AI and Scope 3: Precision on the path to net-zero emissions

Report on the applications of AI for Scope 3 emissions

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CLIMATE LEADERS COALITION

An initiative of THE B TEAM Australasia

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1 | FOREWORD

Addressing greenhouse gas emissions is among the most complex and urgent challenges for business leaders today. Rising to this challenge is not simply a matter of meeting regulatory obligations or ramping up reporting. It demands a complete reimagining of how businesses operate.

At the heart of this challenge lies Scope 3 emissions: the complex, interconnected web of indirect emissions that account for the majority of an organisation's carbon footprint. These emissions are notoriously difficult to measure and manage, but they also represent the greatest opportunity for leadership, innovation and value creation.

This report was developed by CLC members for members. It offers a roadmap to navigate the complexity of Scope 3 emissions through the use of artificial intelligence. It outlines how AI can transform Scope 3 emissions management, offering tools to unify teams, enhance decision-making and accelerate decarbonisation efforts. Importantly, it offers insights from CLC members working on real-world projects today.

AI can automate data collection, mapping and verification processes, enhancing the efficiency and accuracy of Scope 3 emissions management. But AI's potential extends far beyond data tasks. It can help organisations uncover decarbonisation opportunities across the value chain, set emissions reduction targets, and forecast future emissions with unprecedented precision.

To realise the full benefits, business leaders must dismantle silos that prevent collaboration. Too often, sustainability teams and technology teams operate in isolation, limiting their collective impact.

AI is not just a tool for the IT department. Nor is emissions management the sole responsibility of sustainability teams. Achieving real progress will require both technical and sustainability expertise to align under a shared vision. It is this idea of a shared vision that brings the CLC members together.

This report distils some of the learnings and insights CLC members have collected so far on what will be an ongoing conversation and a long journey. We invite you to join us.

Ann Sherry

Climate Leaders Coalition
Co-Chair

John Lydon

Climate Leaders Coalition
Co-Chair

Lynette Mayne

B Team Australasia
Executive Chair

2 | HOW TO READ THIS REPORT

We have structured this report to provide targeted insights for different stakeholder groups while fostering collaboration across sustainability, AI and leadership teams.

Here's how to make the most of it:

C-suite leaders
Use this report as a strategic tool to unify your teams. The executive summary and introduction provide a high-level overview of AI's potential, while practical steps can help your organisation adopt AI responsibly and effectively.

Sustainability professionals
If you're well-versed in the challenges of Scope 3 emissions, focus on the technical sections of this report. Explore how AI can streamline data collection, enhance reporting accuracy, and identify actionable opportunities to reduce emissions.

Data and technology specialists
Understand the context and complexities of Scope 3 management by exploring the sustainability-focused content. The report highlights key pain points that your solutions must address and offers technical guidance on AI tool development for emissions management.

To help you quickly identify sections relevant to your role, look for icons at the top of each page. Each icon represents a stakeholder group or groups to help you to navigate the report with ease.

If you'd like to explore more on optimising Scope 3, please check out the Climate Leaders Coalition publications:

- **Scope 3 Roadmap:** Financing & Commercial Implications
- **Scope 3 Roadmap:** Practical Steps to Address Scope 3 Emissions – Written by CEOs for CEOs
- **Scaling impact on Scope 3:** an update on our continued focus on Scope 3 in 2023.

Every organisation needs a holistic understanding of how AI can transform Scope 3 emissions management. By fostering a shared understanding and mission, this report can help to align your teams as you work together to decarbonise your business.

3 | EXECUTIVE SUMMARY

Artificial intelligence (AI) is emerging as a potentially transformative tool to manage Scope 3 emissions and address long-standing data collection and reporting challenges.

Traditional methods of Scope 3 monitoring and management are often over-burdened by complex value chains with extensive supplier and customer bases, resource demands and unreliable data. Now, AI is automating key processes like spend data mapping, financial category filtering and supplier verification, while delivering greater precision in emissions calculations. Critically, AI enables the standardisation and validation of disparate data sources, ensuring data integrity and consistency, which are foundational for accurate Scope 3 emissions calculations.

AI's value doesn't stop at streamlining data-intensive tasks. AI's applications extend to strategic functions like emissions forecasting, target setting and uncovering decarbonisation opportunities. These capabilities position AI as a critical enabler of systemic sustainability, turning Scope 3 data into actionable insights that move organisations closer to net zero.

Note on AI's environmental footprint:

While this report focuses on the potential for AI to support Scope 3 emissions reductions, it is important to acknowledge that AI technologies themselves have a climate and environmental footprint, including energy use and resource demands. These impacts are not covered here, but will be the focus of an upcoming Climate Leaders Coalition publication exploring the environmental implications of AI adoption

However, applying AI to Scope 3 reporting isn't without its challenges. Issues like data integrity, algorithmic bias and system integration pose real risks. Transparency, accuracy, security and ongoing monitoring must guide AI adoption to build trust and achieve reliable results. Furthermore, implementing AI presents significant data management challenges. Robust data governance frameworks must be established to ensure responsible data handling and prevent data leakage, particularly when integrating diverse supplier data, and this will take time and resources.

This report builds on the Climate Leaders Coalition's previous Scope 3 work, offering practical guidance for sustainability and AI specialists to work together to unlock AI's full potential. This report covers:

- **Opportunities:** How AI can enhance Scope 3 data management and emissions reduction strategies.
- **Case studies:** Real-world examples of organisations using AI to address Scope 3 challenges.
- **Guidelines:** Technical considerations for applying AI responsibly and effectively.
- **Roadmap:** Practical steps for AI adoption that organisations can tailor to meet their decarbonisation goals.

AI can streamline Scope 3 emissions management, boosting efficiency, transparency and accuracy. By automating complexity and providing strategic insights, AI can help companies cut emissions at scale. A key advantage is the ability to create auditable data trails, enhancing the credibility of Scope 3 emissions reports.

To get started, this report suggests four strategies:

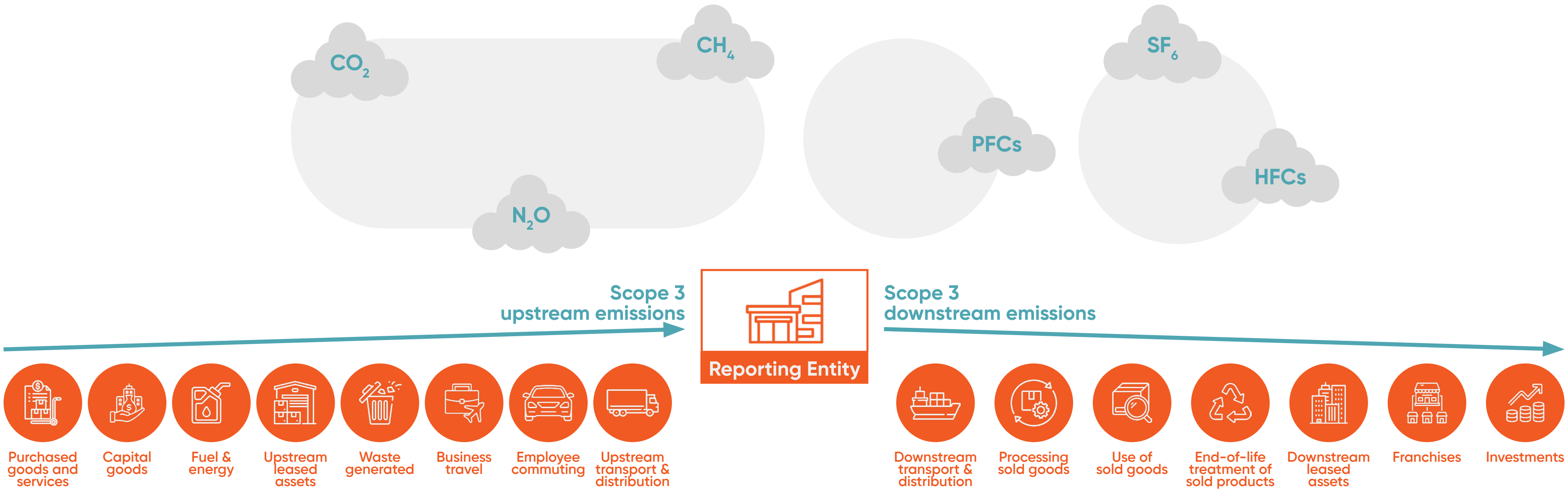
- **Assess:** Identify gaps in your Scope 3 data and evaluate how AI could be used and where it offers the greatest value.
- **Select:** Choose AI tools that align with your specific emissions categories and organisational needs.
- **Implement:** Ensure seamless integration between AI tools and existing data management and reporting systems to meet regulatory requirements.
- **Train and monitor:** Equip staff with AI training and continuously monitor performance to refine applications.

CLC members are harnessing AI to address Scope 3 emissions and are co-building an ecosystem to share experiences and knowledge. With advanced tools now available, businesses can explore practical solutions to navigate this complex challenge, create new partnerships and drive meaningful progress.

AI has seamlessly integrated into our daily lives, yet its potential to drive sustainability is often overlooked. To truly harness AI's transformative power, it must be applied across all sectors, balancing environmental impact with solving complex sustainability challenges. At Microsoft, we are committed to responsible AI and sustainability, focusing on optimising data centre efficiency, advancing low-carbon materials, and improving the energy efficiency of AI and cloud services. We encourage all organisations to join us in this endeavour.

Steven Worrall
Managing Director, Microsoft
Australia and New Zealand

4 | INTRODUCTION



This document aims to advance the mission of the Climate Leaders Coalition (CLC) by sharing insights, knowledge and practical examples between members and partners.

Building on the insights and strategies outlined in previous CLC reports on Scope 3 emissions and climate transition planning, we delve into some of the more challenging aspects of Scope 3 emissions reporting, target setting and abatement. We specifically look at the role that artificial intelligence (AI) technologies could play in addressing some of these key challenges.

One of the CLC's key priorities is to maximise emissions reduction potential by prioritising practical action. This document, therefore, explores how AI can address the complexities of data collection, measurement and decarbonisation efforts for Scope 3 emissions, offering innovative solutions to the challenges faced by organisations across the Australian economy.
This paper is separate from another CLC stream of work underway to investigate the GHG emissions impact of AI itself. The outcomes of this investigation will be documented in a paper to be published by the CLC shortly.

This distinction ensures a focused approach to addressing the unique challenges and opportunities presented by AI in Scope 3 emissions management, without conflating it with the emissions generated by AI technologies.

WHY SCOPE 3 MATTERS

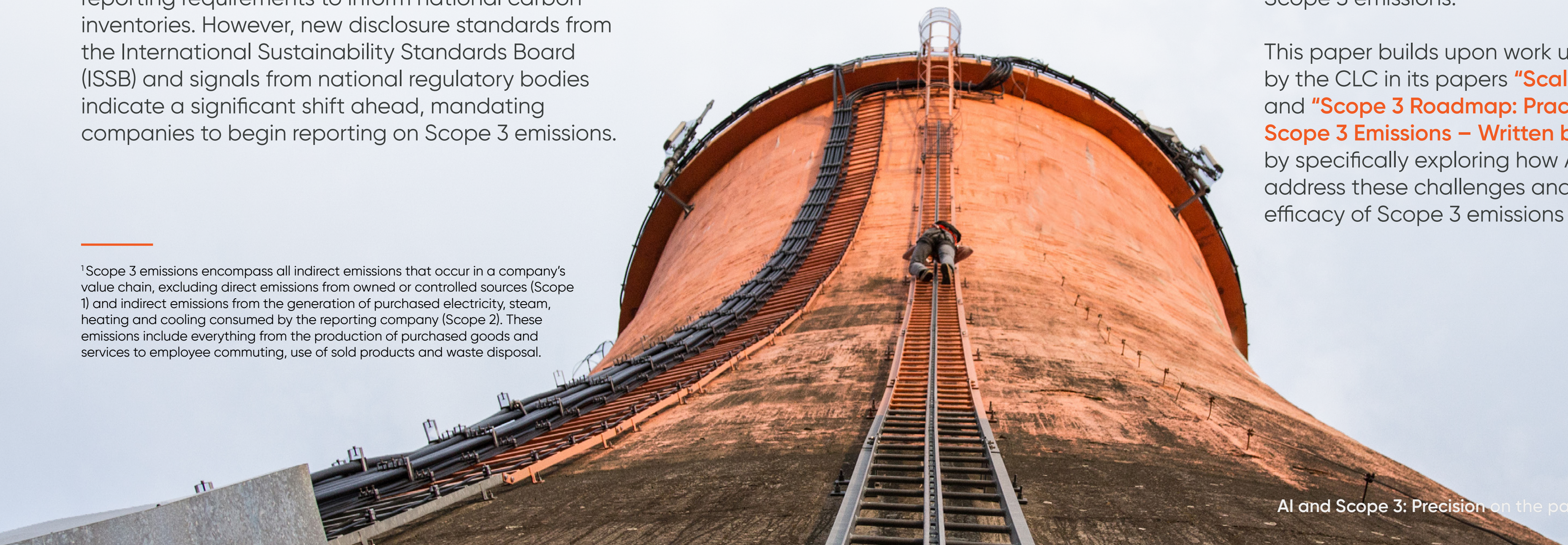
Addressing Scope 3 emissions[1] is critical for tackling climate change, as these emissions typically represent the largest share of an organisation's total environmental footprint. To date, most GHG emissions reporting has focused on scopes 1 and 2, reflecting the accessibility of data and companies' chosen sphere of control. However, accurately measuring and managing Scope 3 is key to decarbonising value chains while also providing companies with valuable insights as they prepare for changing market and operational dynamics in a global net-zero economy.

Traditionally, the reporting of Scope 3 emissions has been voluntary, with primary attention often given to scopes 1 and 2 emissions due to their easier measurement and the direct control by the reporting entity, as well as compliance with mandatory reporting requirements to inform national carbon inventories. However, new disclosure standards from the International Sustainability Standards Board (ISSB) and signals from national regulatory bodies indicate a significant shift ahead, mandating companies to begin reporting on Scope 3 emissions.

In Australia, the introduction of the Australian Sustainability Reporting Standards, specifically the Australian Accounting Standards Board (AASB) S2 Climate-related Disclosures, requires numerous organisations (based on certain criteria) to disclose their Scope 3 emissions, along with information on climate-related risks and other metrics. This aligns with global disclosure practices and responds to the growing demand for transparency and comprehensive climate reporting prevalent in early 2025.

The reporting and management of Scope 3 emissions presents unique challenges for organisations, primarily due to the complexities of data collection and management. Obtaining accurate and comprehensive data from the entire value chain is a significant hurdle, as it involves coordinating with various internal and external stakeholders, including procurement, logistics, sales, suppliers and customers. Dealing with large datasets related to logistics and procurement can be particularly daunting, especially when mapping spend data to emission factors, filtering financial categories to prevent double counting, obtaining and validating supplier-provided information and extracting tonne-kilometre data from freight movement records, for instance. Additionally, organisations face difficulties in setting targets, projecting future emissions, and identifying decarbonisation opportunities for Scope 3 emissions, all of which require sophisticated predictive analytics and optimisation models. These challenges highlight the need for innovative approaches to effectively manage and report on Scope 3 emissions.

This paper builds upon work undertaken previously by the CLC in its papers **"Scaling Impact on Scope 3"** and **"Scope 3 Roadmap: Practical Steps to Address Scope 3 Emissions – Written by CEOs for CEOs"** by specifically exploring how AI can be applied to address these challenges and enhance the overall efficacy of Scope 3 emissions management.



[1] Scope 3 emissions encompass all indirect emissions that occur in a company's value chain, excluding direct emissions from owned or controlled sources (Scope 1) and indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting company (Scope 2). These emissions include everything from the production of purchased goods and services to employee commuting, use of sold products and waste disposal.

AI IN SCOPE 3 EMISSIONS MANAGEMENT

5 | AI IN SCOPE 3 EMISSIONS MANAGEMENT

AI has the potential to be an invaluable tool in managing Scope 3 emissions, offering solutions that significantly streamline specific calculation procedures and data management tasks that have traditionally been resource intensive.

By automating and enhancing complex processes such as mapping spend data, filtering financial categories and verifying supplier information, AI addresses the intricacies that traditional manual methods struggle to manage. Beyond these specific calculations, AI may also be useful to assist with broader applications such as emissions projections, target setting and the identification of decarbonisation opportunities.

A summary of some of the specific challenges common to Scope 3 reporting and decarbonisation efforts, as well as the potential use cases for AI solutions to address these, is presented in the tables below. The associated use cases have been compiled from a representative cross-section of our member organisations, however, should not be considered an exhaustive inventory. The rapid evolution of AI-based solutions for these applications results in a wide spectrum of maturity levels across diverse organisational contexts. This progression is further accelerated by the dissemination of knowledge and collaborative learning initiatives among member entities.

Table 1 outlines the challenges and possible deployment options of AI for Scope 3 measurement; Table 2 highlights the challenges and potential AI use cases for Scope 3 emissions projections and target setting, while Table 3 showcases the challenges and potential use cases for value chain decarbonisation. The Scope 3 categories that the AI solutions would most commonly apply to are prioritised, although it is possible that these solutions could also apply to other categories.

Table 1: Challenges and potential AI use cases for Scope 3 emissions measurement

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Mapping expense data from general ledger to spend-based emission factors	**GL analysis data classification**	**Natural Language Processing (NLP)**
Linking an organisation's financial data, such as from its general ledger (GL) or other sources of expenditure, to emission factors that quantify the GHG emissions can be complex. This is because expenses need to be accurately categorised and mapped to the correct emission factors – a process that is not always straightforward due to variations in categorisation or lack of detailed descriptors. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	AI could be deployed to analyse general ledger information, using descriptors within the data to classify expenditure type to align with the emission factor categories from the chosen environmentally extended input-output (EEIO) database.	Implement a text classification model, like a supervised learning model (e.g. BERT or RoBERTa for financial NLP), to read descriptions in ledger entries and classify them based on EEIO categories. Pre-trained models, fine-tuned on financial data, can significantly improve accuracy in mapping.
Filtering expenditure data	**Expense data analysis to identify Scope 3 exclusions**	**Rule-based filtering with supervised machine learning**
Organisations must meticulously filter spend data to exclude items that are not associated with GHG emissions, such as taxes, or those that are already accounted for in other parts of the GHG inventory, such as payroll, utility spend and logistics spend. This ensures that there is no double counting or omission of relevant data, which requires a thorough understanding of the financial data and the emissions inventory. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	AI could be applied to analyse expenditure data from a general ledger or similar sources to identify expenses that should potentially be excluded from Scope 3 calculations. This exclusion could be based on whether the expenditure is unrelated to generating GHG emissions or has already been accounted for in the organisation's GHG inventory through an alternative data set (e.g. utility data).	Use a decision tree or random forest model to learn patterns in exclusions based on labelled data (expenses previously excluded or included). Coupled with NLP for text recognition, this model can automatically exclude categories aligned with non-GHG expenses.

* Complexity has been determined by the author, with no formal framework applied.

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Adjusting spend or spend-based emission factors to account for alternative currencies, taxes and inflation	**Auto-tune tax adjustment**	**Automated financial data adjustment**
The EEIO databases used for obtaining spend-based emission factors often vary in terms of currency, relevant year for currency values and inclusion or exclusion of taxes and margins. These variations make spend-based calculations in a Scope 3 inventory complex and challenging. Reporters must account for these differences and often must manually adjust either the spend data to align with the selected emission factors or the emission factors themselves. This adjustment process involves applying foreign currency exchange rates, accounting for inflation, and modifying taxes depending on the data. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	AI could be used to ensure that appropriate adjustments for tax, inflation and currency are made to spend data (or directly to the spend-based emission factors) to ensure that the data and emission factors are aligned.	Use a combination of data parsing and regression models (like a linear regression model for inflation or live exchange rate information). These can adjust values for currency changes and inflation rates in real time based on external financial data inputs.
Verifying supplier-provided data	**Analyse disparate data**	**Anomaly detection algorithms**
Verifying or sense checking the accuracy and completeness of primary data provided by suppliers is a significant challenge. Organisations rely on this data to calculate Scope 3 emissions, and any inaccuracies or gaps can lead to incorrect reporting. Establishing robust verification processes and regular communication with suppliers is essential to ensure data integrity. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods, Category 4: Upstream transport & distribution]	AI can act as a sense check on supplier-provided data to determine its plausibility. It could compare the emissions intensity data from suppliers against similar data from industry-average databases or peers. This process can highlight any data discrepancies that may require clarification ensuring that the supplier's emissions boundaries align with those required by the Scope 3 reporter.	Use unsupervised models like isolation forests or autoencoders to detect inconsistencies. These models can compare supplier emissions against industry averages, highlighting outliers for manual review.

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Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Establishing supplier-specific data from secondary sources	**Data Scraping**	**Web scraping and data mining with NLP**
Some publicly available secondary data sources allow supplier-specific data to be quantified without engaging with suppliers directly. For example, the Carbon Disclosure Project (CDP) database includes all three scopes of emissions along with annual revenue information that can be used by a Scope 3 reporter to calculate the emissions associated with a supplier. This uses spend with that supplier as a proportion of total revenue to allocate the emissions to the relationship.. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	AI could be deployed to 'scrape' data from publicly available databases (e.g. CDP[1]), or websites (e.g. company sustainability reports), and apportion these emissions to the Scope 3 reporter using proxy data (e.g. spend with supplier as a proportion of overall supplier revenue). Where the public data is out of date (databases can potentially be 6 – 12 months out of date), this could be flagged and raised as a disclosure item to enhance transparency in reporting. Where the public data is out of date (databases can potentially be 6 – 12 months out of date), this could be flagged and raised as a disclosure item to enhance transparency in reporting.	Use web scraping tools with NLP models to gather emissions data from sources like the CDP. Proxy allocation can be supported by algorithms that calculate proportionate emissions (e.g. based on the spend-revenue ratio).
Establishing tonne-kilometre data from large logistics datasets	**Logistics data analysis**	**Geospatial analysis with machine learning**
Calculating emissions from logistics often requires detailed data on tonne-kilometres (t.km) by transport mode, which measures the transport of one tonne of goods over one kilometre for every type of vehicle deployed in the logistics chain. Extracting and processing this data from large logistics datasets can be daunting, due to the volume of data and the precise tracking and recording of transport activities required. [Applicable Scope 3 categories: Category 4: Upstream transport & distribution; Category 9: Downstream transport and distribution]	AI could analyse logistics data by considering the origin and destination information, as well as the mass of loads transported. This helps in calculating a tonne-kilometre metric for each transport mode and vehicle type used for the freight of products, both upstream and downstream of a Scope 3 reporter.	Use geolocation algorithms combined with regression models to calculate tonne-kilometres. Tools like GPS tracking or geospatial data parsing models (e.g. H3 by Uber for spatial indexing) can manage large logistics datasets for distance calculations.

* Complexity has been determined by the author, with no formal framework applied.
[1] CDP allows limited public access to its data. Full access requires a licence.

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Staff commute and work from home (WFH) emissions	**Data collection and estimation**	**Predictive modelling and data imputation**
This Scope 3 category is usually minor in comparison to other Scope 3 categories; however some organisations spend significant resources collecting data, often through staff surveys, to calculate these emissions. [Applicable Scope 3 categories: Category 7: Employee commuting]	There may be potential use cases for AI to assist with simplifying the data collection or estimation processes by streamlining the survey process or using publicly available data (e.g. census data) to establish a reasonable estimate based on average travel profiles (e.g. distance of average commute by travel mode and breakdown of travel modes) for specific regions. It could potentially also assist with quantifying hours of work from home and/or energy use.	Use clustering algorithms or probabilistic models to estimate commute profiles based on survey or census data. For WFH emissions, regression models could estimate energy usage based on average data for home electricity consumption.
Data privacy concerns in supply chain	**AI-driven emissions tracking from decentralised sources**	**Federated learning for emissions data**
Organisations face significant challenges in sharing sensitive data among supply chain partners due to privacy concerns. This lack of data sharing hinders collective efforts to track and manage emissions. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	There are AI solutions that enable models to learn from decentralised data sources, such as blockchain, ensuring that sensitive information remains private. By facilitating data sharing among supply chain partners without compromising data privacy, this solution supports collective emissions tracking and management.	Federated learning enables AI models to learn from decentralised data sources without sharing sensitive information. This approach allows multiple suppliers to contribute their emissions data to a shared AI model, enhancing the accuracy of emissions tracking while maintaining data sovereignty.

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Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Challenge in regulatory compliance	**Future vision for compliance**	**AI-driven compliance automation**
Evolving guidance from the Greenhouse Gas (GHG) Protocol and related international sustainability standards is a challenge for Scope 3 reporting. Companies must frequently adjust their reporting methods to maintain compliance with evolving frameworks. This requires ongoing updates to methodologies, data collection and reporting systems, making it difficult to maintain consistency and comparability in Scope 3 emissions data while also demanding additional resources. [Applicable Scope 3 categories: All scope 3 categories]	As regulations evolve, AI could anticipate changes, updating compliance templates to keep organisations ahead of policy shifts. For example, AI can flag discrepancies in Scope 3 data from supply chain partners, ensuring accurate reporting.	Generative AI (GenAI) simplifies the process by automating data collection, validation and reporting to meet compliance standards. This ensures that organisations can efficiently track and report their emissions.
Measure deforestation risk to combat greenwashing risk	**Tracking deforestation in the supply chain**	**GenAI change detection algorithms to track vegetation timeline**
Many financial institutions are making commitments to eradicate financing of deforestation, while organisations in other sectors are seeking to address Scope 3 emissions by limiting deforestation in their supply chains. There is significant greenwashing risk if deforestation cannot be accurately measured and attributed to counterparties throughout the supply chain. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 2: Capital goods]	Changes in land cover can be viewed in relatively low resolution and models built that link land area to operating companies.	GenAI improves deforestation tracking by using change detection algorithms that can identify subtle differences in vegetation over time, enabling pre-emptive action and supply chain integrity.

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Table 2: Challenges and potential AI use cases for Scope 3 emissions projections and target setting

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Incorporating the commitments of value chain participants into emissions projections	**Identify value chain emission commitments**	**Natural Language Processing (NLP) and machine learning**
When projecting Scope 3 emissions, particularly for target setting or strategy, understanding value chain commitments – both upstream and downstream – can be useful. This information would allow businesses to better understand how collective value chain efforts contribute to their own emission reduction targets. This would also help to identify gaps where additional focus is needed and encourage strategic engagement with less active members to enhance overall emissions abatement performance. [Applicable Scope 3 categories: All scope 3 categories]	AI can scan public information on emission reduction commitments from key value chain members, such as suppliers, customers, tenants or investees. AI can efficiently sift through vast amounts of data from corporate sustainability reports, news articles, regulatory filings, websites and social media posts to identify and extract relevant information on emission reduction commitments to provide a current comprehensive overview of emissions abatement initiatives of value chain partners.	Utilise NLP models such as BERT or GPT-3 to analyse and extract relevant information from large datasets of publicly available information. Machine learning algorithms can be used to classify and summarise the extracted data. Tools like SpaCy and Hugging Face Transformers can be used for NLP tasks.
Scope 3 emissions projections	**Realistic Scope 3 projection**	**Predictive analytics and time series forecasting**
Projecting Scope 3 emissions out to target years is a key challenge for many organisations. This projection must account for expected business growth or planned restructures, which can significantly impact future emissions. It must also consider the decarbonisation efforts already anticipated within the value chain, such as electricity grid improvements or commitments made by value chain members. Balancing these factors requires a detailed understanding of both internal business growth trajectories and external influences. Accurate emissions forecasting is crucial for setting realistic and achievable Scope 3 emissions targets. [Applicable Scope 3 categories: All scope 3 categories]	AI-driven predictive analytics models can help project Scope 3 emissions and set realistic reduction targets by analysing historical data, current trends and future projections. These models consider factors like business growth, decarbonisation efforts, regulatory changes and technological advancements to provide a comprehensive view of future emissions. They can continuously update predictions with new data, ensuring relevance and accuracy, allowing organisations to proactively adjust strategies and monitor progress against emission reduction targets.	Use predictive analytics models such as ARIMA, Prophet or LSTM networks to forecast future emissions based on historical data and trends. These models can incorporate various factors such as business growth, decarbonisation efforts and external variables. Tools like TensorFlow and PyTorch can be used for building and training these models.
Setting achievable emission reduction targets	**Assess emission target feasibility**	**Advanced data analytics and machine learning**
Supply chain emissions are influenced by numerous stakeholders, varying data availability and diverse operational practices. This complexity makes it difficult to assess the attainability of ambitious targets. Additionally, the lengthy time frames associated with these commitments introduce uncertainty, as technological advancements, regulatory changes and market dynamics can impact feasibility. Therefore, organisations should conduct due diligence to understand the feasibility of achieving emission reduction targets before making public commitments. [Applicable Scope 3 categories: All scope 3 categories]	AI can be a powerful tool for assessing the feasibility of emission reduction targets by evaluating factors like technology maturity, cost and other critical aspects within short-term and long-term timeframes. Using advanced data analytics and machine learning, AI can assess an organisation's emissions profile and then analyse data from sources such as scientific research, industry reports, and market trends. From there, AI can help to evaluate the maturity and scalability of relevant technologies to identify the reduction potential across the profile. For short-term targets, AI provides real-time insights into the availability and effectiveness of existing technologies, aiding immediate sustainability decisions. For long-term targets, AI models various scenarios and predicts the evolution of emerging technologies, considering investment trends, regulatory developments and potential breakthroughs.	Use advanced data analytics and machine learning models such as ensemble methods (e.g. Random Forest, Gradient Boosting) and scenario analysis to assess the feasibility of emission reduction targets. These models can evaluate technology maturity, cost and other critical factors. Tools like Scikit-learn and XGBoost can be used to build these models.

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Table 3: Challenges and potential AI use cases for Scope 3 emissions abatement activities

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Identification of lower emissions alternatives for materials	**Material analysis and alternate suggestion**	**Material informatics using machine learning**
Switching to lower emissions-intensive materials is a key Scope 3 decarbonisation lever, particularly materials used as inputs in product manufacturing or packaging. But identifying potential alternative materials that meet the critical functional requirements of the product (e.g. heat resistance, durability, flexibility, electrical conductivity, colour, feel etc.) is a challenge, as is understanding the potential emission savings. [Applicable Scope 3 categories: Category 1: Purchased goods & services]	AI could potentially analyse existing materials in use and identify potential alternative, lower-emissions materials. It could assess the properties of these alternative materials against the required functional elements to ensure quality is not compromised.	Use material informatics platforms that leverage machine learning models such as neural networks and random forests to analyse material properties and identify lower-emission alternatives. Models like MatGAN (Generative Adversarial Networks for materials) can be used to predict material properties and discover new materials.
Optimising delivery routes	**Identify low-carbon routes**	**Optimisation algorithms and real-time data analytics**
Optimising delivery routes, maximising load capacities and prioritising efficient transport modes is a primary logistics function. This strategy is predominantly cost driven. However, it also presents a significant opportunity for decarbonisation. By carefully planning and streamlining delivery routes, businesses can minimise fuel consumption and reduce emissions. [Applicable Scope 3 categories: Category 4: Upstream transport & distribution; Category 9: Downstream transport and distribution]	AI has the potential to play a significant role in optimising freight delivery routes and switching to less carbon-intensive options. By analysing vast amounts of data, including traffic conditions, weather patterns and historical shipping data, AI algorithms can identify the most efficient routes for transporting goods. This reduces travel distances and fuel consumption, while minimising carbon emissions and costs. AI can also dynamically adjust routes in real-time to avoid delays and congestion, further enhancing efficiency. There may also be instances where AI can recommend switching from one transport mode to another (e.g. road to rail) where feasible, as a means of reducing emissions.	Implement optimisation algorithms such as generative algorithms and linear programming for route optimisation. Use reinforcement learning models for real-time dynamic route adjustments based on current traffic and weather conditions. Tools like Google OR-Tools can be used for vehicle routing problems.

*Complexity has been determined by the author, with no formal framework applied.

Challenge	Potential AI use case AI Implementation Complexity*	AI solution
Increased yield of input material	**Optimise material use**	**Pattern recognition and optimisation algorithms**
Embodied carbon in input materials used in production often represents a sizeable portion of a manufacturer's overall Scope 3 emissions. Initiatives that either minimise the quantity of a material required (e.g. through lightweighting) or maximise the yield of a material (e.g. by reducing wastage from offcuts) can significantly reduce Scope 3 emissions across several categories, including purchased goods and services and waste from operations. [Applicable Scope 3 categories: Category 1: Purchased goods & services; Category 5: Waste generated in operations]	AI algorithms can map out the most efficient cuts of materials to minimise offcuts. By analysing patterns and optimising cutting processes, companies may significantly reduce waste and improve material utilisation.	Use pattern recognition models such as convolutional neural networks (CNNs) to analyse cutting patterns. Implement optimisation algorithms like 'cutting stock problem solvers' to minimise material waste. Tools like AutoCAD with integrated AI plugins can assist in optimising material cuts.
Challenge in supply chain efficiency	**Reinforcement learning for supply chain**	**AI-driven warehouse optimisation**
Improving supply chain efficiency requires optimal decision-making in logistics, manufacturing processes and resource allocation. [Applicable Scope 3 categories: All upstream scope 3 categories]	AI systems can learn optimal strategies through trial and error, which can improve decision-making over time. This can be applied to various aspects of the supply chain to enhance efficiency.	Reinforcement learning can optimise warehouse operations to minimise emissions from material handling and storage systems. It adapts to dynamic supply chain conditions, improving operational efficiency and contributing to net-zero goals.
Transforming employee and consumer engagement	**AI-driven behavioural change**	**Customised sustainability recommendations**
Addressing Scope 3 emissions requires collaboration from both employees and consumers. This collaboration is essential for fostering behavioural change and promoting sustainable practices. [Applicable Scope 3 categories: All upstream scope 3 categories]	AI can encourage behavioural change by offering tailored sustainability insights. Generative AI enables personalised feedback and actionable advice for employees and customers, promoting sustainable habits.	An AI-powered app can suggest carpooling or public transport options to reduce commuting emissions. This approach provides customised sustainability recommendations, helping both employees and consumers adopt more sustainable practices.

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CASE STUDIES

6 | CASE STUDIES

Below, we have curated a sample of illustrative examples, rather than an exhaustive list, to showcase the work of CLC members and other leading companies globally.

Microsoft

With Scope 3 emissions accounting for an estimated 96.5% of its carbon footprint, Microsoft sees supplier collaboration as key to its decarbonisation strategy. Microsoft uses its Sustainability Manager software platform to tackle its own Scope 3 emissions. Sustainability Manager leverages AI to streamline emissions tracking, automate data analysis and forecast future trends. Generative AI simulates different carbon reduction scenarios to assess potential impact. Sustainability Manager also enhances supplier engagement with customisable emissions surveys, real-time data updates and compliance tracking.

SAP

The Emission Factor Mapping with AI feature in SAP Sustainability Footprint Management enhances the accuracy and speed of carbon footprint calculations through automated, intelligent suggestions. The ESG Report Generation with AI capability automatically generates ESG reports. These offerings use AI technologies like semantic search to improve the Scope 3 calculation process, allowing non-technical users to automatically match the most appropriate emissions factor to any product or process.

Schneider Electric

Schneider Electric, in partnership with Google, ASM and HP, is driving supplier decarbonisation through the Catalyze program. This initiative accelerates access to renewable energy across the semiconductor and IT supply chains. Suppliers join Catalyze to gain access to critical support and resources, including the Zeigo Hub, Schneider Electric's AI-powered platform. Ziego uses machine learning to match businesses with optimal renewable energy projects, data analytics to share real-time pricing, trends and financial insights. Zeigo also automates the process of bidding for renewable energy projects.

Worley

Worley is applying AI, including agentic AI, to support lower carbon energy solutions and improve project delivery through data-driven approaches. The company is working with strategic technology partners to develop digital tools that enable automation, remote operations, and more efficient use of data. Worley has committed to deploying AI responsibly, with attention to ethical standards, transparency, privacy, cyber security and ensuring that humans remain integral to the decision-making process. These efforts aim to help customers operate more safely, efficiently, and sustainably.

Telstra

Telstra is actively working to manage its Scope 3 emissions, which are significant, being three times greater than Telstra's Scope 1 and 2 emissions combined. The company collaborates closely with its suppliers to reduce emissions by providing training and support to help them reduce their carbon footprint. Telstra also works with device manufacturers to improve the energy efficiency of Telstra-branded devices. Additionally, Telstra has set a target to reduce its absolute Scope 3 emissions by at least 50% by 2030, from an FY19 baseline, a target that has been verified by the Science Based Targets Initiative. The company uses a mixture of methodologies for calculating Scope 3 emissions, including supplier-specific data, the hybrid method using CDP data, and the spend-based methodology.

Telstra is also leveraging technology to manage and reduce emissions, exploring AI applications to optimize network performance and reduce emissions. The company is investing in renewable energy projects to decarbonize the grid and reduce reliance on fossil fuels, aiming to enable renewable energy generation equivalent to 100% of its consumption by 2025. Telstra is also focusing on reducing the emissions from the products and services it provides to customers, such as the energy used by modems in customers' homes and businesses. These efforts are part of Telstra's broader commitment to achieving net-zero greenhouse gas emissions by 2050.

Laing O'Rourke

Laing O'Rourke uses AI tools to more deeply and accurately understand the work that subcontractors and delivery partners are performing, allowing for more targeted and effective emission reduction strategies. AI driven semantic analysis is applied to each individual transaction we have with our delivery partners, and can then distil the type of work and associated emission profile that should be used. These transactions can number in the many hundreds of thousands over a reporting period, and what would take months of human labour to categorize can be done in minutes with AI. More than just the productivity improvement, the quality and accuracy of the reporting is substantively increased, as previous analysis would have to categorize the emissions at a much higher level, which meant that much detail and insight was lost.

AGL

AGL is investing in Electrify Now, a home electrification tool that estimates household savings in carbon and energy bills. It provides personalised emissions impact by modelling each household's load profile. The AI-driven calculation engine analyses consumption patterns to identify optimal electrification opportunities, predicts energy usage based on behaviours, and recommends tailored solutions for potential emissions reduction and bill savings. This approach helps customers make informed decisions about transitioning from fossil fuels, directly supporting AGL's decarbonisation goals.

Mondra

Mondra automates Life Cycle Assessment (LCA) for food and retail businesses, enabling them to measure and reduce their Scope 3 emissions with precision. Traditional LCA methods struggle with fragmented data, inconsistent formats and varying levels of granularity. Mondra's AI-powered chatbot, Sherpa, automates LCAs and enhances emissions tracking. Sherpa, built on Microsoft Azure OpenAI, identifies carbon-intensive components in more than 30,000 products and one million unique ingredients. One retailer used Sherpa to reformulate a lasagne recipe, cutting emissions by 18%.

P&G

With Scope 3 emissions responsible for over 90% of its total footprint, Procter & Gamble (P&G) deployed an AI-powered analytics platform to enhance emissions tracking and supplier collaboration. This platform uses machine learning to harmonise and validate supplier data, and identify cost-effective pathways for emissions reduction, such as material changes and process optimisations. More than 70% of suppliers are participating in P&G's emissions tracking and sustainability initiatives.

Lectra

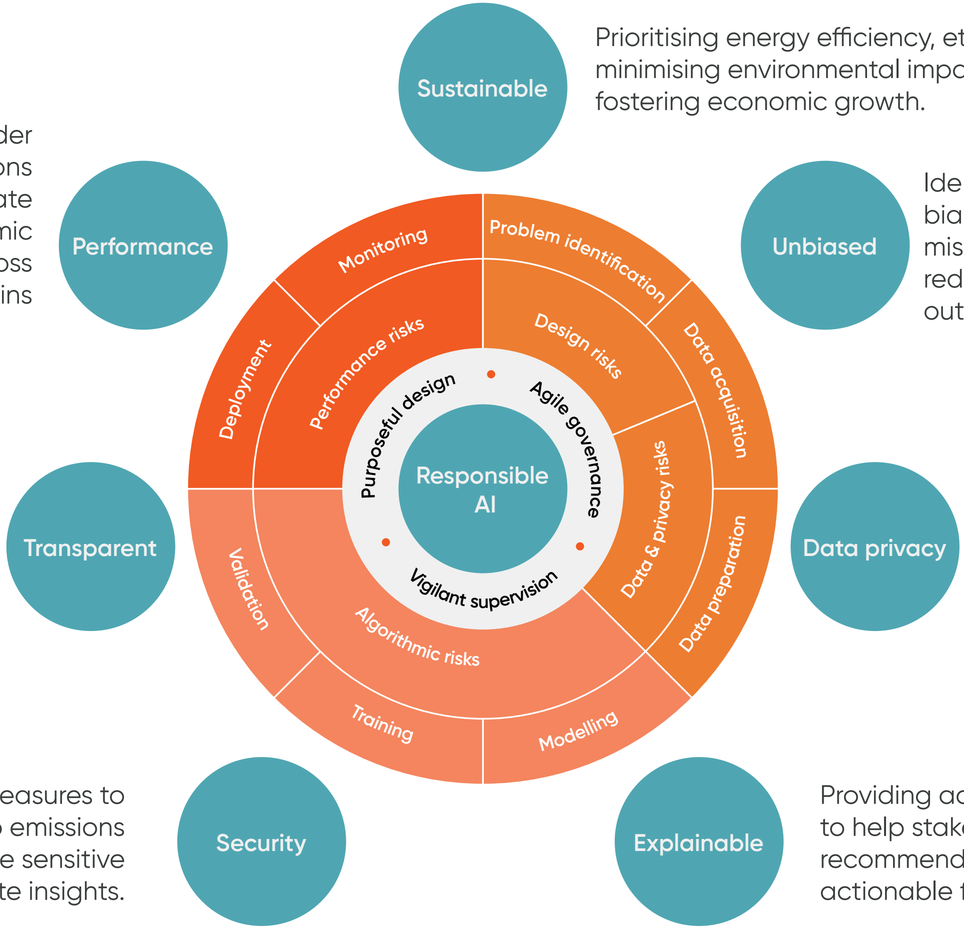
Textile manufacturing generates vast amounts of material waste, particularly during the fabric-cutting process. Lectra, a leader in cutting solutions, implemented AI-driven optimisation algorithms in its Vector fabric cutting machines to enhance material utilisation. AI analyses cutting patterns to maximise fabric use. Machine learning identifies optimal layouts for different fabric types, while linear programming solvers minimise waste in real time. The goal? To reduce material waste across textile manufacturing, lower production costs and increase sustainability in fashion and fabric industries.

7 | CONSIDERATIONS WHEN APPLYING AI

Ethical use of AI starts with adherence to legal standards, data privacy laws and industry-specific regulations to maintain compliance and build trust.

7.1 | RESPONSIBLE AI

The framework below illustrates the key challenges encountered when applying AI to Scope 3 emissions reporting, along with mitigation strategies. Each component addresses the unique complexities of managing and interpreting emissions data through an AI-driven approach, prioritising transparency, accuracy and security in emissions tracking.



Sustainable: Prioritising energy efficiency, ethical and optimal data use, minimising environmental impact, ensuring social inclusivity and fostering economic growth.

Performance: Addressing AI model performance under varied emissions data and conditions to maintain reliable and accurate results, crucial for managing dynamic and complex Scope 3 emissions across supply chains

Unbiased: Identifying and mitigating data and model biases to prevent skewed insights that may misrepresent emissions sources or overestimate reduction impacts, ensuring fair and accurate outcomes.

Transparent: Ensuring AI processes and data sources are clear, so stakeholders understand how Scope 3 emissions data is processed and interpreted, enabling trust in decarbonisation insights.

Data privacy: Protecting sensitive company and supplier data used in emissions modelling, aligning with regulatory requirements and safeguarding against data misuse or breaches.

Security: Ensuring robust security measures to prevent unauthorised access to emissions data, which could compromise sensitive information and lead to inaccurate insights.

Explainable: Providing accessible explanations of AI model decisions to help stakeholders comprehend emissions reduction recommendations, making complex outcomes actionable for non-technical teams.

For a detailed breakdown of each Responsible AI challenge in Scope 3 emissions management, please refer to the Appendix B.

7.2 | COMPLIANCE AND REGULATION

Understanding and following global and regional regulations is essential for transparent Scope 3 emissions reporting. Frameworks including the ISSB standards, the European Union's Corporate Sustainability Reporting Directive (CSRD), Australia's AASB S2 Climate-related Disclosures and the Californian Climate Disclosure Regulations. Frameworks that mandate Scope 3 emissions reporting, as well as associated assurance requirements linked to each of these mandatory reporting schemes, need to be front of mind when deploying AI solutions. These regulations align with global practices and respond to growing demand for transparency in climate reporting.

This preface provides an overview of key considerations for leveraging AI while ensuring alignment to compliance and regulations.

By integrating these considerations, organisations can harness the full potential of AI for Scope 3 emissions, ensure risk mitigation and enhance corporate reputation and stakeholder trust.

Responsible AI application

AI should be applied ethically and responsibly (RAI) to encourage trust in its use and application for Scope 3 calculations and compliance. Refer to the section on RAI for key components and considerations for establishing a robust framework.

Model governance

Establishing protocols for model development, validation and monitoring is important to ensure AI models are accurate, reliable and free from biases. Regular audits and assessments help identify and mitigate potential risks. Transparency of methodologies used to calculate emissions, including emission factors and assumptions, is also crucial.

Data governance

Clear policies for data collection, storage and processing ensure data integrity and compliance with relevant regulations. Documenting the origins and nature of the data used, including data from suppliers and logistics providers, is essential.

Regulatory compliance & assurance

AI models must adhere to international and local regulations, such as the ISSB and the Australian Sustainability Reporting Standards. They must ensure accurate and compliant reporting in line with the National Greenhouse and Energy Reporting (NGER) Scheme and the Australian Securities and Investments Commission (ASIC) climate risk disclosure requirements. AI enabled Scope 3 solutions should be traceable, explainable and well documented to address assurance requirements.

Data governance

For entities with global presence, AI applications and outcomes should be aligned with relevant global ESG reporting frameworks, such as the Global Reporting Initiative (GRI) and the International Sustainability Standards Board's (ISSB) IFRS S2 Climate-related Disclosures.

Continuous monitoring

Continuous monitoring and updating AI applications and models ensures ongoing compliance with evolving regulations and standards for Scope 3 reporting. Conducting regular audits and reviews of AI-driven Scope 3 calculations helps identify and address compliance issues. Documenting incidents or discrepancies related to emissions data, along with corrective actions, is also essential.

8 | OPPORTUNITIES AND OBSTACLES TO AI TOOL DEVELOPMENT

8.1 | TECHNICAL GUIDELINES

Technical guidelines that have been applied by CLC member organisations reflect three generalised steps: data collection and management; algorithm development; and implementation and deployment. Each area has been found to enhance climate action capabilities, reduce emissions-related risks, and advance strategic sustainability goals.

Data collection & management

1 Understand data requirements

Effective Scope 3 emissions reduction requires sourcing a wide range of data, including direct suppliers, third-party logistics providers, industry databases, and internal corporate systems.

2 Assess & prepare data

Reliable emissions tracking is dependent on the accuracy of data provided. AI models can precisely identify emissions patterns, detect inefficiencies and recommend reduction strategies, provided the underlying data is accurate and complete.

3 Process data, catering for assurance

Integrating diverse data sources provides a holistic view of Scope 3 emissions. AI solution designs should support seamless data integration through Application Programming Interfaces (APIs) and compatible data formats with built-in validations to ensure accuracy and consistency across datasets.

Algorithm development

4 Model selection

Selecting suitable AI models is crucial for analysing and forecasting emissions. The model choice depends on data characteristics, desired accuracy and computational efficiency.

5 Model development

AI models should undergo rigorous training to minimise errors and improve real-world applicability. Regular re-training on updated data is recommended to keep models responsive to evolving climate factors and supply chain dynamics.

6 Model evaluation

Establishing relevant performance metrics is essential for evaluating AI models used in Scope 3 emissions applications. Specific sustainability impact metrics (e.g. GHG emissions reduction per unit) help align model performance with environmental objectives.

Implementation & deployment

7 Architectural considerations

A robust architecture that is future-proof and designed for scalability is essential for deployment of AI tools in emissions management to ensure reliable analysis across supply chain networks.

8 Integration & interoperability provisions

AI solutions and tool designs must consider interoperability and seamless integration with existing corporate systems, such as enterprise resource planning (ERP) and GHG accounting systems to provide an efficient end-to-end emissions management solution.

9 Modular & adaptable design

As sustainability targets evolve, AI tools and solutions need to be able to scale and adapt to new data inputs, model updates and regulatory standards for which flexible and modular solutions are recommended.

8.2 | OBSTACLES TO AI ADOPTION

Despite the transformative potential of AI technologies, there are challenges which must be overcome to enable widespread adoption.

Implementation hurdles

Companies frequently lack the necessary capabilities, enablers, talent, culture, governance and processes to convert promising AI concepts into tangible Scope 3 emission reductions. They flounder by depending on traditional skills and implementation methods.

Regulatory gaps

AI advancements are rapid and regulatory policies and standards are not keeping pace. These regulatory gaps need to be addressed to enable and encourage the application of AI for decarbonisation.

Data availability and quality

Generative AI are dependent on large datasets for accuracy, and these are often lacking in emerging sustainability domains.

Risk aversion

Hesitation to leverage AI also stems from concerns about trust, data accuracy and transparency, and potential risks to brand and reputation.

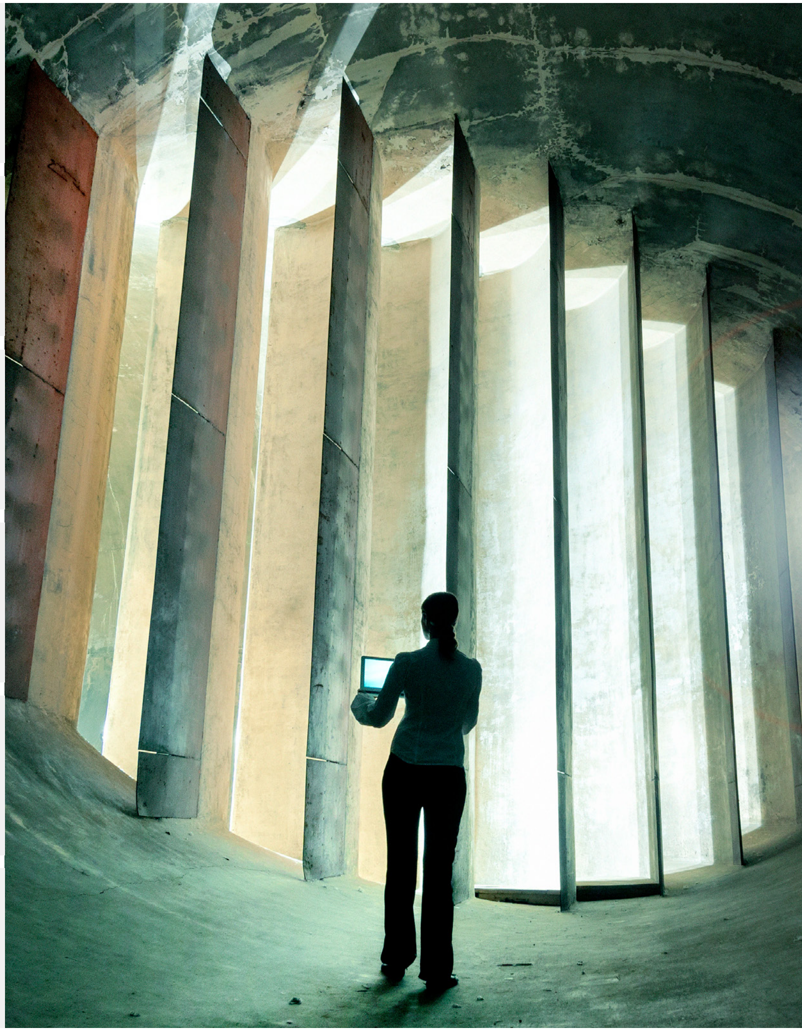
High energy use, infrastructure and computational power

AI models are resource-intensive, requiring significant computational resources and infrastructure.

For detailed discussions on the topic, please refer to the CLC's paper on "The Impact of AI Adoption on Sustainability: Strategies, Case Studies, and Future Trends".

High initial investment of resources

AI is expected to eventually lead to significant efficiencies in Scope 3 emissions management. However, there is likely to be a significant amount of resource-intensive upfront work required to validate the systems and processes.



HOW TO ADOPT AI TO MANAGE SCOPE 3 EMISSIONS

9 | HOW TO ADOPT AI TO MANAGE SCOPE 3 EMISSIONS

By implementing a strategic approach to AI-driven emissions management – especially in tackling the key challenges of Scope 3 reporting and abatement – organisations can significantly enhance their emissions reporting and compliance capabilities. Central to this effort are robust data governance frameworks, including data sources from the entire value chain, to ensure precise and comprehensive tracking of Scope 3 emissions.

As AI technologies continue to evolve, the importance of responsible application in emissions reporting cannot be overstated. Ensuring transparency, fairness and accuracy in AI-driven processes builds trust and supports compliance with global and regional regulations. By fostering a culture of continuous improvement and rigorous reporting standards, organisations can leverage AI to effectively meet regulatory and voluntary requirements and contribute to broader climate action efforts.

Looking ahead, reinforcing the foundations outlined in the activities outlined below will support impactful integration of AI technologies into existing emissions management practices. Importantly, organisations may elect to undertake the below activities in an alternate sequence, based on their maturity in managing Scope 3 emissions.

1 Map Scope 3 data governance

Establish robust data governance framework to effectively manage Scope 3

Data sources

Identify all relevant data sources, including suppliers, logistics providers and waste management companies.

Data management

Develop data management policies to ensure data quality, accuracy and consistency.

Data integration

Implement data integration techniques, such as Application Programming Interfaces (APIs) and data lakes, to consolidate data from disparate sources.

Data stewardship

Assign data stewardship roles to oversee data governance and ensure compliance with regulatory requirements.

2 Identify automation opportunities

Leverage AI to automate data collection, analysis and reporting processes, reducing manual effort and improving accuracy.

Data collection & reporting

Conduct a thorough assessment of current data collection and reporting processes to identify areas for automation.

Implement AI

Implement AI-powered tools for real-time data collection and monitoring.

Apply machine learning

Use machine learning algorithms to analyse data and generate insights for emissions reduction.

Automate reporting

Automate reporting processes to ensure timely and accurate submission of Scope 3 emissions data.

3 Develop AI governance framework

Establish governance structures to manage the risks and ethical considerations associated with AI applications.

AI governance policies

Develop AI governance policies that address transparency, explainability and bias mitigation.

AI ethics committee

Create an AI ethics committee to oversee the development and deployment of AI tools.

Audits & reviews

Implement regular audits and reviews of AI systems to ensure compliance with governance policies.

Training

Provide training and education to stakeholders on AI governance and ethical considerations.

4 Pilot projects and use cases

Test AI solutions through pilot projects and document successful case studies to build a knowledge base.

Identify use cases

Conduct a thorough assessment of current data collection and reporting processes to identify areas for automation.

Engage stakeholders

Implement AI-powered tools for real-time data collection and monitoring.

Monitor & optimise

Use machine learning algorithms to analyse data and generate insights for emissions reduction.

Document & share

Automate reporting processes to ensure timely and accurate submission of Scope 3 emissions data.

CALL TO ACTION

10 | CALL TO ACTION

Scope 3 emissions are complex, critical and impossible to ignore. AI has the power to turn an enormous global challenge into rapid and real-world progress – but only with the right human expertise at the table.

Business leaders in the CLC are bringing together sustainability experts, data specialists and AI teams to tackle Scope 3 emissions. From our learnings, we suggest four strategies to get started:

Assess

Identify gaps in your Scope 3 data and evaluate where and how AI offers the greatest value to improve accuracy and cost efficiencies.

Select

Choose AI tools that align with your specific emissions categories and operational needs.

Implement

Ensure seamless integration between AI tools and existing data management and reporting systems to meet regulatory requirements.

Train & monitor

Equip staff with AI training and continuously monitor performance to refine applications and optimise impact.

CLC members are harnessing data and AI to address Scope 3 emissions and are co-building an ecosystem to share experiences and knowledge. With a growing range of advanced tools now available, businesses can explore practical solutions to navigate this complex challenge, create new partnerships and drive meaningful progress.

ACKNOWLEDGING OUR CLC LEARNING & SHARING JOURNEY

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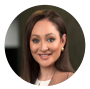

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11 | APPENDICES

11.1 | APPENDIX A: TECHNICAL FRAMEWORK FOR AI IN SCOPE 3 EMISSIONS MANAGEMENT

This appendix expands on the analysis of the key technical components required for effective AI tool development in Scope 3 emissions reduction and decarbonisation.

Data collection & management

Understand data requirements

Scope 3 emissions tracking requires data from multiple layers of the supply chain, covering supplier emissions, transportation, raw material extraction, production energy use and waste management. Key data sources include:

- **Supplier reports:** Emissions and resource use data collected directly from suppliers.
- **Lifecycle assessments (LCAs):** Detailed analyses of environmental impacts across the lifecycle of products.
- **Logistics providers:** Data on transportation emissions from shipping and distribution partners.
- **Industry databases and public sources:** Benchmark data from government or industry databases to validate and supplement supply chain information.

Assess and prepare data

Data integration for emissions tracking should accommodate diverse data types and sources to enable comprehensive analysis. Recommended approaches include:

- **APIs and ETL pipelines:** Use of APIs or ETL (Extract, Transform, Load) processes to ensure smooth data transfer and alignment across disparate sources.
- **Standardisation of formats:** Leveraging standard data formats like XML or JSON helps streamline data handling and reduce integration challenges.

Process data, catering for assurance

Data accuracy is critical for reliable emissions insights. Advanced validation methods should include:

- **Anomaly detection algorithms:** Machine learning-based anomaly detection can flag unexpected variances in data that may indicate quality issues.
- **Data cleaning and normalisation:** Pre-processing steps to remove errors, handle missing values and normalise data across sources help maintain consistency.
- **Audit trails:** Keeping detailed logs of data inputs, transformations, and validations enhances data traceability and regulatory compliance.

Algorithm development

Model selection

Selecting appropriate AI models for emissions reduction should align with the specific nature of Scope 3 emissions data, which is often complex and multivariate. Recommended models include:

- **Predictive models:** Suitable for forecasting emissions trends based on historical data (e.g. time-series forecasting models).
- **Classification models:** Useful for categorising emissions sources by intensity or impact level (e.g. logistic regression, decision trees).
- **Optimisation algorithms:** Applied for developing emissions reduction strategies by optimising factors such as resource use, production scheduling and transportation routes.

Model training

Model training should be rigorous, using high-quality, representative datasets. Key considerations include:

- **Cross-validation and hyperparameter tuning:** Applying cross-validation techniques to ensure the model generalises well to unseen data and adjusting hyperparameters to optimise model performance.
- **Data augmentation:** Leveraging standard data formats like XML or JSON helps streamline data handling and reduce integration challenges.

Model evaluation

Selecting the right metrics ensures models are performing effectively in emissions-related applications. Relevant metrics include:

- **Mean Absolute Error (MAE) and Root Mean Square Error (RMSE):** Commonly used for assessing prediction accuracy in emissions forecasts.
- **Precision and recall:** Important in classification tasks to ensure both relevance (precision) and coverage (recall) of predictions.
- **Environmental impact metrics:** Custom metrics such as GHG emissions reduction per unit output can directly measure the environmental benefit of AI models in emissions reduction.

Implementation & deployment

Architectural considerations

A well-designed architecture is essential for scaling AI tools in emissions management. Key requirements include:

- **Cloud infrastructure:** Cloud solutions (e.g. AWS and Azure) offer scalability, data storage and computing power needed for large-scale emissions analysis.
- **Edge computing for real-time analysis:** This can reduce latency and improve responsiveness.

Integration & interoperability provisions

Ensuring compatibility with current systems, such as ERP or carbon accounting software, is vital for efficient data exchange and unified reporting. Approaches include:

- **Middleware and API gateways:** Middleware enables smooth data flow between AI tools and existing systems, while API gateways facilitate secure communication and data exchange.
- **Data warehouse integration:** Integrating with a central data warehouse allows emissions data to be consolidated and accessed by various departments, enhancing accessibility and alignment with organisational data strategies.

Modular and adaptable design

To keep pace with evolving sustainability goals, AI tools must be both scalable and adaptable. Recommendations include:

- **Modular system design:** Modular architectures enable updates or expansions without disrupting the overall system.
- **Microservices architecture:** Allows for easy scaling of specific services, such as emissions prediction or data validation, without overhauling the entire system.

11.2 | APPENDIX B: DETAILED VIEW OF RESPONSIBLE AI (RAI) CHALLENGES IN SCOPE 3 EMISSIONS

Challenge	Mitigations			
Transparency The complexity of both the data sources required for Scope 3 emissions (such as supplier and transportation data) and the AI algorithms used to process this data can make it challenging for end users to understand data usage and outcomes.	**Documentation:** Provide comprehensive documentation of the AI system, including its design, data sources (especially emissions-related data), and decision-making processes.	**Open source:** Where possible, and taking data privacy into account, use open-source algorithms and models to allow for external review and validation.	**Audit trails:** Maintain detailed logs of data sources and AI system operations for emissions accountability.	
Explainability AI models used for Scope 3 emissions calculations can be complex and lack inherent explainability, making it difficult for stakeholders to understand emissions estimates or calculations generated by the system.	**Explainable AI (XAI):** Implement techniques to clarify AI decisions, such as SHAP or LIME, particularly where emissions data impacts results.	**User interfaces:** Design interfaces to clearly communicate AI-driven emissions estimates.	**Education:** Educate stakeholders on AI and emissions reporting for transparency.	
Bias issues Bias in AI models may affect Scope 3 emissions estimates, particularly if input data from supply chains is skewed or incomplete. These biases can undermine the accuracy of emissions tracking and reporting.	**Diverse data:** Source diverse and representative data from a wide range of suppliers to reduce bias in emissions calculations.	**Bias detection tools:** Use fairness metrics and bias audits to detect and minimise skew in emissions data.	**Mitigation strategies:** Apply bias mitigation techniques, such as re-weighting data, to ensure balanced Scope 3 calculations.	
Performance issues Scope 3 emissions calculations often require high data volumes and complex processing, which can strain AI model performance. This may lead to slower processing or degraded accuracy over time if not continuously monitored.	**Benchmarking:** Set performance metrics specific to emissions data processing.	**Optimisation:** Enhance model efficiency to handle large-scale, complex emissions data.	**Scalability:** Ensure AI systems can accommodate growth in emissions data volume.	**Continuous monitoring:** Monitor AI systems to prevent performance drop-offs in emissions reporting.
Data privacy Scope 3 emissions reporting relies on extensive supplier and partner data, which raises privacy concerns. Protecting individual identities and maintaining data confidentiality are essential in emissions data aggregation.	**Data anonymisation:** Apply anonymisation techniques to emissions data to safeguard privacy.	**Access controls:** Restrict data access to authorised personnel to maintain confidentiality.	**Compliance:** Follow data protection laws applicable to emissions data.	**Data minimisation:** Use only essential data for Scope 3 calculations.
Security AI models for emissions data are susceptible to security threats, such as data breaches or adversarial attacks. This could compromise sensitive supplier data used in Scope 3 emissions reporting.	**Secure development practices:** Follow secure coding standards to safeguard emissions data.	**Encryption:** Encrypt emissions data to protect against unauthorised access.	**Regular security audits:** Conduct security assessments to identify vulnerabilities in emissions data handling.	**Incident response plan:** Prepare for security incidents involving emissions data.
Sustainability AI has adverse sustainability implications including high energy consumption, hardware e-waste and the carbon footprint of data centres. Ethical concerns and the impact on jobs and society must be addressed to ensure responsible and sustainable AI deployment.	**Energy efficiency:** Optimise algorithms and hardware to reduce energy consumption and use renewable energy sources for data centres.	**E-waste management:** Implement recycling programs and design hardware for longer lifespans and easier upgrades.	**Ethical AI practices:** Develop and enforce guidelines to ensure fairness, transparency and accountability in AI systems, and invest in workforce reskilling programs.	

11.3 | APPENDIX C: GLOSSARY

Term	Definition
AASB	Australian Accounting Standards Board – An Australian Government agency that develops and maintains financial reporting standards.
AI	Artificial Intelligence – Technology that enables machines to mimic human intelligence, including learning, reasoning and self-correction.
API	Application Programming Interface – A set of rules that allows different software entities to communicate with each other.
ARIMA	AutoRegressive Integrated Moving Average – A statistical analysis model that is used to forecast future points in a series by using past data point.
ASIC	Australian Securities and Investments Commission – Australia's corporate, markets and financial services regulator.
AutoCAD	A 2D and 3D computer-aided design (CAD) software application developed by Autodesk.

Term	Definition
BERT	Bidirectional Encoder Representations from Transformers – A machine learning model used for NLP tasks
Blockchain	A decentralised digital ledger technology that securely records transactions across multiple computers in a way that ensures the integrity and transparency of the data without the need for a central authority
CDP	Carbon Disclosure Project – An organisation that supports companies and cities to disclose their environmental impact.
CLC	Climate Leaders Coalition
CSRD	Corporate Sustainability Reporting Directive – A European Union directive that requires companies to disclose information on the way they operate and manage social and environmental challenges.
Data Parsing	The process of analysing and converting raw data into a structured format that is easier to understand and manipulate.

Term	Definition
Decision Tree	A predictive modelling technique that uses a tree-like structure to represent decisions and their potential outcomes.
EEIO database	Environmentally Extended Input-Output database – A database used to link economic data with environmental data to calculate emissions.
ETL	Extract, Transform, Load – A process in database usage and data warehousing.
GenAI	Generative Artificial Intelligence – A subset of artificial intelligence that uses generative models to produce text, images, videos or other forms of data. These models learn the underlying patterns and structures of their training data and use them to produce new data based on the input, which often comes in the form of natural language prompts.
GHG	Greenhouse Gas – These atmospheric gases trap heat, contributing to the greenhouse effect and global warming. These gases absorb and emit infrared radiation, leading to the warming of the Earth's surface.
GL	General Ledger – A complete record of all financial transactions over the life of a company.

Term	Definition
Google OR-Tools	A free and open-source software suite developed by Google for solving linear programming (LP), mixed integer programming (MIP), constraint programming (CP), vehicle routing (VRP) and related optimisation problems.
Gradient Boosting	An ensemble machine learning technique that combines the predictions from several models to improve the overall predictive accuracy. It is particularly useful for regression and classification problems.
GRI	Global Reporting Initiative – An international independent standards organisation that helps businesses, governments and other organisations understand and communicate their impacts on issues such as climate change, human rights and corruption.
GPS	Global Positioning System – A satellite-based radio navigation system that provides geolocation and time information to a GPS receiver anywhere on or near the Earth where there is an unobstructed line of sight to four or more GPS satellites.
GPT-3	Generative Pre-trained Transformer 3 – An autoregressive language model that uses deep learning to produce human-like text.
ISSB	International Sustainability Standards Board – An organisation that develops global standards for sustainability reporting.
LCA	Life Cycle Assessment – A technique to assess environmental impacts associated with all the stages of a product's life from cradle to grave.

Term	Definition
LIME	Local Interpretable Model-agnostic Explanations – A technique to explain the predictions of any machine learning classifier.
LSTM	Long Short-Term Memory – A type of recurrent neural network used in deep learning.
MatGAN	Generative Adversarial Networks for materials – A machine learning model used to predict material properties and discover new material.
NGER	National Greenhouse and Energy Reporting - An Australian framework for reporting greenhouse gas emissions and energy consumption
NLP	Natural Language Processing – A branch of AI that focuses on the interaction between computers and humans through natural language.
Prophet	A forecasting tool developed by Facebook for time series data.
PyTorch	An open-source machine learning library based on the Torch library, used for applications such as computer vision and natural language processing.
Random Forest	An ensemble learning method used for classification, regression and other tasks.

Term	Definition
RoBERTa	An ensemble learning method used for classification, regression and other tasks.
Scikit-learn	Scikit-learn (formerly known as scikits.learn and also known as sklearn) is a free and open-source machine learning library for the Python programming language.
Scope 3 emissions	Indirect greenhouse gas emissions that occur in a company's value chain, excluding direct emissions from owned or controlled sources (Scope 1) and indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting company (Scope 2).
SHAP	SHapley Additive exPlanations (SHAP) interprets machine learning model outputs using Shapley values from cooperative game theory. SHAP provides a clear understanding of each feature's contribution to predictions, ensuring fairness and comprehensibility.
SpaCY	An open-source software library for advanced NLP in Python.
TensorFlow	An open-source software library for dataflow and differentiable programming across a range of tasks, primarily used for machine learning applications such as neural networks.
WFH	Work from home.
XGBoost	Extreme Gradient Boosting is an open-source software library that provides a scalable, distributed gradient-boosted decision tree (GBDT) machine learning framework.

Ernst & Young ("EY") was engaged on the instructions of the B Team Australasia in their capacity of convenor of the Climate Leaders Coalition (CLC) to assess and document potential Artificial Intelligence (AI) decarbonisation use cases solutions, for use in a report ("Report") in accordance with the engagement agreement dated [26 September 2024].

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