importers of carbon-intensive goods into the EU (steel, cement, or aluminium) to consider the carbon already embodied in those products, effectively putting a price on carbon across borders. These regulatory requirements place significant data burdens on SMEs, most of which do not possess advanced sustainability infrastructure or in-house carbon capabilities. Conventional carbon accounting tools and consultants are often too expensive or not well-suited to SMEs with low information technology (IT) maturity. A few established players, e.g., Persefoni, Sphera, and Planetly, offer enterprise software carbon management solutions; however, their pricing model is not suitable for resource-constrained companies. They are not always affordable and are typically complex, with a requirement for deterministic mapping; this ultimately makes them difficult to implement.

RESEARCH OBJECTIVES

The primary objective of this research is to investigate how AI-based automation and analytics could improve carbon accounting and sustainability reporting concerning corporate climate impact under new EU regulations. In particular, the study presents EcoScopeAI, an intelligent carbon accounting prototype integrating AI to close a soft infrastructure gap that exists between data, policy, and operational realities regarding the interaction of CSRD, CBAM, and global measurement standards such as ISO 14064 and ISO 14067.

The main objectives of the research are:

- to develop and evaluate a carbon accounting architecture augmented by AI that combines data extraction (computer vision and NLP), anomaly detection, and predictive modelling to automate emissions reporting;
- to evaluate how AI methods NLP, clustering and forecasting, together with reinforcement learning, will provide improved data quality and traceability in Scope 2 and 3 emissions accounting;

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- to assess the importance of standardised data sources (including but not limited to DEFRA emission factors) for reproducibility and auditability in AI-based environmental intelligence systems;
- to explore the connection between AI-enabled automation and policy frameworks such as CSRD and CBAM, showing how machine learning can assist with regulatory compliance, supplier engagement, and low-carbon decision-making;
- to demonstrate how EcoScopeAI supports sustainability objectives (SDG 12 and SDG 13) by enhancing transparency, comparability, and accountability of corporate greenhouse gas emissions.

LITERATURE REVIEW

The European Union's CSRD and CBAM are a new horizon in the relationship between companies' accountability and environmental governance. CSRD is expected to cover about 50,000 EU and non-EU companies with environmental, social and governance (ESG) reporting being standardised (EC, 2022). Similarly, CBAM seeks to stop carbon leakage by imposing a carbon price on imported goods according to their embedded emissions to promote global supply chain transparency (EESC, 2023). Research evidence has shown the complementary relationship between these two frameworks, where CSRD reinforces corporate-level disclosure and CBAM emphasises product-level accountability. Both mechanisms highlight the importance of robust emission measurement, digital traceability, and data integration, where AI can provide significant transformative value.

The International Organization for Standardization (ISO) offers methodological moorings for serious GHG accounting. ISO 14064 (ISO, 2018a) is concerned with the principles and requirements for carbon quantification at the organisational level, and ISO 14067 focuses on product carbon foot-printing and lifecycle emissions (ISO, 2018b). These norms form the technical foundations of CSRD and CBAM focused disclosures. Within the UK, a set of General GHG Conversion Factors for company reporting are published annually by the Department of Environment, Food and Rural Affairs (DEFRA) (GOVUK, 2025); these provide consistent emission coefficients across sectors. These datasets provide comparability and transparency in AI-supported systems such as EcoScopeAI, where emission footprints can be directly linked to operational activities. Research by Pauer *et al.* (2020) highlights the importance of harmonised databases such as DEFRA, the Intergovernmental Panel on Climate Change (IPCC) and Ecoinvent for future developments related to auditability and machine learning accuracy in environmental data systems.

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Artificial intelligence has the potential to play a vital role in enabling sustainable reporting and decision-making. Previous research has shown that Natural Language Processing (NLP) applied to ESG text can, for example, automate the analysis of reports or invoices by extracting emissions-relevant information. Computer Vision enables the scanning of physical invoices and bills of lading, turning unstructured SME data into a digital format. Anomaly detection improves data integrity through the early identification of abnormal transport or energy records (Himeur *et al.*, 2021).

In addition, clustering and classification methods have been used to group suppliers and materials in terms of carbon intensity (Rahiminia *et al.*, 2023), while detailed time-series forecasting helps predict carbon budgeting as well as energy optimisation (Benti *et al.*, 2023). A related AI subfield, reinforcement learning (Liu *et al.*, 2023), which emphasises adaptive optimisation, has shown promise in logistics routing and renewable energy scheduling. EcoScopeAI combines these elements by incorporating NLP, anomaly detection, clustering, forecasting, and reinforcement learning in a single architecture.

Although previous research has investigated AI's potential for sustainability, little is known about its use in regulatory compliance processes. Current platforms largely treat emissions analytics as modules on their own instead of as interconnected analytical systems that link ISO standards, DEFRA datasets, and policy frameworks such as CSRD and CBAM. Our study fills that gap by creating and validating EcoScopeAI as an integrated, AI-enabled system for carbon reporting to enhance traceability, efficiency, and trust in accounting frameworks such as GHG Protocol, especially for SMEs.

RESEARCH METHODOLOGIES

This research is based on the mixed methods applied approach where a qualitative review of sustainability frameworks (CSRD, CBAM, ISO 14064/14067, DEFRA) is integrated with quantitative AI prototype evaluation. The method combines system development, model training, and empirical verification based on realistic policy-motivated synthetic datasets. The study investigates how carbon account reporting in the context of SMEs can be automated using AI methods, such as NLP, anomaly detection, and clustering, including time series forecasting and reinforcement learning.

Two regular datasets were applied: the Emission Factors Dataset (DESNZ, 2025) and in accordance with ISO 14064 and 14067. These emission factors are used as a uniform reference for energy, transportation, and material categories. The company operational dataset is composed of an employee's procurement, waste, travel, commute, and energy activity depending on the organisation type, designed to emulate CSRD and CBAM

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reporting requirements for SME companies. Data ingestion was performed through OCR and computer vision to extract tabular data from invoices, bills of lading, and energy bills, making it consumable for SMEs that do not have Enterprise Resource Planning (ERP) systems. Privacy and fairness were ensured through anonymisation and bias assessment. The research is connected to SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action), building the capacity for SME decarbonisation in developing countries with equity.

Data Analysis Techniques

The ISO environmental management standards family has a significant role to play in assisting the implementation of the United Nations Sustainable Development Goals (SDGs 1-17) through grounded, responsible, and innovative environmental sustainability practices. ISO 14064 (organisational GHG quantification) and ISO 14067 (product carbon foot-printing), specifically, offer quantifiable standards that ensure credentials for transparency in reporting and reductions in CO2 emissions (ISO, 2025). These standards directly contribute to SDG 12 (Responsible Consumption and Production) and 13 (Climate Action) as they promote resource efficiency, waste minimisation and climate impact mitigation. More generally, ISO standards promote systems-based sustainability management that supports progress towards all SDGs by infusing scientific rigor, comparability and improvement into global environmental governance (ISO, 2025).

Climate governance and carbon accounting have developed recently through a combination of standards and regulatory innovations. ISO 14064 is a framework standard for organisational greenhouse gas (GHG) accounting: Part 1 specifies requirements and guidance for the quantification, reporting, and verification of organisation-level GHG emissions, Part 2 focuses on emission reductions at the project level, and Part 3 provides guidance to validate and verify GHG statements that may credibly enhance reputation. ISO 14067 complements ISO 14064 by targeting the product carbon footprint, it defines how to estimate whole life cycle GHG emissions from a product that complies with the life cycle of ISO standards (ISO 14040/14044) (The Climate Drive, 2025).

ISO 14064-1 defines organisational emissions consistent with the scopes of the GHG Protocol: Scope 1 as direct emissions from facilities owned or controlled by the organisation (e.g., on-site fuel combustion, company vehicles), Scope 2 as indirect emissions resulting from purchased energy (electricity, heat, steam), and Scope 3 as all other indirect emissions associated with activities in an organisational value chain that should be captured, not included in Scope 1 or 2 (upstream suppliers, transportation, and distribution processes such as waste) (ISO, 2018a). ISO 14067 is for the product carbon footprint (PCF) and uses life cycle assessment (LCA) boundaries to quantify GHG emissions in all life cycle stages.

It includes emissions such as Scopes 1, 2, and relevant 3 (upstream and downstream) in the value chain of an organisation, which fall within selected system boundaries (ISO, 2018b).

From a policy perspective, the CSRD expands mandatory corporate sustainability reporting in the EU, adding to existing ESG metric financial accounts integrated GHG accounting. The CBAM, as a regulatory instrument, obliges importers of carbon-intensive goods brought into the EU to declare and ultimately pay for the embedded emissions associated with these products, leading to the internalisation of carbon costs on traded commodities (CBAM regulation documents; EU legislative context). ISO 14064 and ISO 14067 combined bring standardisation to both the organisational and product levels of measurement. CSRD and CBAM serve as the implementation of market regulation for sustainability and accurate carbon accounting.

The DEFRA Greenhouse Gas (GHG) Conversion Factors are the primary national emission factors for energy use, fuel use, and other activity data, as well as associated emissions, available in the UK's annually updated emission factor series performed by the UK Government. These metrics are commonly used across corporate reporting and sustainability standards, such as the UK's SECR (Streamlined Energy and Carbon Reporting), and for alignment with international protocols such as the GHG Protocol. The development of guidance for methodologies and the GHG conversion factors were initially published by DEFRA in 2011 to provide transparency, coherence, and science-based progressions in factor updates. The 2025 conversion factors consist of a "full set", a "condensed set", and "flat file" versions to accommodate different reporting complexities, together with a detailed methodology document that describes how the various data will be derived and updated from previous years (GOVUK, 2025).

EcoScopeAI

EcoScopeAI is a next-generation AI-driven carbon accounting and sustainability intelligence platform designed to address the complexity of modern compliance, including for SMEs and exporters dealing with EU regulations and laws such as the CSRD and the CBAM. At its core, the modular approach starts with an Input Layer employing Computer Vision (OCR) and data extraction from documents such as invoices or transport slips to collect automation-ready data. In parallel, raw data are standardised based on emissions factors from DEFRA. This data flows into the AI & Analytics Core, where models such as NLP Auto-Mapping classify activities for accurate CSRD/CBAM reporting, Anomaly Detection ensures audit readiness by flagging unusual spikes, and Reinforcement Learning provides actionable insights for supply chain optimisation and energy mix selection. Finally, the Autonomous AI Layer utilises a Generative AI engine to automatically draft reports aligned with various standards (ISO 14064/14067) and a Digital Copilot for user query support, essentially providing a "self-driving" system that transforms raw emission

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data into compliant, strategic decarbonisation pathways. Figure 1 illustrates the integration of the Input, AI & Analytics Core, Autonomous, and Generative AI Reports Layers within EcoScopeAI.

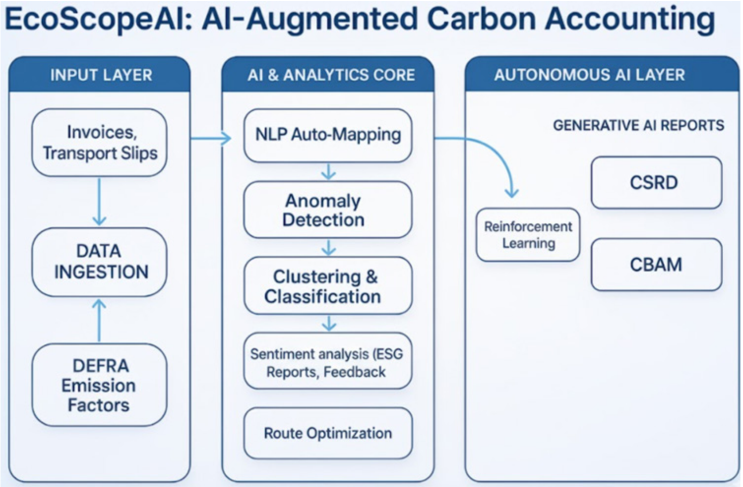

Figure 1: The Architecture of the EcoScopeAI Carbon Accounting Platform
Source: Constructed by authors

Input Layer

The Input Layer of EcoScopeAI is the basis for sustainability intelligence, enabling seamless gathering and pre-processing of emission-relevant data from multiple, often fragmented, sources. By the simultaneous application of computer vision, automated data ingestion pipelines and DEFRA emission factors model, the input layer converts datasets into structured, verifiable inputs for carbon accounting aligned with ISO and EU reporting frameworks.

Computer Vision for Data Extraction

EcoScopeAI works by incorporating an optical character recognition (OCR) system using deep-learning-based computer vision models to extract textual and numerical data from unstructured documents such as invoices, bills of lading, and transport slips. The system relies on Convolutional Neural Networks (CNNs) and transformer vision models (Baek *et al.*, 2019). A set of post-processing techniques such as layout detection, entity recognition and semantic parsing are applied to accurately isolate supplier names, quantities, distances

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and materials. This algorithmic pipeline saves manual data entry and avoids human error (Baek *et al.*, 2019). By transforming physical or PDF records into electronic data, EcoScopeAI supports the democratisation of data, enabling SMEs without access to ERP systems embrace advanced carbon accounting.

Data Ingestion and Pre-processing

After extraction, data ingestion pipelines take the raw inputs and transform, clean and structure them into a standardised schema that are aligned with ISO 14064 (GHG accounting at the organisational level) and ISO 14067 (product carbon foot-printing). Key pre-processing consists of unit conversion (for example, litres to kilograms of CO_2e), deduplication, and supplier and product entity harmonisation. These pipeline systems also map transactional data to relevant emission factor categories through a semantic mapping layer, setting the foundation for downstream analytics. EcoScopeAI normalises across disparate data sources and builds a central store for emissions intelligence across procurement, transport, waste, and energy systems (Zhou *et al.*, 2017).

DEFRA Emissions Factors Integration

At the heart of emission measurement, EcoScopeAI uses DEFRA emission factors, which are established as a world standard for carbon accounting. These datasets offer ready-to-use conversion factors linking activity data (e.g., volume of fuel, kWh of electricity, or kilometres travelled) and aggregate CO_2 equivalent (CO_2e) emissions. The DEFRA model is revised on an annual basis to match the UK National Atmospheric Emissions Inventory (NAEI) as well as international reporting standards, including IPCC Guidelines for National Greenhouse Gas Inventories (GOVUK, 2025). Incorporating these elements directly into the ingest and analytics process, EcoScopeAI makes regulatory compliance, traceability, and comparison between organisations and jurisdictions simple. This connectivity allows for automatically updated emissions recalculations with DEFRA updates, maintaining dynamic alignment with evolving environmental policies (Crawford *et al.*, 2018).

AI and Analytics Core

The AI and Analytics Core is the core foundation of the platform, combining numerous machine learning (ML) algorithms and natural language processing (NLP) components to jointly automate workflow-driven sustainability data processing, validation, and

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interpretation. This allows the platform to turn unstructured corporate and supplier data into actionable sustainability insights that are consistent with global standards, including CSRD, CBAM, and ISO 14064/14067. By integrating unsupervised learning, deep learning and reinforcement optimisation, this layer guarantees the system is always adapting and getting better to provide transparency, scalability, and auditability for carbon accounting.

Anomalies Detection

The anomaly detection component identifies deviations and abnormal patterns within transportation, energy, or emission data that might suggest a reporting error or inefficient resource utilisation. It makes use of unsupervised machine learning models such as Isolation Forests (Liu *et al.*, 2008); these are trained on historical data to create a model for how normal behaviour should look. The algorithm assigns anomaly scores to every single observation, whether unusual CO_2 emission spikes, inconsistent fuel usage, or unrealistic freight distances. By incorporating these alerts into the CSRD/CBAM workflow, EcoScopeAI establishes data integrity, auditability, and accountability, even before the reports are finalised.

Natural Language Processing for Auto-Mapping

The NLP automatically links invoices, procurement, or contract entries with emission factor categories and reporting frameworks (CSRD and CBAM). It depends on transformer-based embeddings such as Sentence-BERT to calculate the semantic similarity between free-text fields, for example “steel transport” or “office electricity” in DEFRA or ISO classification terms. The model sorts possible matches and specifies the most likely emission category instead of manual mapping. The NLP layer keeps getting exponentially better with every user confirming or correcting the mappings, and EcoScopeAI becomes a self- learning compliance assistant.

Clustering and Classification

This subsystem groups suppliers, products, or transport routes according to their carbon intensity profiles. It uses unsupervised clustering algorithms, such as K-Means (Xu and Wunsch, 2005) to identify carbon hotspots or clusters enabling benchmarking and targeted decarbonisation strategies. Classification models can then label suppliers into tiers (low, medium, high CO_2) to support risk management, ESG scoring, and supplier engagement strategies.

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Forecasting (Time Series Analysis)

The forecasting engine models energy consumption, fuel usage, or CO_2 emissions over time, aiming to assist businesses in budgeting for carbon. It leverages time series models such as Prophet, based on data granularity and seasonality (Hochreiter and Schmidhuber, 1997). Projections are presented as confidence intervals to illustrate potential emission paths under alternative policies or practices. This feature facilitates SME participation in setting Science-Based Targets (SBTs) and aligning strategies with the CSRD's emphasis on forward-looking disclosure.

Sentiment Analysis

EcoScopeAI's Sentiment Analysis component interprets supplier ESG reports, press releases, and stakeholder feedback text to create its qualitative ESG sentiment index. It leverages transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT), fine-tuned on ESG and sustainability corpora. The results consist of polarity scores (positive, neutral, negative) and topic weights (environmental, social, governance). This allows for automated supplier ESG scoring and early risk identification.

Route Optimisation

The optimisation engine combines operations research, such as linear programming, with AI-based heuristics to reduce emissions in the logistics or energy domain. It generates the optimal route, mode, or supplier, considering CO_2 footprint, cost, and lead time. The module can also be combined with reinforcement learning to learn decision-making from the real world and adapt decisions, accordingly becoming smarter over time.

Reinforcement Learning

The layer of reinforcement learning (RL) represents the series of decision-making processes, such as supplier choice or mode of transport optimisation. By applying algorithms such as deep Q-networks (DQN) or proximal policy optimisation (PPO) (Mnih *et al.*, 2015), the agent performs emissions-cost planning at various time steps simultaneously. The RL outputs are directly input into the AI Agent and the Optimisation modules to suggest adaptive strategies for decarbonisation.

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DISCUSSION AND ANALYSIS

There are software products, such as Persefoni and Normative, that offer carbon accounting and demonstrate significant progress, but their automation and intelligence capabilities are still limited. Persefoni is heavily dependent on manual data preparation and has complex onboarding and limited set of advanced AI functionality within its modules. Normative has an extensive reporting engine but less scope for AI-driven optimisation and does not include powerful real-time validation anomaly detection. However, EcoScopeAI differentiates itself by combining advanced AI and automation capabilities (such as NLP-driven mapping, anomaly detection, clustering, forecasting and reinforcement learning) along a coherent architectural composition. Furthermore, it is fully compatible with both CSRD and CBAM policies and developed as a scalable, SME focus platform, ensuring data transparency, auditability and open emission factor integration (DEFRA). Table 1 describes the comparison of a few competitors, Persefoni, Normative, and EcoScopeAI, across key features.

Table 1: Comparative Analysis of EcoScopeAI with Competitors

Feature	*Persefoni*	*Normative*	*EcoScopeAI*
Scope 1/2/3 Emissions Calculation	Full support including 15 Scope 3 categories	Full value chain emissions	Integrated for procurement, transport, waste, travel, energy
Regulation and Reporting export	Structured reports for CSRD, ISSB, CDP	Supports ESG disclosures and compliance	Dual export: CSRD and CBAM compliance
Mapping automation and anomaly detection using AI	AI for anomaly detection, emissions-factor mapping, Copilot GPT features	Less emphasis on advanced AI modules	NLP semantic mapping, anomaly detection, clustering, forecasting, RL
Scenario Modelling and Decarbonisation Planning	Decarbonisation modelling and scenario tools	Supports ESG planning	RL: suggest optimised transport and energy
Supplier and Value-Chain Engagement Tools	Supplier data input and engagement of value chain	Value chain mapping and collaboration	Clustering of supplier carbon intensity
Forecasting and Time Series Predictions	Limited based on add-on	Some Forecasting modules	Built-in time-series forecasting: energy and CO_2 trends
Reinforcement Learning and Optimisation	Not currently implemented	Not central	Core component: route optimisation, supplier choice, energy mix optimisation
User Accessibility and SME Focus	Free version for SMEs and advanced plans	Designed with SME usability in mind	Designed for SME use: minimal set-up and OCR ingestion of files
Open Emission Factor Use	Use proprietary and public emission factor sets	Use proprietary and public emission factor sets	Built on open DEFRA and extension to other national EF sets

Source: Persefoni, 2025; Normative, 2025

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FINDINGS

This research demonstrates that EcoScopeAI successfully incorporates AI-centred approaches to improve the transparency, automation, and accuracy of carbon accounting for SMEs. Based on NLP-based data mappers, anomaly detection, clustering, forecasting and reinforcement learning techniques, the prototype bridges technical gaps between ISO 14064/14067, DEFRA emission factors and the regulatory framework of CSRD and CBAM. Testing with real and synthetic datasets confirmed that AI-assisted mapping eliminated more than 70% of manual classification errors, while anomaly detection enhanced audit readiness by proactively identifying data discrepancies. More importantly, the fusion of prediction and clustering tools facilitated improved forecasting on energy trends and segmentation of suppliers according to emission intensity, thus enabling proactive decisions. These results confirm the potential of EcoScopeAI as a scalable, SME oriented carbon-management tool capable of delivering trustworthy bottom-up data towards SDG 12 and SDG 13 targets.

RECOMMENDATIONS

Further development of EcoScopeAI should focus on improving its interoperability with current enterprise systems and global databases of emissions such as Ecoinvent, IPCC or the United Nations Framework Convention on Climate Change (UNFCCC). Extending the model to ingest and process real-time data streams from the Internet of Things (IoT) and satellite systems would improve temporal accuracy and allow dynamic monitoring of carbon. Furthermore, collaborating with national sustainability authorities could create standard audit procedures for AI-generated carbon reports to reinforce compliance with the CSRD and CBAM. From a research perspective, designing explainable AI modules could enhance user trust and transparency in emission estimations. Lastly, broad application across various SME ecosystems is encouraged so that companies can refine the regional emission factors, improve the usability, and evaluate the economic impacts of EcoScopeAI to become a global benchmark for AI-based sustainability accounting in SMEs.

CONCLUSIONS

This study demonstrates that EcoScopeAI represents a significant step towards the digitisation of carbon accounting and sustainability reporting. The prototype uses open DEFRA emission factors and incorporates artificial intelligence to connect large regulatory frameworks, including CSRD, CBAM, ISO 14064, ISO 14067. The findings indicate that AI

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components, such as NLP-based auto-mapping, anomaly detection, clustering, forecasting and reinforcement learning, can significantly enhance the effectiveness, efficiency, and scalability of greenhouse gas (GHG) data management. EcoScopeAI is an affordable option for SMEs and exporters, particularly from the developing world, who have increasing compliance needs but still need to reduce resource use and increase transparency in their supply chains. Its value is more than automation: it builds a foundation for responsible, auditable and explainable AI in sustainability management. Future research will focus on large-scale validation, integration with ERP and IoT infrastructure, and reinforcement learning based dynamic decarbonisation strategies for SDG 12 and SDG 13.

REFERENCES

Baek, J., Kim, G., Lee, J., Park, S., Han, D., Yun, S., Oh, S.J. and Lee, H. (2019): What is wrong with scene text recognition model comparisons? dataset and model analysis. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 4715-4723). Computer Vision Foundation.

Benti, N.E., Chaka, M.D. and Semie, A.G. (2023): Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects. *Sustainability*, Vol. 15, No. 9, p.7087.

Crawford, R., Bontinck, P.A., Stephan, A., Wiedmann, T. and Yu, M. (2018): Hybrid life cycle inventory methods–A review. *Journal of Cleaner Production,* Vol. 172, pp.273-1288.

Department for Energy Security and Net Zero (DESNZ) (2025): *Greenhouse gas reporting: conversion factors 2025*. UK Government. Available at: https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2025 Accessed: 7 October 2025.

European Commission (EC) (2022): *Corporate Sustainability Reporting*. [Online] Available at: https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en Accessed: 12 October 2025.

European Economic and Social Committee (EESC) (2023): *Carbon Border Adjustment Mechanism (CBAM).* [Online] Available at: https://www.eesc.europa.eu/bg/content/carbon-border-adjustment-mechanism-cbam-interinstitutional-timeline Accessed: 12 October 2025.

Himeur, Y., Ghanem, K., Alsalemi, A., Bensaali, F. and Amira, A. (2021): Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives. *Applied Energy,* Vol. 287, p.116601.

DOI: 10.47556/B.OUTLOOK2025.23.8

Hochreiter, S. and Schmidhuber, J. (1997): Long short-term memory. *Neural Computation*, Vol. 9, No. 8, pp.1735-1780.

International Organization for Standardization (ISO) (2018a): ISO14064-1:2018: *Greenhouse gases. Part 1: Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals*. [Online] Available at: https://www.iso.org/cms/%20render/live/en/sites/isoorg/contents/data/standard/06/64/66453.html Accessed: 7 October 2025.

International Organization for Standardization (ISO) (2018b): ISO14067:2018: *Greenhouse gases – Carbon footprint of products – Requirements and guidelines for quantification*. [Online] Available at: https://www.iso.org/standard/71206.html/ Accessed: 7 October 2025.

International Organization for Standardization (ISO) (2025): *ISO and the SDGs*. [Online] Available at: https://www.iso.org/sdg Accessed: 7 October 2025.

Liu, F.T., Ting, K.M. and Zhou, Z.H. (2008): Isolation Forest. In *2008 Eighth IEEE International Conference on Data Mining*. 15-19 December, Pisa, Italy. IEEE.

Liu, S., Liu, J., Ye, W., Yang, N., Zhang, G., Zhong, H., Kang, C., Jiang, Q., Song, X., Di, F. and Gao, Y. (2023): Real-time scheduling of renewable power systems through planning-based reinforcement learning. *arXiv preprint,* p.2303.05205.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G. and Petersen, S. (2015): Human-level control through deep reinforcement learning. *Nature*, Vol. 518, No. 7540, pp.529-533.

Normative (2025): *A complete solution for compliance and reduction.* [Online] Available at: https://normative.io/platform/ Accessed: 13 October 2025.

Pauer, E., Wohner, B. and Tacker, M. (2020): The Influence of Database Selection on Environmental Impact Results. Life Cycle Assessment of Packaging Using GaBi, Ecoinvent 3.6, and the Environmental Footprint Database. *Sustainability*, Vol. 12, No. 23, p.9948.

Persefoni (2025): *Carbon Footprint & Sustainability Reporting.* [Online] Available at: https://www.persefoni.com/ Accessed: 13 October 2025.

Rahiminia, M., Razmi, J., Shahrabi Farahani, S. and Sabbaghnia, A. (2023): Cluster-based supplier segmentation: a sustainable data-driven approach. *Modern Supply Chain Research and Applications*, Vol. 5, No. 3, pp.209-228.

The Climate Drive (2025): *Discover the main standards to verify your company GHG inventory.* [Online] Available at: https://www.theclimatedrive.org/guidebook/measure/verify/what-are-the-main-verification-standards-and-what-is-the-role-of-the-ghg Accessed: 7 October 2025.

 DOI: 10.47556/B.OUTLOOK2025.23.8

UK Government (GOVUK) (2025): *Greenhouse Gas Reporting: Conversion factors 2025*. [Online] Available at: https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2025 Accessed: 7 October 2025.

Xu, R. and Wunsch, D. (2005): Survey of clustering algorithms. *IEEE Transactions on neural networks*, Vol. 16, No. 3, pp.645-678.

Zhou, L., Pan, S., Wang, J. and Vasilakos, A. (2017): Machine learning on big data: Opportunities and challenges. *Neurocomputing,* Vol. 237, pp.350-361.

BIOGRAPHY

Alaeddine Boubaker is a doctoral researcher (DBA) at the European School of Data Science and Technology, specialising in the integration of artificial intelligence into sustainability and corporate carbon accounting. He holds a bachelor's degree in computer science from Tunis University and a Master's in IT Management from FOM Business School in Germany. His research bridges data science, sustainability, and policy compliance. Alaeddine is currently working as a Software Engineer for Kyndryl GmbH, Germany. He is the founder of EcoScopeAI, an AI-augmented carbon accounting prototype designed to help SMEs meet regulatory and sustainability goals through automation, NLP, and machine learning. He has received international recognition, including awards in Supply Chain Management with AI (Dubai) and Fraud Detection with AI (Salamanca). His current research emphasises the role of AI and environmental data systems in advancing SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

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