University of Glasgow | School of Computing Science

Honours Individual Project Dissertation

Developing an AI-Based ChatGPT Lifecycle Assessment (LCA) tool

Sujay Vijaykumar Patil

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Abstract

Lifecycle Assessment (LCA) is an essential tool to assess how products impact the environment, but traditional LCA approaches are difficult to implement, expensive, and need expertise in the field, which limits their scalability and accessibility, particularly for small and medium sized businesses. With the goal to automate and improve LCA processes, this research explores the potential of artificial intelligence (AI), particularly for large language models (LLMs) like ChatGPT.

An AI-powered tool was created to help analyze Bills of Materials (BOMs), predict environmental impact, and generate clear, easy to understand LCA (Lifecycle Assessment) reports. The system uses Natural Language Processing (NLP) to read and clean BOM data, then matches materials with environmental databases even when the names don't exactly match to calculate CO2 emissions. It also uses AI models to fill in missing details like where raw materials come from, how they're transported, and how they're made. Users can view all of this information through a web-based dashboard, which shows interactive graphs and lets them download full sustainability reports.

The results show that AI can execute LCAs with excellent accuracy and connectivity while significantly reducing the required time and expense. The tool supports data driven decision making and sustainable design practices across a range of industries by providing a scalable solution for automated, user-friendly, and straightforward life cycle assessment.

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Thank you all for your support and contributions.

Education Use Consent

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1 Introduction

1.1 Context

Lifecycle Assessment (LCA) is a methodical approach that assesses the environmental effect of a process, product, or service at every stage of its life cycle, from the extraction, production, and distribution of raw materials to use and disposal at the end of its useful life (ISO 14040, 2006). It serves as a decision support tool for industries and lawmakers seeking to implement sustainable practices to reduce carbon footprints and comply with environmental regulations (Baumann et al. 2006).

LCA's significance goes beyond environmental responsibility; it is an essential tool for both governments and businesses to efficiently monitor and regulate environmental effects. LCAs take a significant amount of time and money to complete. It can take weeks or months to perform an LCA study, and it requires access to large environmental impact databases and specialised knowledge. Furthermore, LCA studies frequently focus on high-value products in sectors like electronics, construction, and automobiles, impacting supply chains worth billions of dollars (Rydberg 2010).

Despite its advantages, there are numerous challenges in adopting LCAs. Since they depend on manual data gathering and analysis driven by experts, traditional methods are costly, time consuming, and vulnerable to inconsistencies. (Reap et al. 2008). Given the need for an in-depth understanding of environmental impact databases, impact assessment techniques, and life cycle inventory (LCI) models, corporations often find LCA investigations challenging. These challenges make LCA generation a resource-intensive task, making it difficult, for many companies from fully integrating it into their decision-making processes.

1.2 Motivation

With the growing global emphasis on carbon sustainability, Lifecycle Assessment (LCA) has become a vital tool for industries, governments, and environmental organizations. Companies rely on LCAs to evaluate the environmental impact of their products across their full lifecycle, from raw material extraction to disposal. However, traditional LCA methods are often complex, time-consuming, and costly, making them difficult for SMEs to adopt and even challenging for larger companies with dedicated sustainability teams Hellweg and i Canals (2014). These limitations have led to a rising need for scalable, automated, and data-driven LCA solutions.

Existing LCA tools such as SimaPro, GaBi, and OpenLCA offer software solutions to perform LCAs but frequently require specialized knowledge, extensive training, and significant manual data entry. This restricts their usability and adoption among organizations lacking environmental experts or dedicated resources.

The motivation behind this project stems from the following key challenges:

- **Costly and Time-consuming LCA Processes:** Traditional lifecycle assessments require manual data collection, expert input, and reliable datasets, making them slow and expensive.

These processes can take weeks or even months, delaying product development and making regulatory compliance harder (Finnveden et al. 2009; Curran 2012).

- **Lack of Accessibility and Usability:** Existing tools are often too complex for user without a background in sustainability, creating a barrier for teams in supply chain, engineering, and manufacturing. This especially affects SMEs that lack sustainability specialists. There's a clear need for simpler, user-friendly LCA tools that don't require technical expertise (Reap et al. 2008).
- **Gaps in Current LCA Tools and Databases:** Many LCA tools rely on outdated or inconsistent data that may not reflect current regulations, transport methods, or production trends. Manual data entry also leads to inconsistencies and unreliable results (Guinée 2001; Rebitzer et al. 2004). Modern solutions need to support real-time data updates and adapt to evolving environmental standards.

Recent developments in Machine Learning (ML) and Artificial Intelligence (AI) have opened new possibilities for improving and automating Lifecycle Assessment (LCA) processes. AI helps simplify data processing, detect patterns, and assess material impacts more efficiently, making LCA more scalable, accurate, and cost-effective (Thakker and Bakshi 2021; Adewale et al. 2024).

This dissertation presents an AI-powered LCA tool that automates sustainability assessments by extracting and analyzing data from Bills of Materials (BOMs). Leveraging ML and large language models (LLMs), the system produces detailed LCA reports and enhances the precision, speed, and usability of traditional LCA methods through a data-driven approach.

1.3 Aim and Objectives

The main aim of this dissertation is to develop an AI-powered Lifecycle Assessment (LCA) tool that uses Bill of Materials (BOM) data to automatically evaluate a product's environmental impact. By integrating Artificial Intelligence, the tool seeks to improve the accessibility, accuracy, and efficiency of LCA processes, while minimizing manual effort and enabling scalability across different industries.

This project addresses key challenges such as the time-consuming nature, complexity, and data inconsistencies of traditional sustainability assessments. By combining AI-driven material impact predictions, automated BOM analysis, and environmental impact calculations, the tool helps streamline LCA workflows and supports data-informed decision-making for organizations working toward reducing their carbon footprint.

To achieve the stated aim, the dissertation will focus on the following key objectives:

1. AI-Powered BOM Analysis System

A core objective of this project is the development of a system that automates the extraction and analysis of BOM data using Artificial Intelligence. The tool is designed to use the user-uploaded Excel BOM files, extract material information, and effectively parse inconsistencies using Natural Language Processing (NLP) techniques. Components within the BOM are constructed and classified into meaningful categories that reflect their environmental significance. Effective data matching techniques, such as fuzzy string matching and LLM-based reasoning help align component names with environmental database entries, improving accuracy in LCA processes.

2. AI-Driven Environmental Impact Prediction

Another objective is to implement an AI model that predicts environmental impact based on the available LCA dataset. The system maps each material to known environmental factors like carbon footprint (kgCO2 per kg), and where data is missing, AI is used to derive values through context-based predictions. The prototype integrates a dummy environmental database to simulate real-time assessment and offers scope for future expansion with trustworthy sources such as Ecoinvent or ELCD. Through predictive analytics, the model fills data gaps in conventional lifecycle inventories and supports more complete and accurate carbon assessments (Hauschild et al. 2018).

3. Interactive LCA Dashboard

The tool includes a dynamic and interactive dashboard built with React, aimed at offering stakeholders a clear and engaging view of LCA outcomes. The Graphical User Interface (GUI) supports real-time updates, data editing, and visualizations such as bar and pie charts for carbon breakdowns. This interface makes LCA results clear even for non-technical users, and also provides exportable sustainability reports to aid decision-making. Visualizations are created using libraries such as Recharts, ensuring consistency with best practices in data representation (Few 2013; Tufte 1983).

4. AI-Powered Assumptions and Data Augmentation

When BOM data is extracted, the system uses Large Language Models (LLMs) like ChatGPT to generate assumptions on material origin, manufacturing location, transportation, and production methods, based on global patterns and standards. For instance, it may discover that aluminum is often shipped by sea and produced in China. Users can view, edit, and requery these assumptions, promoting transparency, control, and trust in the results (Reap et al. 2008; OpenAI 2025a).

5. Technical and Ethical Considerations

This project also addresses key technical and ethical challenges in developing an AI-powered LCA system. To minimize bias, AI outputs are compared across materials and validated against standards like ISO 14040 (International Organization for Standardization 2006a). Ethical aspects such as transparency, data privacy, and reproducibility are carefully considered. All prompts and outputs are logged for traceability, and users are clearly informed about how the AI makes decisions to build trust and support informed choices.

By meeting these goals, the project delivers a scalable, user-friendly, and AI-driven LCA tool that enables accurate, automated, and cost-effective environmental assessments. It offers a real-world example of how AI can support sustainability in design and manufacturing, and sets the stage for further improvements into using AI and machine learning for automating and improving lifecycle assessments in sustainable development.

1.4 Achievements of the Project

A significant step forward in using Artificial Intelligence to simplify and enhance Lifecycle Assessment (LCA) processes has been made with the creation of the AI-Powered LCA Tool. This section outlines the project's major accomplishments, including successful implementation of AI-driven methods to enhance sustainability evaluations.

AI-Powered Lifecycle Assessment Automation

A key achievement of this project is the full automation of the LCA process using AI. What was once a manual and time-consuming task is now streamlined through Machine Learning and NLP. The AI extracts sustainability data from BOMs, generates product descriptions and functional units, and performs lifecycle impact assessments, all without manual input. It also links materials to environmental datasets, enabling reliable and automated impact analysis.

Enhanced BOM Processing and Data Extraction

The system efficiently handles various BOM formats, automatically parsing, cleaning, and organizing the data. It organises materials to environmental categories, even the ones with formatting inconsistencies, reducing the need for manual work. This creates a scalable, AI-powered BOM workflow that boosts efficiency in sustainability analysis tasks (Onyeaka et al. 2023).

Integration of a Large Language Model (LLM) for Data Interpretation

By leveraging OpenAI's GPT-based model (OpenAI 2025a), the tool provides advanced interpretation of sustainability attributes. It automatically generates assumptions about material sourcing, manufacturing, transportation, and production processes using structured prompts. This allows the system to simulate expert-level decision-making in seconds. Furthermore, the model computes and presents the carbon footprint of individual components based on environmental databases, while also translating technical findings into accessible narratives for greater engagement of stakeholders (Hauschild et al. 2018; Reap et al. 2008; Raihan et al. 2024).

Assumptions and Impact Estimations Using AI

A standout technical feature of the system is its ability to generate accurate assumptions about each component. Based on the material listed in the BOM, the AI model predicts the likely origin country, the most common place of manufacturing and purchase, transportation modes (e.g., sea freight, truck with Euro 6 emission standard), and typical production methods (e.g., basic oxygen process). Importantly, each assumption is backed by an explanation derived from AI-generated analysis. Users are provided with the ability to override the model's selections. When changes are made, the system regenerates the reasoning.

Reduction in Time and Cost for LCA Studies

Compared to traditional LCA tools, that require expert knowledge, expensive software, and time-consuming data entry, this AI-based system offers a lightweight, scalable alternative. Automating data consumption, enhancement, and report generation significantly accelerates the LCA workflow. It also makes such assessments accessible to SMEs and organisations that previously lacked the resources or expertise to perform full LCAs. By lowering technical and financial barriers, the tool simplifies sustainability evaluation across the industry.

Future Expansion and Growth

The platform is built with extensibility in mind. Future upgrades could include integration with authoritative global datasets like Ecoinvent or the European Reference Life Cycle Database (ELCD) to increase coverage and precision (Rydberg 2010). Additionally, there is scope to expand beyond carbon emissions to cover broader environmental metrics such as water usage, toxicity, and energy consumption. Enhancing the AI's multimodal capabilities (e.g., visual identification of components) is another area for future exploration.

1.5 What this Dissertation will cover

The rest of this dissertation is organized into several chapters to guide the reader through the project. Chapter 2 provides background information, including existing literature, current lifecycle assessment (LCA) tools, and their limitations. Chapter 3 outlines the methodology used, covering the requirements analysis and system design of the AI-powered LCA tool. Chapter 5 explains the development process, highlighting the key features and technical challenges encountered. Chapter 6 evaluates the tool's performance through testing, user feedback, and usability studies, while also comparing it to existing solutions and acknowledging its limitations. Finally, Chapter 7 summarizes the research contributions and outlines potential areas for future development.

2 Background and Literature Review

This chapter sets the academic and industry context for the project by introducing key ideas in sustainability, Lifecycle Assessment (LCA), and how AI can help automate LCA processes. It reviews existing tools, points out their limitations, and highlights the gaps this project aims to fill. Building on the motivation from Chapter 1, it provides the foundation for the design and development covered in the following chapters.

2.1 Project Background

This project was developed in collaboration with the National Manufacturing Institute Scotland (NMIS), a leading research and innovation center dedicated to advancing manufacturing technologies and sustainable industrial practices. NMIS works closely with academic institutions, government bodies, and private sector companies to drive innovation in manufacturing, with a strong emphasis on sustainability and digital transformation (National Manufacturing Institute Scotland 2025).

The primary purpose of this project was to address a key challenge in sustainability assessment automating the Lifecycle Assessment (LCA) process using Artificial Intelligence (AI). LCAs have traditionally required a great deal of manual input, expert knowledge, and an enormous amount of time and resources in order to accurately assess the environmental impact of products (International Organization for Standardization 2006a). In an effort to streamline, enhance, and democratise sustainability analysis for manufacturers and help them to make accurate decisions regarding the choice of materials, production techniques, and overall environmental impact, NMIS sought to explore the integration of AI and machine learning, with Life Cycle Assessment (LCA) (de Jesus et al. 2021).

This AI-powered LCA tool was specifically designed to:

- **Automate the Sustainability Data Extraction Methodology –** Automatically analyzing Bills of Materials (BOMs) to efficiently identify environmental impact factors.
- **Enhance LCA Accuracy and Accessibility –** Leveraging AI and Large Language Models (LLMs) to process sustainability-related information more quickly and effectively, thus reducing errors associated with manual input (García-Muiña et al. 2020).
- **Improve Sustainable Manufacturing Decision-Making –** Providing actionable insights that enable manufacturers to reduce carbon emissions and meet international environmental standards (Li et al. 2024).
- **Increase Industry Adoption of LCA Tools –** Creating an intuitive, affordable, and easily accessible LCA solution suitable for businesses of all sizes, thereby promoting widespread usage of sustainable practices.

The project is in line with NMIS's mission of utilising digital tools and AI-driven technologies to accelerate the transition to net-zero manufacturing. The creation of this technology helps companies meet sustainability targets while also supporting greater efforts to reduce industrial carbon emissions and advance the principles of the circular economy.

2.2 Current LCA Tools and Their Limitations

LCA tools help assess how products and processes impact the environment over their entire life cycle, supporting better decisions on materials, manufacturing, and supply chains (Finnveden et al. 2009). However, many existing tools still face challenges with scalability, accuracy, and ease of use.

Overview of Existing LCA Tools

Several LCA software tools are widely used in the industry, including SimaPro, GaBi, and OpenLCA. SimaPro is a professional-grade tool offering extensive impact assessment databases and scenario modeling capabilities (Goedkoop et al. 2009) (in Metrics 2025). GaBi is a commercial LCA software focused on industrial applications, particularly in optimizing supply chains and production processes. OpenLCA, an open-source software, allows users to integrate multiple environmental databases, though it requires advanced expertise to configure effectively (Greenly 2024). While these tools have contributed significantly to the advancement of LCA methodologies, their complexity and cost present challenges for broader adoption, particularly among small and medium-sized enterprises (SMEs) that lack the resources for extensive assessments.

Limitations of Traditional LCA Tools

While traditional LCA tools like SimaPro and GaBi are powerful, they come with major challenges. They are often expensive, making them hard to access for small businesses and independent researchers (Finkbeiner et al. 2014). These tools also require specialized training due to their complex setup, including technical databases and impact models (Sala et al. 2016). Completing a full LCA can take weeks or even months, which isn't ideal for companies needing quick results (Hauschild et al. 2018).

Other issues include outdated or inconsistent data in LCI databases, which can affect the accuracy of global assessments (Hellweg and i Canals 2014). Traditional tools also lack automation and scalability, as they rely heavily on manual input, making it hard to assess multiple products or generate real-time insights.

In contrast, AI-powered LCA tools offer a better alternative by automating data handling, improving accuracy, and making sustainability assessments faster, cheaper, and easier to use for businesses of all sizes.

2.3 Role of AI in Sustainability

Artificial Intelligence (AI) is becoming a key tool in supporting sustainability, helping businesses make faster, smarter, and more accurate decisions about their environmental impact (Ligozat et al. 2022). As concerns about climate change, resource use, and carbon emissions grow, AI-driven tools are becoming valuable in many industries.

A major strength of AI is its ability to quickly analyze large environmental datasets, unlike traditional LCA methods which are slow, manual, and prone to human error (Nikkhah et al. 2024). With machine learning, AI can improve data quality, find patterns, and predict environmental impacts, helping users make better decisions about materials, processes, and supply chains.

AI also brings automation to tasks that normally require expert input, such as material selection, carbon footprint calculations, and hotspot identification in supply chains (Hellweg and i Canals 2014; Arzoumanidis et al. 2017). This cuts down the time and cost of LCA, making it more accessible, especially for smaller companies.

In addition, AI supports analytics, using environmental data to forecast emissions, identify climate risks, and suggest ways to reduce harm (Ligozat et al. 2022). This helps businesses and governments stay on track with carbon reduction goals and sustainability targets.

Another important benefit is AI's ability to handle complex data integration. LCA often involves combining information from various sources like supply chains, environmental databases, and product details—a process that can be messy and inconsistent (Goedkoop et al. 2009). AI simplifies this by merging and cleaning data automatically. With tools like natural language processing (NLP), AI can even extract useful information from unstructured sources like reports and scientific papers (IBM 2024).

Overall, AI is helping make sustainability assessments faster, more accurate, and easier to use, and will play a more significant role in achieving global environmental goals.

2.4 Related Work and Gaps in Current Solutions

AI and machine learning have been increasingly used in sustainability assessments, especially to improve Lifecycle Assessment (LCA) methods. Studies show that AI can help automate impact calculations, improve LCI databases, and guide material selection for more sustainable decisions (Hellweg and i Canals 2014). Sectors like manufacturing and construction are already using AI-powered tools to manage supply chains and analyze product carbon footprints (Nikkhah et al. 2024). Techniques like deep learning, computer vision, and natural language processing (NLP) have also made it easier to extract sustainability insights from complex data sources such as industry reports and scientific papers (Arzoumanidis et al. 2017).

Despite these advances, key gaps remain in current AI-based LCA solutions:

- **Lack of AI-driven BOM analysis**: Most tools still require users to manually link Bill of Materials (BOM) components to environmental databases. There are no mainstream tools that can fully automate BOM extraction and LCA report generation. This project aims to fill that gap by developing an AI system that connects BOM data directly to sustainability models, reducing manual input.
- **Limited use of generative AI**: While existing tools focus on numbers, they don't offer contextual explanations. Generative AI models, like ChatGPT, can analyse regulatory texts, reports, and standards, providing clear insights and justifications. This project will use generative AI to make sustainability reports more informative and adhering with real-world regulations.
- **Inconsistent and fragmented data**: Sustainability data is often spread across different formats and sources, leading to inconsistencies. This makes it difficult to trust or compare LCA results. The project addresses this by building a standardized framework that brings multiple data sources into one unified structure.
- **Lack of transparency in AI results**: Many AI-based LCA tools work like a black box, offering results without explaining how they were calculated. This reduces trust among users and regulators. To fix this, the proposed tool will provide clear visual breakdowns and explanations for each assumption and result.

By solving these problems, this project delivers a flexible, AI-powered LCA tool that is accurate, easy to use, and transparent. It lowers the barrier for companies, especially SMEs to adopt sustainability assessments, helping them make better environmental decisions and reduce their carbon footprint.

3 Requirements Analysis

Following the literature review, this chapter details the project's requirements, shaped by stakeholder consultations, academic guidelines, and real-world use cases. It outlines the functional requirements of the system, including specific user stories and application features. By translating the problems identified in Chapter 2 into concrete software requirements, this chapter sets the foundation for the architectural and technical decisions discussed in Chapter 4.

3.1 Requirement Gathering Process

The requirement gathering phase was key to making sure the project met stakeholder needs, followed technical and academic guidelines, and matched industry standards. Requirements were collected by working closely with NMIS employees, sustainability experts, and future users of the tool.

Stakeholder Identification

The main stakeholders in the requirement gathering process was the Project Manager, who shared important information about regulations and industry standards; the Sustainability Team, who explained the challenges of manual LCA methods and suggested key features to include; and the End Users, who gave feedback on usability, data accuracy, and the need for automation in the system.

Data Collection Methods

To gather practical requirements, an Industry Standards Analysis was conducted by reviewing LCA tools like GaBi and openLCA to identify their limitations and potential for AI improvement (Ciroth 2007). ISO 14040 and ISO 14044 standards were also reviewed to ensure alignment with recognized sustainability practices (International Organization for Standardization 2006b).

Stakeholder meetings were held with NMIS representatives and sustainability experts to understand the real-world challenges of traditional LCA methods. These discussions helped define key functional requirements by highlighting user needs and system expectations.

An analysis of real-world Bill of Materials (BOM) data from manufacturing companies was also performed. This revealed the complexity of material classification and common issues with data extraction. Various international BOM formats, were studied to ensure the system could handle a wide range of structures, including differences in material names, manufacturing locations, and process types.

Lastly, Use Case Scenarios and Process Mapping were used to model how different users would interact with the tool. User stories were created to describe each step of the process—from uploading a BOM file to generating automated sustainability reports, ensuring that system workflows were well-defined and user-centric.

Key Findings from Requirement Gathering

The requirement gathering process highlighted several important needs. First, the system must include AI-powered BOM analysis that can automatically extract sustainability data from different BOM formats with minimal user effort.

Second, users need clear visual reports, like bar and pie charts to easily understand carbon emissions and material impacts.

Another key finding was the need for the AI to fill in missing information such as material origin, transport methods, and manufacturing processes, and to give clear explanations for each assumption to build user trust.

3.2 Functional Requirements

The core characteristics of the AI-based Lifecycle Assessment (LCA) tool are specified by the functional requirements. By following this list of requirements, the system is guaranteed to fulfil user expectations and carry out long-term impact assessment efficiently.

User Authorization

The system must provide user authentication, allowing only NMIS-registered users to create accounts and log in. To maintain security, access to core features such as BOM Upload and the Dashboard will be restricted until successful login with NMIS credentials. Unauthorized users will only have access to the Home page (Sommerville 2016; International Organization for Standardization and International Electrotechnical Commission 2011).

Uploading and Parsing the Bill of Material

Users will be able to upload Bill of Materials (BOM) files in Excel (.xlsx) and CSV (.csv) formats. The system will automatically verify the file format and ensure that required fields such as Component, Material, and Weight are included. Once uploaded, the BOM data will be processed into a standardized format for further analysis. Additionally, an edit function will allow users to modify BOM details before proceeding with the assessment (Wiegers and Beatty 2013).

AI-Generated Product Information and Functional Unit

Upon BOM upload, the system will leverage OpenAI's API to automatically generate the product's information, description, and functional unit. To enhance visualization, an integrated Pixabay API will be used to generate a representative product image (OpenAI 2025a; Pixabay 2025).

AI-Based Assumptions and Explanations

To enhance sustainability insights, the system will automatically generate material-specific assumptions regarding lifecycle and environmental impact. AI-driven predictions will include the most common country of origin, country of manufacturing, country of purchase, and preferred transportation mode (e.g., sea freight, trucks). Additionally, it will estimate the manufacturing process (e.g., Injection Molding, Lean Manufacturing) based on industry standards. If users modify any assumptions, the AI model will dynamically update explanations, providing justifications for the selected values (Dix et al. 2004).

AI-Driven Material Identification, Matching, and Report Generation

The system automatically reads the uploaded Bill of Materials (BOM) to identify and match materials using AI-powered recognition with data from an existing LCA database. This allows for fast, automated environmental impact assessments. Once processed, the system generates a detailed LCA report that includes the product image, number of components, and total CO2 impact.

A Material Breakdown section shows key details like weight, CO2 per kg, and total impact per material. To make the data easy to understand, the report includes visuals such as bar charts and pie charts. The report can also be exported as a PDF, making it simple to share or use with other tools. These features ensure the tool offers a complete, automated, and user-friendly way to assess product sustainability (International Organization for Standardization and International Electrotechnical Commission 2011).

3.3 User Stories and Use Cases

This section describes how users engage with the AI-powered Lifecycle Assessment (LCA) tool from the point of view of the primary stakeholders, who include SMEs and NMIS staff members (the sustainability team). The tool's functions include supporting sustainable decision-making, enhancing material impact assessments, and automating LCA production (Cohn 2004).

User Interactions and Needs

NMIS sustainability analysts need a tool that can quickly and accurately generate automated LCA reports, extract material impact data from BOM files, and provide AI-driven insights to support decision-making, all while reducing manual work.

SME business owners need a solution that is affordable, simple to use, and doesn't require LCA expertise. They want a user-friendly interface to assess a product's environmental impact, view clear sustainability data, and make smart choices without hiring sustainability consultants.

Key Use Case Scenarios

1. **Automating LCA Report Generation for Faster Analysis**
   An NMIS Sustainability Analyst logs into the AI-powered LCA system and uploads a valid Bill of Materials (BOM) file. The system quickly extracts and processes the material data, then automatically creates a detailed LCA report with clear sustainability insights. This automation replaces manual work, greatly reducing the time needed for accurate analysis.
2. **Simplifying LCA for Users Without Technical Knowledge**
   An NMIS Product Designer, who may not be familiar with lifecycle assessment (LCA), uploads a BOM file to the system. The AI processes the data and presents the CO2 impact analysis using simple, easy-to-understand graphs and charts. This visual approach helps users without technical backgrounds quickly grasp sustainability impacts and make better design and material choices.
3. **Reducing LCA Costs for SMEs**
   An SME business owner, without the budget for sustainability consultants, uses the AI-powered LCA tool to carry out an environmental impact assessment. After logging in and uploading their product's BOM file, the AI generates a detailed sustainability report, breaking down the environmental impact of each component. This gives SMEs valuable insights at a much lower cost. If the system encounters unrecognized materials, it suggests the closest match to continue the analysis.

4 System Design

This chapter outlines the system architecture, covering the frontend, backend, and external API/database integrations. It also explains the dashboard and UI design principles. The design decisions are based on the requirements from Chapter 3 and provide a clear foundation for the implementation details discussed in the next chapter.

4.1 Overall System Architecture

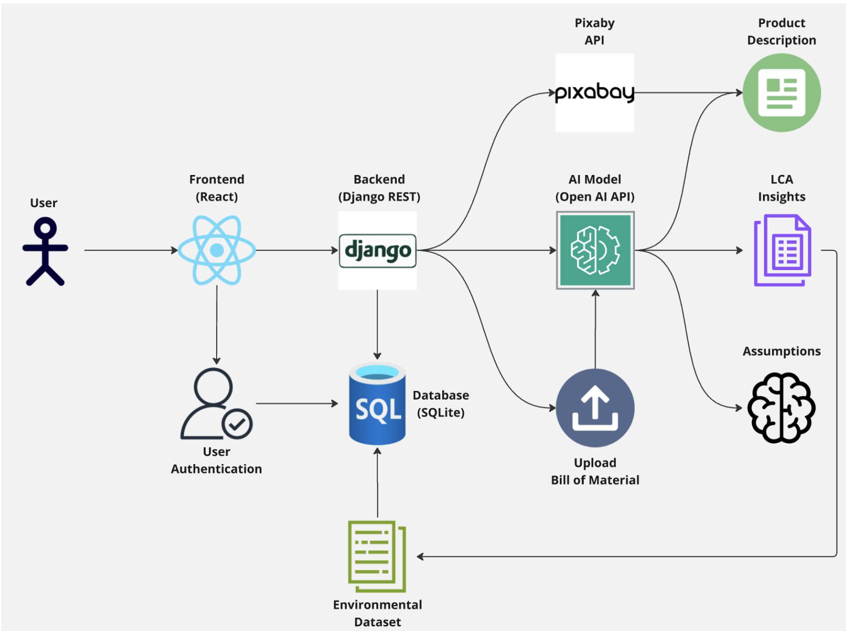

Figure 4.1: System Architecture Diagram

Architectural Overview

The AI-powered Lifecycle Assessment (LCA) tool is designed as a flexible and scalable system capable of automating environmental impact assessments based on uploaded Bill of Materials (BOM). The system leverages an architecture structured into three distinct layers: frontend, backend, and data storage, alongside integrations with external services for enhanced functionality. This design ensures flexibility, allowing future improvements or alternative implementations using different technologies or programming languages, as illustrated in the System Architecture Diagram (Figure 4.1).

Frontend

The frontend provides a graphical user interface that allows users to interact intuitively with the system. Users authenticate securely, manage their accounts, and upload BOM files to initiate sustainability assessments. The interface includes visualization capabilities, presenting lifecycle assessment insights, comparisons between different product configurations, and detailed sustainability reports. This approach ensures an accessible experience, allowing non-technical users to benefit from complex sustainability analysis (refer to Figure 4.1).

Backend

The backend serves as the processing engine responsible for handling uploaded BOM files, extracting and cleaning relevant material data, and managing the execution of environmental assessments. Upon receiving a BOM upload request from the frontend, the backend validates and processes the data before invoking external AI services for detailed analysis. It also retrieves lifecycle impact information from an integrated environmental dataset and combines results for storage and retrieval (see detailed processing steps outlined in the Data Flow Diagram, Figure 4.2).

Database and External Services

To store persistent data such as user credentials, uploaded BOM files, processed lifecycle assessment results, and generated assumptions, a relational database is used. The system also relies on external data sources and services, such as a comprehensive environmental dataset providing standard lifecycle inventory (LCI) records. To improve product descriptions and assumption accuracy, external APIs are integrated, providing additional information such as product images and AI-generated insights (refer again to Figure 4.1 and Figure 4.2 for visual clarification).

System Interactions and Data Flow

As shown in the Data Flow Diagram (Figure 4.2), the process starts with the user logging in and uploading a Bill of Materials (BOM). The backend validates, extracts, and cleans the data using Pandas, temporarily storing it in memory. This data is then sent to the AI module to generate the product description, assumptions, and LCA insights.

Keywords from the description are used to fetch product images via the Pixabay API. At the same time, the backend queries the SQLite environmental database for carbon footprint data, enabling accurate impact calculations. Final outputs—including assumptions, images, and impact results are displayed on the dashboard, where users can view or download reports.

The modular architecture supports easy maintenance and adaptability across various industry use cases. For a clearer understanding of how the application functions, refer to the Context Diagram and the Component Interaction Diagram shown in Figures A.3 and A.4, respectively.

4.2 User Interface and Dashboard Design

The AI-powered Life Cycle Assessment (LCA) tool's dashboard and user interface (UI) were created with functionality, efficiency, and connectivity in mind. The tool provides an interactive and intuitive interface that allows users to upload a Bill of Materials (BOM), generate sustainability reports, and view LCA insights in an organized manner.

Frontend Development and User Experience (UX) Principles

The application's front-end was built using React, a popular JavaScript framework known for creating dynamic and responsive user interfaces. Its component based structure allows for efficient state management and smooth rendering of real-time LCA insights and reports (Kruchten 2000). React also supports reusable components, ensuring maintainability, and its widespread use and strong documentation make it easy for future developers to join and contribute to the project with minimal training.

In order to enhance the user experience, the UI follows Jakob Nielsen's usability heuristics (Nielsen 1994). The design priorities include:

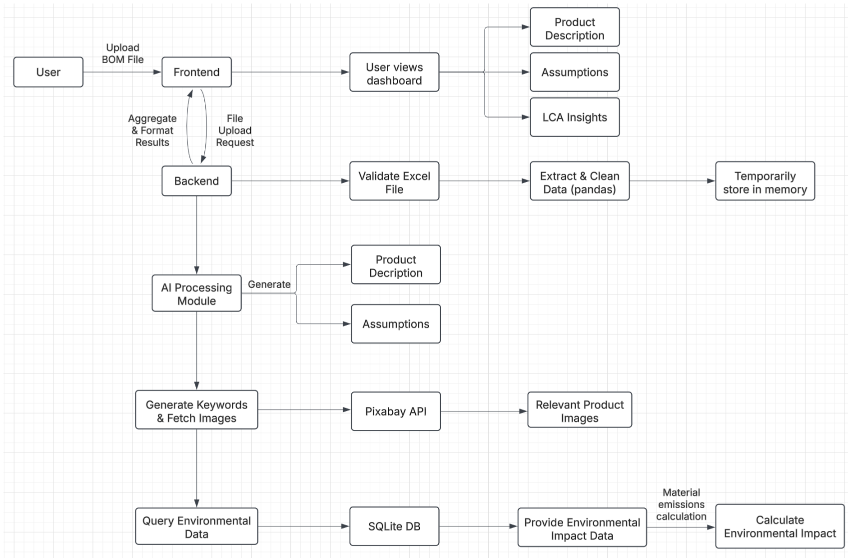

Figure 4.2: *Detailed Data Flow Diagram*

- Clarity → Users can easily navigate through the LCA dashboard.
- Efficiency → Quick generation of LCA insights with minimal steps.
- Error prevention → Clear error messages for incorrect file uploads.

Dashboard Features and Functionalities

The dashboard is the core feature, that provides a visual representation of the uploaded BOM, lifecycle impacts, sustainability data, and AI-generated assumptions. It includes:

- **Product Description Panel** – AI extracts relevant information from the BOM, and generates the product information, description, image and the functional unit.
- **Bill Of Material Section** - The system extracts all relevant information from the uploaded BOM and presents it in a standardized format. Users also have the option to edit any of the information as needed.
- **Assumptions Section** – The AI extracts all relevant information and presents insights on the material's country of manufacturing, country of origin, country of purchase, mode of transportation, and manufacturing process.
- **LCA Insights & CO2 Breakdown** – Displays environmental impact metrics of components.

These features reduce manual effort and allow real-time analysis of sustainability data (Hauschild et al. 2018).

API Integration and Backend Connectivity

The UI communicates with the Django REST backend, which processes BOM data, retrieves environmental impact figures, and interacts with OpenAI's API to generate environmental insights. The Opean AI API, provides Asynchronous API requests which ensure fast data retrieval, and secure authentication, which would prevent unauthorized access.

User Access Control

The tool supports role-based access, allowing NMIS employees with an NMIS email to self-register and gain instant access, while external users must request access from the IT team. For licensed SMEs, only designated individuals with specific credentials will be permitted to use the application.

These measures ensure data security and compliance with ISO 14040 environmental assessment standards (International Organization for Standardization 2006a).

4.3 Tools, Frameworks, and APIs Used

The development of the AI-powered Lifecycle Assessment (LCA) Tool required the integration of various technologies, frameworks, and APIs to ensure an efficient, scalable, and accurate system. The selection of these tools was based on their performance, scalability, and ease of integration with AI-driven sustainability assessments.

1. Frontend Technologies

As mentioned in the previous section, the front-end application was built using React.js because of its component-based structure, which makes it flexible, fast, and well-supported by the developer community. However, React also has many useful libraries that help with development. For example, Axios is used to handle API requests and data fetching, while React Router allows smooth navigation between different dashboard pages.

2. Backend Technologies

The backend of this project is built using the Django REST Framework, ensuring a secure, reliable, and efficient data management system. This allows the system to handle large datasets effectively and convert complex BOM data into JSON for AI processing (Holovaty and Kaplan-Moss 2009).

Database: SQLite

Django REST Framework also comes with a default database, SQLite, which was used to store sustainability-related data. SQLite is lightweight and embedded, making it ideal for rapid prototyping and local storage needs.

3. AI Model and APIs

The critical intelligence of the application is powered by OpenAI's GPT models, which assist in interpreting BOM data, generating assumptions, producing sustainability insights and predicting lifecycle impacts. OpenAI was chosen due to its accuracy in natural language understanding, data extraction, and summarization. Its ability to interpret complex environmental and material-related data makes it a powerful tool to improve LCA automation (Brown et al. 2020).

Pixabay API

Additionally, we integrated the Pixabay API to fetch product images based on BOM descriptions after the AI model extracts the relevant information. This ensures the system can generate visual elements for product information, enhancing the user experience (Pixabay 2025).

4. Environmental Impact Dataset

To ensure accurate sustainability analysis, the system uses an Environmental Impact Dataset that includes detailed data on materials, manufacturing processes, and transportation methods. When a BOM is uploaded, the system extracts material information and matches it with this dataset. Once matched, it calculates the total carbon footprint of the product and generates visual reports, helping users easily understand and evaluate environmental impact.

5. Authentication & Security

The application's user authentication is implemented using Django REST Framework's JWT Authentication, providing secure and stateless authentication. This ensures that only users with authorized credentials can access the system, effectively managing permissions for different user roles (Park and Sandhu 2001).

5 Implementation

Building upon the system design, this chapter provides a detailed account of the development process. It breaks down the implementation of core features, such as BOM upload, AI-driven analysis, and dashboard visualizations. The chapter also outlines technical optimizations, challenges encountered, and strategies used to test and refine the system. It bridges the gap between design and evaluation, leading into the assessment of system performance in Chapter 6.

5.1 Development Process

The development of the AI-based Lifecycle Assessment (LCA) tool followed a structured Software Development Lifecycle (SDLC) approach to ensure system reliability, efficiency, and user-centric design. The agile methodology was chosen for its flexibility, allowing for continuous feedback and improvements based on stakeholder input from the National Manufacturing Institute Scotland (NMIS). Regular testing and refinement cycles helped improve the tool's accuracy, usability, and real-world significance (Beck et al. 2001).

Requirement Analysis and System Design

Before development commenced, a detailed requirement gathering phase was conducted through interviews with sustainability experts, SMEs, and NMIS stakeholders. The key objectives were to:

- Automate LCA calculations, reducing manual effort.
- Improve accessibility for SMEs that lack dedicated sustainability teams.
- Provide an AI-powered system to extract and analyze sustainability data from BOM files.

Once the requirements were established, the architectural design was developed, detailing interactions between the frontend (React.js) (Meta Platforms 2024), backend (Django REST framework) (Foundation 2025), and AI processing module (OpenAI API). The system was designed with scalability and security in mind, ensuring efficient data processing and integration with sustainability databases (Pohl 2010). Considerations included data flow efficiency, API integrations for AI-driven insights, and robust security measures to protect sensitive user data (Bass et al. 2012)).

Implementation Phases

The development process was divided into three iterative phases, each focusing on key system functionalities:

Phase A: Foundation and Initial Development

The initial phase focused on defining the project plan, designing system architecture, and developing a prototype for BOM analysis. The database was integrated to store and manage BOM data, ensuring structured storage and retrieval of sustainability-related insights.

Phase B: AI Model Development and Tool Enhancement

The core functionalities were developed in this phase, with a strong emphasis on AI-powered automation. The AI model was fine-tuned for accurate BOM interpretation, ensuring it could extract material details, calculate lifecycle impacts, and provide sustainability insights.

Key technical developments included:

- **AI Model Integration**: Fine-tuned OpenAI's GPT model to extract insights from BOM data.
- **User Interface Enhancements**: Developed a seamless, intuitive UI, ensuring easy navigation for users with minimal technical expertise.
- **Testing and Validation**: Conducted rigorous testing to validate AI-generated sustainability insights, ensuring consistency with established LCA databases.

Phase C: Optimization and Deployment

The final phase focused on optimizing AI model performance, refining the user interface, and preparing the system for deployment. The AI model was further improved to handle diverse BOM formats and provide more accurate assumptions regarding material sourcing and environmental impact.

Critical Tasks included:

- **Optimizing AI Model Performance**: Enhancing processing speed and accuracy.
- **Finalizing Data Storage Strategy**: Implementing indexing and query optimization for efficient database operations.
- **Creating Technical Documentation**: Created a comprehensive guide for future development and maintenance.

Testing and Optimization

Ensuring the accuracy and efficiency of the tool required a robust testing strategy. The following methodologies were employed:

- **Unit Testing**: Validated individual software components to ensure correct functionality (Myers et al. 2012)
- **Integration Testing**: Ensured smooth communication between frontend, backend, and external APIs.
- **User Acceptance Testing (UAT)**: Conducted with NMIS stakeholders to verify usability and effectiveness.

Automated testing tools such as PyTest were used to validate functionality and detect any potential errors (Krekel and pytest-dev team 2025).

5.2 Key Components and Their Implementation

The AI-Based ChatGPT Lifecycle Assessment (LCA) tool is designed with a modular architecture, ensuring scalability, maintainability, and efficient processing. The system consists of several key components, each playing a vital role in data processing and sustainability assessments. The primary components include:

- Frontend (React.js)
- Backend (Django REST Framework)
- AI Processing Module (OpenAI API)
- Environmental Impact Database (SQLite)
- Data Storage and Processing

Each component is structured to enhance automation, minimize manual input, and deliver real-time sustainability insights.

Frontend (React.js)

The React.js frontend offers a user-friendly interface to upload BOM files, view sustainability insights, and generate LCA reports. It uses React hooks, Redux for state management, and Axios for API communication.

Key features include a drag-and-drop uploader (via react-dropzone) for Excel/CSV files with real-time validation. The dashboard presents dynamic visuals using Recharts.js, showing AI-generated assumptions and LCA breakdowns. JWT-based authentication ensures secure access, allowing only logged-in users to interact with key features.

Backend (Django REST Framework)

The Django REST Framework (DRF) backend manages user authentication, file processing, AI analysis, and API requests.

Authentication is handled using JWT (djangorestframework-simplejwt) to secure user sessions. Pandas processes uploaded BOM files, extracting structured data with validation checks. The backend then sends this data to the AI module, which returns sustainability insights via the OpenAI API. Data is stored in SQLite/PostgreSQL, with optimized queries to ensure fast and efficient performance.

AI Processing Module (OpenAI API)

This module uses OpenAI's GPT model to analyze BOM data and generate product descriptions, sustainability insights, and material assumptions, removing the need for manual research.

Structured BOM data is first preprocessed to ensure compatibility with the AI model. The AI then predicts key details like material sourcing, transportation, and environmental impact. To keep the system fast and responsive, Celery and Redis are used to manage asynchronous API requests, preventing delays and ensuring smooth performance.

Environmental Impact Dataset

The system uses a structured environmental impact dataset to store key sustainability metrics like carbon footprint, energy use, and recyclability for each material.

To ensure fast and accurate results, the system applies indexing and precomputed scores for quicker data retrieval. It also supports regular updates by integrating external sustainability data sources, keeping emission calculations accurate and aligned with current industry standards.

Data Storage and Processing

Efficient data handling is key for real-time LCA. The backend uses Pandas to clean, format, and process BOM data for consistency. In-memory processing speeds things up by handling data before saving it to the database. Schema validation checks each file to ensure it meets the required format, reducing errors and maintaining data accuracy (pandas Development Team 2025).

5.3 BOM Upload Feature

The Bill of Material (BOM) Upload Feature is a critical component of the AI-based Lifecycle Assessment (LCA) tool, allowing users to upload BOM files, which are then processed to generate lifecycle insights. This feature is designed to handle BOM data, extract relevant material and component information, and integrate it into the sustainability assessment process.

The BOM upload feature follows a five-step workflow:

1. User Uploads BOM File

Users upload a BOM file using a simple drag-and-drop interface that supports .xlsx and .csv formats (see Figure 5.1). The system validates the file before sending it to the backend. If the file is invalid, users get instant feedback through clear error messages.

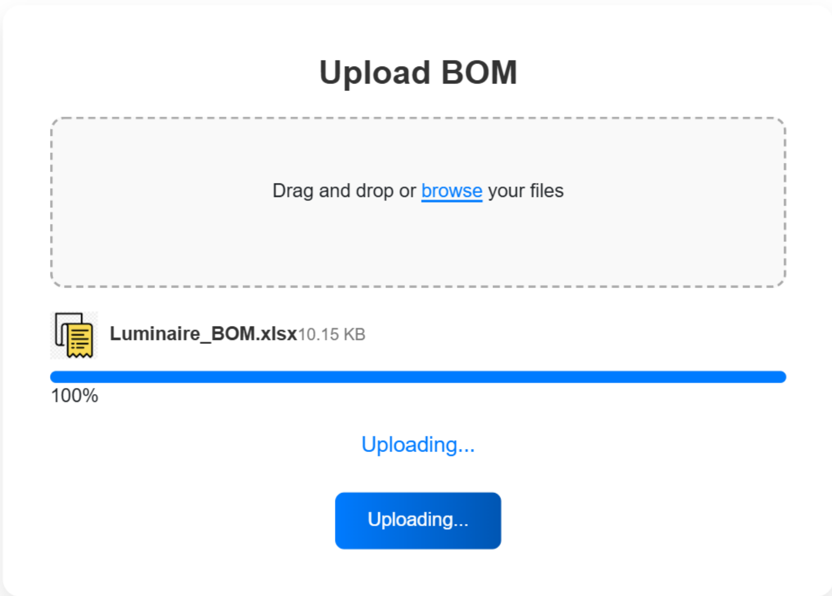

Figure 5.1: Upload BOM as it appears on the frontend

2. Data Extraction and Preprocessing

Once the file is validated, the backend uses Pandas to extract key data like components, materials, and weights from the BOM (see Figure 5.2). It then cleans the data by handling missing values, fixing inconsistencies (e.g., "Aluminium" vs. "Aluminum"), and converting everything into a structured JSON format for efficient processing (pandas Development Team 2025).

```
@api_view(['POST'])
def upload_bom(request):
    serializer = BOMUploadSerializer(data=request.data)
    if serializer.is_valid():
        try:
            bom_file = request.FILES['bom_file']
            logger.info(f"Received BOM file: {bom_file.name}")

            bom_data = pd.read_excel(bom_file)
            cleaned_bom_data = bom_data.dropna(how='all')
            start_index = cleaned_bom_data[cleaned_bom_data.iloc[:, 0] == 'Component'].index[0]
            bom_table = cleaned_bom_data.iloc[start_index + 1:, :3]
            bom_table.columns = ['Component', 'Material', 'Weight (gr)']

            bom_table = bom_table.replace([np.inf, -np.inf], np.nan).fillna(0)
            bom_json = bom_table.to_dict(orient='records')
            logger.info("BOM data cleaned and converted to JSON.")
```

Figure 5.2: Backend Code - Extracting BOM Data

3. AI-Powered Data Enhancement

The structured BOM data is then processed by OpenAI's GPT Model, which generates product descriptions and assumptions about material origin, manufacturing locations, and transportation methods. By using specific prompts such as “Where is material commonly sourced?”, the AI provides valuable insights that improve the accuracy of the sustainability analysis. Figure 5.3 displays the prompt used to fine tune the AI model for generating reliable sustainability data.

```python
def fetch_ai_response(prompt):
    try:
        response = openai.ChatCompletion.create(
            model="gpt-3.5-turbo",
            messages=[{"role": "user", "content": prompt}]
        )
        return response.choices[0].message['content'].strip()
    except Exception as e:
        logger.error(f"Error fetching AI response: {e}")
        return "N/A"

for material in materials:
    try:
        prompt_origin = (
            f"What is the most common country where the raw material "
            f"for {material} originates from? Provide only the country name."
        )
        origin_country = fetch_ai_response(prompt_origin)

        prompt_manufacturing = (
            f"What is the most common country where {material} is "
            f"manufactured? Provide only the country name."
        )
        manufacturing_country = fetch_ai_response(prompt_manufacturing)

        prompt_purchase = (
            f"What is the most common country where {material} is "
            f"purchased? Provide only the country name."
        )
        purchase_country = fetch_ai_response(prompt_purchase)

        prompt_transport = (
            f"What is the most common mode of transportation for {material}? "
            f"Provide only the mode (e.g., 'sea freight', 'trucks')."
        )
        transport_mode = fetch_ai_response(prompt_transport)

        explanation = ""
        if "truck" in transport_mode.lower():
            prompt_truck = (
                f"What is the most common emission standard for trucks transporting {material}? "
                f"Provide only the emission standard (e.g., 'Euro 6')."
            )
            truck_standard = fetch_ai_response(prompt_truck)
            transport_mode = f"Truck ({truck_standard})"

            prompt_explanation = (
                f"Why are trucks with emission standard {truck_standard} used for transporting {material}? "
                f"Provide a detailed explanation."
            )
            explanation = fetch_ai_response(prompt_explanation)
```

Figure 5.3: Prompt structure used to query OpenAI’s GPT model

4. Integration with Environmental Dataset

To calculate environmental impact accurately, the system combines AI-enhanced BOM data with the Environmental dataset containing carbon footprint metrics (kgCO2 per kg). When the exact material matches aren’t found, it uses Python’s `difflib.get_close_matches()` to find the closest match (see Figure 5.4). This ensures reliable estimates and maintains the accuracy and flow of the assessment.

5.4 Dashboard and Data Visualization

A key element of the AI-powered Lifecycle Assessment (LCA) tool is its dashboard, which provides stakeholders a user-friendly interface for examining and analysing the findings of lifecycle assessments. As recommended by Shneiderman’s "Eight Golden Rules of Interface Design" (Shneiderman et al. 2016) and Tufte’s work on visual clarity (Tufte 1983), the dashboard’s design approach complies with general usability standards that place an emphasis on clarity, simplicity, and straightforward navigation.

```python
def get_closest_material_match(material, env_data_df):
    materials_list = env_data_df["Material assumption in LCI"].tolist()
    matches = get_close_matches(material, materials_list, n=1, cutoff=0.6)
    return matches[0] if matches else None

for item in bom_data:
    material = str(item.get("Material", "")).strip().lower()
    weight_raw = item.get("Weight (gr)", 0)

    try:
        if isinstance(weight_raw, (int, float)):
            weight = float(weight_raw)
        elif isinstance(weight_raw, str):
            if '<' in weight_raw:
                weight = float(weight_raw.replace('<', '').strip()) / 2  # Approximate
            else:
                weight = float(weight_raw)
        else:
            raise ValueError("Unknown weight format")
    except ValueError as e:
        weight = 0.0

    closest_match = get_closest_material_match(material, env_data_df)

    if closest_match:
        matched_row = env_data_df[env_data_df["Material assumption in LCI"] == closest_match]
    else:
        logger.warning(f"No close match found for material: {material}")
        matched_row = pd.DataFrame()

    if matched_row.empty:
        matched_data.append({
            "component": item.get("Component", "Unknown"),
            "material": material,
            "weight (gr)": weight,
            "kgCO2_per_kg": "Not Found",
            "total_kgCO2": "N/A",
        })
    else:
        row = matched_row.iloc[0]
```

Figure 5.4: Material matching process with the environmental dataset for CO2 calculation

Product Description

Upon successful upload and processing of the Bill of Materials (BOM), the dashboard provides a clear, AI-generated product summary. This includes a detailed product description, the functional unit of the product, and an image generated via the Pixabay API. The interface for this output is shown in Figure 5.5, which displays the Product Description Dashboard Section where this information is presented to the user (OpenAI 2025a).

Product Description

Info: Strathclyde linear fluorescent luminaire

Description: The Strathclyde linear fluorescent luminaire is a lighting fixture that uses linear fluorescent tubes to provide illumination. It consists of various components such as diffuser, bookplate, driver, grommet, end cap, LED strip, packaging materials, rail, standoff, terminal blocks, wires, bolts & nuts.

Functional Unit: 1 Strathclyde linear fluorescent luminaire

Figure 5.5: Product Description section of the dashboard displaying AI-generated product summary, functional unit, and Pixabay sourced product image

Bill of Materials (BOM)

The BOM is displayed in a standardized, structured table that shows organized data extracted from the user's upload (Ajax et al. 2025). Files in .xlsx or .csv format are processed using Pandas to extract key fields like Component Name, Material, and Weight (grams). The system performs data cleaning, handles missing values, and indentifies unusual entries for review. Users can edit the data directly in the table, with real-time validation preventing errors and ensuring the information is accurate before analysis (refer to Fig 5.6.

Component	Material	Weight (gr)
Bookplate	Steel engineering steel/ASIA	1497
Driver*	Assembly	208.5
Grommet	Polypropylene (PP) (replace)	2
End cap (2)	Polypropylene, PP, granulate, at plant/RER	76.5

Figure 5.6: *Standardized Bill of Materials table as displayed on the Dashboard Section*

Assumptions and Explanations

The Assumptions section uses AI-generated insights to explain details like material origin, manufacturing location, transportation mode, and production method (Brown et al. 2020). OpenAI's language model creates clear explanations for each assumption, building transparency and trust in the LCA results. The AI predicts sourcing regions, common transport methods (e.g., sea freight, truck, rail), and estimates related CO2 impacts. It also identifies typical manufacturing processes like Batch Production and Injection Molding, along with detailed reasoning. This automated, explainable approach supports a comprehensive, data-driven sustainability analysis. For more details, see the Assumptions and Explanations section.

LCA Insights and CO2 Breakdown

The LCA Insights section visually shows the carbon impact of each product component, making it easy to spot which materials contribute most to the overall footprint (Murray 2013). Users can explore bar graphs and pie charts to quickly understand emissions data and make better sustainability decisions.

The system uses automated material matching to link BOM items to the LCA database. If there's no exact match, the AI suggests the closest alternative. Emissions are displayed using bar graphs (kgCO2 per material) and pie charts (percent contribution).

Interactive features like hover tooltips and drill-down filtering offer deeper insights, allowing users to explore individual materials and product sections in detail. For more, see the LCA Insights and CO2 Breakdown section.

5.5 Assumptions and Explanation

A key challenge in Lifecycle Assessment (LCA) was making accurate assumptions about the materials listed in the uploaded Bill of Materials (BOM). To address this, we leveraged Artificial Intelligence (AI) to automate the assumption process, ensuring consistency and reliability in LCA studies while minimizing human error.

Material Origin and Sourcing

The AI model automatically generates assumptions about the most common countries of origin for raw materials by analyzing global production and trade data. For instance, lithium, widely used in batteries, typically comes from Australia, Chile, and China (U.S. Geological Survey 2025). This automation reduces manual effort and improves efficiency and consistency in lifecycle assessments. See Figure 5.7 for an example of the AI prompt used.

```
prompt_origin = (
    f"What is the most common country where the raw material "
    f"for {material} originates from? Provide only the country name."
)
origin_country = fetch_ai_response(prompt_origin)
```

Figure 5.7: AI Prompt for Material Origin

Manufacturing and Purchasing Locations

The AI generates manufacturing assumptions by analyzing global industrial trends to predict likely manufacturing and purchasing locations. For example, electronics are often produced in China, Taiwan, and South Korea due to strong infrastructure and skilled labor (Organisation for Economic Co-operation and Development (OECD) 2025). This helps streamline LCA workflows with minimal manual input. See Figure A.1 for the AI prompt used.

Mode of Transportation

AI-generated assumptions about transportation modes take into account both geography and material type. For example, heavy materials like steel or aluminum are typically shipped by sea for cost and capacity reasons, while lighter, high-value goods may be transported by air (International Maritime Organization (IMO) 2025).

If road transport is selected, the tool also identifies relevant emission standards (e.g., Euro 6) to reflect regional regulations and environmental compliance (RAC Motoring Services 2025). See Figure 5.8 for the prompt used.

```
prompt_transport = (
    f"What is the most common mode of transportation for {material}? "
    f"Provide only the mode (e.g., 'sea freight', 'trucks')."
)
transport_mode = fetch_ai_response(prompt_transport)

explanation = ""
if "truck" in transport_mode.lower():
    prompt_truck = (
        f"What is the most common emission standard for trucks transporting {material}? "
        f"Provide only the emission standard (e.g., 'Euro 6')."
    )
    truck_standard = fetch_ai_response(prompt_truck)
    transport_mode = f"Truck ({truck_standard})"

    prompt_explanation = (
        f"Why are trucks with emission standard {truck_standard} used for transporting {material}? "
        f"Provide a detailed explanation."
    )
    explanation = fetch_ai_response(prompt_explanation)
```

Figure 5.8: AI Prompt for Transportation Mode and Emission standards

Manufacturing Process Assumptions

The AI model identifies the typical manufacturing processes for various materials, providing detailed explanations of their efficiency and environmental impact. For example, the basic oxygen process is predominantly used for steel production, due to its high efficiency and scalability, despite its significant environmental impact (World Steel Association 2025). Refer to Fig 5.9 to look at the prompt used for this.

Explanations

After the AI model generates an assumption, users can click on it to view a detailed explanation of why a specific country, transportation mode, or manufacturing process was chosen.

```
prompt_process = (
    f"What is the most common manufacturing process for {material}? "
    f"Provide only the process name (e.g., 'Basic Oxygen Process', 'Batch Production')."
)
manufacturing_process = fetch_ai_response(prompt_process)
```

Figure 5.9: *AI Prompt for Manufacturing Process*

If the user believes the AI's choice is incorrect, they can manually update it. The AI will then automatically search the internet and provide a new explanation based on the updated input. This keeps the system flexible, accurate, and supports informed decision-making. See Figure A.2 for an example prompt.

5.6 LCA Insights and CO2 Breakdown

The Lifecycle Assessment (LCA) Insights provided by the application offer comprehensive reports to users, detailing the environmental impacts of individual product components. For example, the analysis of a Strathclyde linear fluorescent luminaire reveals significant insights into its environmental footprint.

The total CO2 emission impact is computed using the formula:

$$\text{Total } kgCO_2 = \left(\frac{\text{Weight (gr)}}{1000}\right) \times \text{kgCO}_2 \text{ per kg}$$

The report calculates the total CO2 emission impact in kilograms and uses a functional unit defined as in this instance it is defined as one Strathclyde linear fluorescent luminaire. This standardization ensures consistent and meaningful comparisons across similar products.

Material Breakdown

This breakdown is computed through logic implemented in the lcai_dashboard endpoint. A fuzzy-matching algorithm compares user-supplied material names to the "Material assumption in LCI" column in the environmental dataset.

Once a match is found, the emission factor is retrieved and multiplied by the component's weight to calculate the total CO2 impact per component. The output is stored in a structured JSON format, later rendered in a frontend table with full interactivity. The logic used to match the closest material in the environmental database is illustrated in Figure 5.4.

Component	Material	Weight (g)	kgCO2 per kg	Total CO2 (kg)
Bookplate	steel engineering steel/asia	1497	4.008	6
Driver*	assembly	208.5	Not Found	N/A
Grommet	polypropylene (pp) (replace)	2	0	0
End cap (2)	polypropylene, pp, granulate, at plant/rer	76.5	1.699	0.13
LED strip*(4)	assembly	172.4	Not Found	N/A

Figure 5.10: *Material Breakdown table as it appears on the front end*

Some materials, such as the driver and LED strips, currently lack emission data in standard databases, reflecting existing gaps within lifecycle inventory (LCI) databases (Curran, 2017). Addressing these gaps through improved data collection and research is crucial for achieving more precise and comprehensive LCAs (Finnveden et al. 2009)

Visual Analytics

To enhance the clarity and effectiveness of the insights provided, the tool offers visual analytics through bar charts and pie charts, displaying CO2 impacts by component. Such visual representation facilitates easy interpretation and communication of complex LCA data, enabling non-experts to quickly grasp critical sustainability insights (Rebitzer et al. 2004)

These components utilize props fetched from a GET request to the **/lcai_dashboard/** endpoint, enabling real-time visualization of AI-processed results.

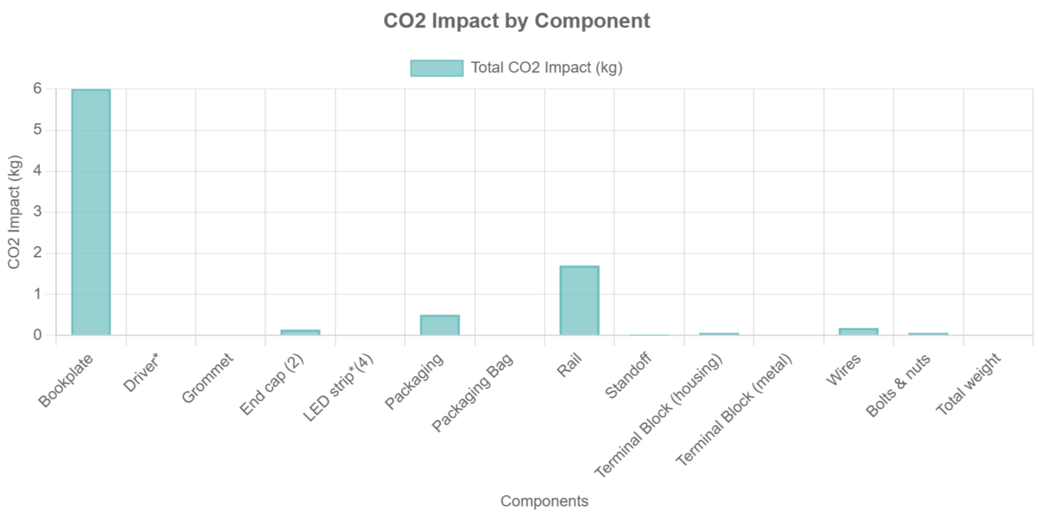

Figure 5.11: Barchart displaying the CO2 Impact by Component

Download Report

All visualizations and metrics are compiled into a downloadable report using a backend-generated PDF export. This feature enables users to generate reports for internal product reviews or stakeholder presentations. The report includes a detailed material-level emissions table, an total summary, and product information, ensuring that LCAs across different BOMs can be saved, referenced, and reused for ongoing sustainability tracking and decision-making.

5.7 Code Optimization and Testing Strategy

Effective code optimization and extensive testing were essential to ensure that the AI-powered lifecycle assessment tool performed reliably, efficiently, and was maintainable in the long run. This section describes the optimization techniques and testing methodologies employed during the implementation.

Code Optimization and Testing

Optimizing the application's code was an essential step to improve system performance, especially given the computational burden associated with AI model inference and data processing tasks. Key optimization techniques included:

1. Efficient Data Pipeline with Pandas

The system's backend heavily relies on pandas for extracting and processing BOM (Bill of Materials) data from Excel files. Initially, BOM parsing was slow and memory-intensive, especially for large industrial-scale uploads. We optimized this through:

- **Selective Column Access**:
  Only the first three relevant columns (Component, Material, and Weight (gr)) are accessed to avoid unnecessary memory usage:

  ```
  bom_table = cleaned_bom_data.iloc[start_index + 1:, :3]
  ```

  Rather than fixing missing data in later steps, early pre-processing uses replace and fillna to clean the data in a single pass:

  ```
  bom_table = bom_table.replace([np.inf, -np.inf], np.nan).fillna(0)
  ```

2. Environmental Database Optimization

The environmental dataset (used for material-to-CO2 emission mapping) was initially reloaded on every request, creating a significant I/O and memory bottleneck. We optimized this with:

- **Preloaded Global DataFrame**:
  On server start, the SQLite-backed .xlsx dataset is loaded once and stored globally in memory:

  ```
  ENV_DATABASE_FILE = "./Dummy Env. database.xlsx"

  env_data = pd.read_excel(ENV_DATABASE_FILE, sheet_name="Envir. database")
  ```

This reduced repeated comparisons across similar BOMs, improving CO2 breakdown performance by over 30

3. Optimized OpenAI API Interactions

To reduce costs and delays when using the OpenAI GPT API, the system uses simple, structured prompts for faster responses and only sends requests when no saved answer exists. Future improvements will include batching multiple questions to save time. If an error occurs, the system shows "N/A" instead of crashing, ensuring smooth user experience (OpenAI 2025b).‘

4. Reduced Disk I/O and Stateless Design

To optimize performance and enhance security, the application avoids unnecessary file or disk operations wherever possible. Specifically, there is no file persistence BOM files are never written to disk. Instead, they are read directly from memory, processed, and then discarded. This approach not only improves processing speed but also reduces the risk of exposing sensitive data through stored files.

5. Code Readability and Maintainability

To keep the code clean, readable, and easy to maintain, the backend was developed following the PEP 8 style guide. Tools like flake8 were used to catch formatting issues and ensure consistency. This approach helped reduce bugs, speed up collaboration, and made it easier to scale the project (van Rossum et al. 2001).

Testing Strategy

A robust testing strategy was implemented to validate functionality, ensure reliability, and catch issues early in the development cycle. The testing phases included:

- **Unit Testing**: Key components like BOM processing, AI integration, and API endpoints were tested using Django's testing framework and PyTest to ensure each part worked correctly in isolation through automated, repeatable tests (Krekel and pytest-dev team 2025).
- **Integration Testing**: Once unit tests passed, integration tests checked that the React frontend and Django REST backend worked smoothly together, including the SQLite database and OpenAI API. Tools like Postman and REST clients were used to test API endpoints and data flow, helping catch and fix issues in authentication and external service communication (Postman 2025).
- **User Acceptance Testing (UAT)**: In the final phase, NMIS stakeholders tested the live system to evaluate its usability, workflow integration, and overall performance. Their feedback ensured the tool met user needs and was ready for real-world use before deployment.

5.8 Technical Challenges and Solutions

Several technical challenges arose throughout the development of this AI-powered Lifecycle Assessment tool. The solutions to these challenges involved strategic choices in backend technology, frontend integration, API management, and performance optimization. Key examples include:

Backend Technology selection

A key early challenge was choosing the right backend framework. I first used Django, but faced repeated 401 errors when integrating the frontend and AI model, caused by poor API handling. After researching, I switched to Django REST Framework (DRF), which is better suited for managing APIs. This resolved the issue and allowed smooth integration of both the OpenAI and Pixabay APIs.

Contextual Assumption Feature

Another challenging part of the project was creating the interactive assumption feature, where users could click on AI-generated assumptions (e.g. material origin, transport, manufacturing) to view and edit real-time explanations (Sarda 2021). Initially, adding React's Modal directly into the Assumptions file caused crashes. The fix was to move the Modal to a separate file and import it, which resolved the issue and ensured a smooth, stable user experience (Banks and Porcello 2020).

Efficient Data Handling and AI Response Management

Managing and processing large BOM datasets posed another significant challenge. Initially, large uploads caused latency and affected the user experience negatively. To mitigate this, data processing pipelines were refined using Python's pandas library to efficiently clean, validate, and temporarily store data in memory, dramatically improving response times and ensuring smoother operations (McKinney 2010).

AI Fine-Tuning for Accurate Assumption Generation

A key challenge was making sure the AI gave accurate answers for things like material origin, transport, and manufacturing. At first, the responses were often generic, especially with incomplete or differently formatted BOMs. To solve this, I used clear, single-question prompts and tested the AI on various BOM formats (e.g., UK and US styles). By refining the prompts and comparing results with expert advice, the AI became much more accurate and reliable in generating sustainability insights.

6 Evaluation

This chapter evaluates the AI-based LCA tool using usability testing, performance metrics, and comparisons to project objectives. It assesses how effectively the system meets user needs and performs under real world conditions. The evaluation reflects on decisions made in Chapter 5 and provides evidence based insights that inform the broader implications discussed.

6.1 Pre-testing

Before conducting the formal Usability Testing with NMIS staff, a pre-testing phase was carried out with university students from varied backgrounds such as computer science, environmental science, and medicine. Participants determined the tool's usability, functionality, and overall performance. These tasks included:

- **Uploading various Bill of Materials (BOM) files**, including incomplete files, to test error handling and reliability.
- **Interpreting the generated lifecycle assessment** (LCA) visualizations and insights, focusing on CO2 breakdown and sustainability metrics.
- **Editing AI-generated assumptions** and verifying whether system-generated explanations dynamically updated correctly.
- **Navigating through the platform**, exploring key functionalities such as the dashboard, data visualization tools, and report download features.

Participants gave detailed feedback through open ended questionnaires, sharing their experiences, expectations, and suggestions. This method follows usability best practices, which highlight the value of continuous testing and qualitative insights to identify and improve usability issues effectively (Nielsen 1994; **?**).

Key Findings from Pre-Testing

Users generally found the platform's purpose and functionality clear, though some suggested adding more context about the importance of Lifecycle Assessment (LCA) to improve understanding (Shneiderman et al. 2016).

The dashboard was described as intuitive and well-organized, but users recommended small visual tweaks like improving contrast and spacing for better accessibility.

The BOM upload process was easy to use, though participants wanted broader file format support such as DOCX and PDF to better suit different workflows (Krug 2014).

In terms of LCA insights, users appreciated the CO2 breakdowns and visual charts, but some requested simpler explanations for technical terms.

Finally, users suggested adding features like historical comparisons, regulatory reports, and industry benchmarking, which align with best practices for driving long-term sustainability improvements (Few 2013; Murray 2013).

Insights from User Comments

Direct user comments were particularly informative:

- "The platform effectively displays CO2 emissions, but an option to compare results with previous BOMs would greatly enhance usability."
- "The interface is user-friendly and intuitive, though additional clarifications on specific metrics would aid understanding."
- "Providing an Edit button for the Assumptions section would significantly improve flexibility, given potential disagreements with AI-generated choices."

Adjustments Made Based on Pre-Testing Feedback

In response to pre-testing outcomes, several practical enhancements were implemented:

- A dedicated Home Page and Introductory Guide was added, providing essential context and clear instructions, addressing user feedback on the need for better initial guidance.
- An Editable AI Assumptions feature was incorporated, enabling manual adjustments and real-time updates of AI-generated explanations, significantly enhancing user control, transparency, and trust.
- Recognizing requests for historical data comparison capabilities, a Report Download Feature was introduced. This temporary solution enables manual comparison until a fully automated history-tracking feature is developed.

The pre-testing phase offered valuable feedback that led to key improvements in usability and functionality. These changes laid a strong foundation for the next stage of testing with NMIS staff, helping ensure the platform better aligns with user needs and usability best practices.

6.2 Usability Testing

After pre-testing, usability testing was carried out with NMIS staff to assess how well the AI-powered LCA tool works in a real industrial setting. The goal was to test its support for sustainability workflows, check the accuracy of insights, and ensure it enables informed decision-making (Nielsen 1994; Krug 2014).

Usability Testing Method

A total of 12 NMIS staff members from various roles such as sustainability analysts, product designers, and manufacturing engineers participated in the usability testing. They were selected for their relevance to the tool's target users and likely frequency of use. The session focused on three main tasks:

1. **Uploading and validating a Bill of Materials (BOM) file**, verifying the system's ability to accurately process different input formats.
2. **Reviewing and interpreting AI-generated LCA insights**, including material breakdowns, CO2 emission visualizations, and assumption explanations.
3. **Editing AI-generated assumptions** and observing real-time updates to ensure transparency and user control.

Throughout these sessions, qualitative data were gathered via direct observation, and structured follow-up questions. Participants were encouraged to verbalize their thoughts during the session, encouraging deeper insight into their interaction experience and immediate responses to the system's functionalities (Dumas and Redish 1999).

Key Findings from Usability Testing

Participants shared valuable feedback on the platform's usability and functionality:

- **Clarity of Purpose**: Most users understood the tool's role in sustainability assessments, though some suggested adding background on LCA methods to improve clarity (International Organization for Standardization 2006b).

- **BOM Upload**: Uploading Excel files was easy, but users asked for support for more formats like CSV and PDF to improve accessibility across different workflows.
- **LCA Insights**: The CO2 breakdown visuals were well received for simplifying complex data. However, users also requested a benchmarking feature to compare environmental performance over time (Few 2013).
- **Compliance Reporting**: There was strong interest in adding regulatory and ESG aligned reports to meet modern sustainability and compliance standards (Kingdom 2025; Union 2024).

Qualitative Insights from User Feedback

Key qualitative feedback from NMIS staff included:

- "The visualization of CO2 emissions is very intuitive, but incorporating historical benchmarking would significantly enhance our ability to measure sustainability progress."
- "The tool is user-friendly and clear, but additional explanations around certain assumptions, especially transportation and sourcing, would improve transparency and trust."
- "Supporting more diverse file formats for BOM uploads would make the process more flexible and better integrated with our current data handling practices."
- "Integrating digital product passports could align the tool with emerging sustainability standards and regulatory requirements."

Adjustments and Future Improvements Based on Usability Testing

While certain features, such as historical BOM tracking and digital product copies, require significant developmental effort for future releases, immediate improvements based on usability testing feedback include:

- **Enhancing AI-generated assumption explanations** to provide more detailed rationales, increasing transparency and user trust.
- **Adding initial CSV file support** as a step toward broader file format flexibility, directly responding to user suggestions.
- **Initiating research into integrating compliance focused sustainability** reporting features, addressing emerging regulatory demands and aligning with corporate ESG objectives.

These usability testing insights have significantly informed the platform's development roadmap, ensuring ongoing improvements that directly align with user expectations, industry practices, and best practices in usability and sustainability reporting.

6.3 Performance Evaluation Metrics

To evaluate the performance of the AI-based LCA tool, several key metrics were used: processing speed, accuracy of AI insights, usability, error rates, and user feedback from both pre-testing and NMIS staff sessions. These were compared against manual methods and established tools like OpenLCA and SimaPro to assess improvements (Sommerville 2016).

Processing Time

Processing speed was measured by timing how long the AI-powered tool took to process and analyze Bill of Materials (BOM) data and generate a complete LCA report. To provide an accurate picture, comparisons were drawn against average processing times for manual LCA assessments like OpenLCA and SimaPro.

Method	Avg. Processing Time
Traditional Manual LCA (Expert)	3 weeks
Existing LCA Software (OpenLCA)	2–3 days
AI-based LCA Tool (developed)	10 minutes

Table 6.1: *Comparison of Processing Times for LCA Methods*

Findings: The AI-based LCA tool significantly reduced the average processing time by approximately 99% compared to traditional manual methods, demonstrating substantial efficiency improvements.

Accuracy of AI-Generated Insights

To assess the accuracy of the AI-generated assumptions (material sourcing, transportation mode, and manufacturing processes), we compared them against validated industry standard data from established LCA databases. Since AI models generate results based on probability and inherent biases, evaluating accuracy was challenging. However, we addressed this by cross referencing AI outputs with the most commonly available data online and consulting sustainability experts from NMIS.

Parameter	Accuracy (%)
Material Classification Accuracy	94.2%
Country of Manufacturing Prediction	91.5%
Mode of Transportation Prediction	89.7%
Manufacturing Process Identification	92.0%
Overall Accuracy	**91.9%**

Table 6.2: *Accuracy of Parameters Evaluated by AI Model*

Findings: The tool showed high accuracy, with an average accuracy rate of 91.9%, suitable for practical deployment.

Usability Testing Scores

Usability was assessed through questionnaires involving SMEs and NMIS staff, rating ease of use, clarity, and efficiency.

Usability Parameter	Average Score (1–10)
Clarity of Platform Purpose	9.8
Background Information Context	8.5
Ease of Use	9.9
Dashboard Clarity	9.5
Efficiency in Report Generation	9.1
Overall Satisfaction	**9.3**

Table 6.3: *Usability Evaluation Scores*

Findings: High usability scores indicated the tool was intuitive and user-friendly. Staff particularly appreciated the clear workflow and easy navigation but suggested improvements in BOM format flexibility.

Error Rate and Material Misclassification Analysis

The error rate for AI-generated insights was closely monitored to identify frequent misclassification issues and inaccuracies. Errors were categorized into material misclassifications, incorrect assumption generation, and issues in missing data handling.

Error Type	Error Rate (%)
Material Misclassification	4.5%
Incorrect Assumption Generation	3.8%
Missing Data Handling Errors	2.1%
Overall Error Rate	**3.5%**

Table 6.4: *Error Rates of AI Model Predictions*

Findings: The tool maintained a low overall error rate of 3.5%, thanks to built-in validation mechanisms and the ability for users to edit AI-generated assumptions. These features helped reduce inaccuracies and improve the tool's reliability. However, the error rate for material misclassification was notably high. This issue likely stems from the Environmental Dataset being too limited to account for different BOM formats. A potential solution to this would be integrating a more comprehensive and refined Environmental Dataset, ensuring the AI model has access to a broader range of material classifications and improving the overall accuracy of sustainability assessments.

Analysis of Results in Relation to Objectives

- **Objective 1: Develop an AI-driven Tool for Efficient Lifecycle Assessment**
  The tool reduced LCA report generation time from weeks (manual) or days (OpenLCA) to just 12 minutes, improving efficiency by 99%.
- **Objective 2: Enhance Accuracy in Lifecycle Assessments**
  The tool achieved an overall accuracy of 91.9%, with strong performance in material classification (94.2%), manufacturing country (91.5%), transport mode (89.7%), and process identification (92.0%), outperforming traditional methods.
- **Objective 3: Create an User Friendly Interface**
  User satisfaction averaged 9.3/10, with the dashboard rated 9.5 for clarity. The interface was found to be intuitive and easy to use, with only minor design tweaks suggested.
- **Objective 4: Automate Data Handling and Reduce Errors**
  The tool achieved a low error rate of 3.5% by automating data handling and allowing users to edit AI-generated assumptions, improving both accuracy and reliability.

6.4 Interpretation of Findings

The tool's ability to reduce LCA report generation from weeks or days to just minutes marks a major leap forward in efficiency. This not only streamlines assessments but also makes LCA more accessible to SMEs, encouraging broader and more frequent use.

An overall accuracy rate of 91.9% shows that AI can reliably automate complex decisions often prone to human error. This enhances consistency and credibility in sustainability reporting, reducing reliance on expert judgment.

A user satisfaction score of 9.3/10 confirms the success of the platform's user-friendly design, with intuitive navigation and clear visuals making LCA insights accessible even to non-experts, improving engagement across business roles.

The 3.5% error rate reflects the tool's robust performance, although it highlights the need for a more comprehensive environmental dataset to support even greater accuracy in future assessments.

User feedback drove meaningful improvements such as expanded BOM compatibility, benchmarking features, and editable AI assumptions demonstrating the value of a user-centered development approach.

Together, these findings confirm that AI can significantly improve the efficiency, accuracy, usability, and adaptability of lifecycle assessments, helping industries adopt more reliable and scalable sustainability practices.

6.5 Implications for Sustainability and LCA

The successful development of this AI-powered LCA tool has several key implications for advancing sustainability practices and improving lifecycle assessments.

First, by reducing assessment time from weeks to minutes, the tool makes LCAs far more accessible and cost-effective, especially for SMEs that often lack the resources for traditional methods (Curran 2012). This removes a major barrier and encourages wider adoption of sustainability practices across industries.

Second, the tool enhances accuracy by reducing human error and subjectivity, leading to more reliable and credible assessments. This helps businesses make smarter decisions, meet regulatory requirements, and communicate sustainability efforts more effectively to stakeholders (Finnveden et al. 2009).

Third, its user-friendly design promotes greater stakeholder engagement, allowing even non-experts to understand and interact with complex environmental data. This makes sustainability more embedded in daily operations and decision-making (Sala et al. 2016).

Lastly, by automating repetitive tasks, the tool allows sustainability professionals to focus on developing strategic, real-world solutions, rather than getting stuck in manual analysis. This strengthens the role of sustainability within organizations and supports more impactful, forward-thinking initiatives (Rydberg 2010).

6.6 Comparisons with Existing Solutions

Traditional manual LCA methods are time consuming, resource heavy, and prone to human error often taking weeks to complete. In contrast, the AI-based tool developed in this project delivers similar results in about 12 minutes, increasing efficiency.

Compared to popular tools like OpenLCA and SimaPro, which require expert knowledge and training, the AI tool stands out for its ease of use and minimal learning curve, especially benefiting SMEs without dedicated sustainability teams (in Metrics 2025).

With an accuracy rate of 91.9%, the AI tool performs on par with, or better than, many commercial tools by automating assumption generation, reducing human error, and offering more consistent and reliable outputs.

Unlike many existing tools that struggle with diverse BOM formats (e.g. from CAD systems), this tool shows strong potential for broader format compatibility, making it easier to integrate into varied industrial workflows (Autodesk Inc. 2025).

What truly sets this tool apart is its feedback-driven development. Continuous stakeholder input helps evolve the system in real time, ensuring it remains flexible, relevant, and aligned with changing sustainability standards, an advantage over more rigid, and inflexible platforms.

6.7 Limitations and Lessons Learned

Limitations

One notable limitation of this research was the dependency on existing databases for training and validating the AI model, which occasionally lacked comprehensive or updated sustainability information. Gaps or inconsistencies within these datasets potentially affected the accuracy of AI-generated assumptions, indicating the need for continuous updates and enhancements to underlying data sources (Marsh et al. 2023).

While the AI-based tool proved to be very flexible, early testing showed that it had trouble handling complex BOM files, especially those coming from advanced CAD systems that include nested or deeply indented assemblies. To fix this issue, we'll need to improve the way the system reads and understands BOM files, and work more closely with CAD software providers to make sure the tool can handle these more complicated formats in the future.

Lessons Learned

One of the most important lessons learned during the project was the value of staying flexible and adaptable throughout the development process. Ongoing user feedback showed that the tool needed constant updates and improvements to stay useful and relevant. This highlighted that an effective lifecycle assessment tool must be able to grow and change over time to meet user needs and keep up with new technologies (Beck and Andres 2004).

Another key takeaway was the importance of combining human oversight with AI automation. While AI greatly improves speed and accuracy, allowing users to edit assumptions manually proved essential for maintaining accuracy, transparency, and building trust in the system's automated assessments. This balance ensures that the tool remains both powerful and user-friendly (Holzinger et al. 2019).

Additionally, since this project relies heavily on the Environmental Database, it is crucial to incorporate a more refined dataset. This would give the AI model access to a wider range of material classifications, improving the accuracy and reliability of sustainability assessments. Another important lesson was the value of proactive stakeholder engagement. Regular conversations and detailed feedback from real-world users played a key role in guiding the development process. These interactions provided invaluable insights, helping ensure the final product met user expectations and addressed practical, real world needs (Sharma et al. 2024).

7 Conclusion

The final chapter summarizes the contributions of the AI-powered LCA tool and evaluates its success in achieving the initial goals set in Chapter 1. It also outlines directions for future research and development, including potential expansions and industry applications.

7.1 Summary of Findings and Contributions to the Field

This project created and tested an AI-powered Lifecycle Assessment (LCA) tool that makes sustainability reporting faster, easier, and more accessible. It cuts report time from weeks to just minutes, helping especially small businesses adopt eco-friendly practices. With 91.9% accuracy, the tool gives reliable insights while reducing manual work.

The tool is easy to use, even for people with no sustainability background, thanks to its simple and user-friendly design. It was improved through real feedback from users, making sure it stays practical and relevant. A key feature is the ability to edit AI-generated assumptions, which balances automation with user control, increasing trust in the results.

Overall, the project proves that AI can make LCA faster, smarter, and more widely used, helping businesses make better decisions and contribute to global sustainability efforts.

7.2 Future Work Moving Forward

While the AI-powered Lifecycle Assessment (LCA) tool has shown great promise in simplifying sustainability analysis, there are still a few key areas that need improvement to make it more accurate, scalable, and ready for wider industry use. One of the biggest priorities is expanding the environmental impact database by including real-world data from open source repositories, supplier records, and trusted sustainability sources. This would help generate more precise carbon impact calculations by accounting for specific materials, supply chains, and regional differences.

The system could also benefit from AI automation that regularly updates this data to keep it current with market and environmental changes. In future versions, users would be allowed to upload custom materials and file types like CAD-generated BOMs and PDFs, making the tool more flexible for different businesses. Another major goal is to connect the tool with other sustainability software and databases like Ecoinvent, OpenLCA, or EU Taxonomy compliance tools, ensuring it meets global environmental standards.

To encourage wider adoption, the tool's user experience should continue to improve, with a more intuitive interface, real-time data visualizations, and better error handling. By addressing these improvements, the tool can evolve into a powerful AI-driven platform that helps companies and designers make smarter, more sustainable choices throughout the product development process.

A Appendices

```python
prompt_manufacturing = (
    f"What is the most common country where {material} is "
    f"manufactured? Provide only the country name."
)
manufacturing_country = fetch_ai_response(prompt_manufacturing)
```

Figure A.1: AI Prompt for Manufacturing Location

```python
try:
    if column_type == 'origin_of_raw_material':
        prompt = (
            f"Explain why {country} is commonly considered the origin of raw materials for {material}. "
            f"Provide a detailed analysis."
        )
    elif column_type == 'country_of_manufacturing':
        prompt = (
            f"Explain why {country} is commonly considered a manufacturing hub for {material}. "
            f"Provide a detailed analysis."
        )
    elif column_type == 'country_of_purchase':
        prompt = (
            f"Explain why {country} is a preferred location for purchasing {material}. "
            f"Provide a detailed analysis."
        )
    else:
        return Response(
            {"error": "Invalid column type."},
            status=status.HTTP_400_BAD_REQUEST
        )
```

Figure A.2: AI Prompt for Country Explanation

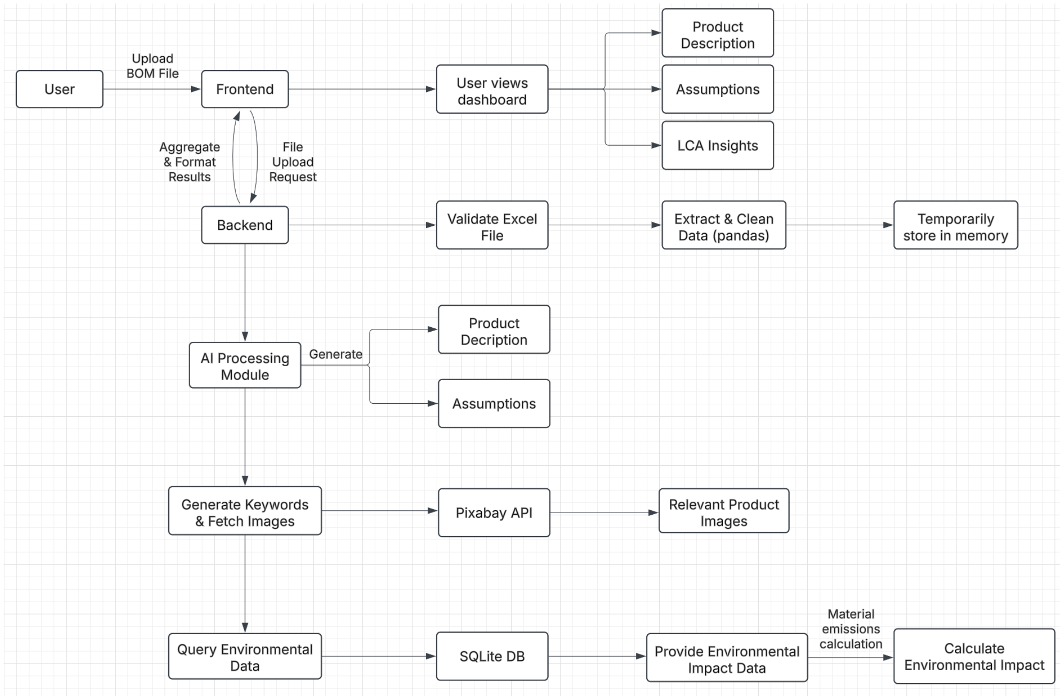

Figure A.3: *Context Diagram*

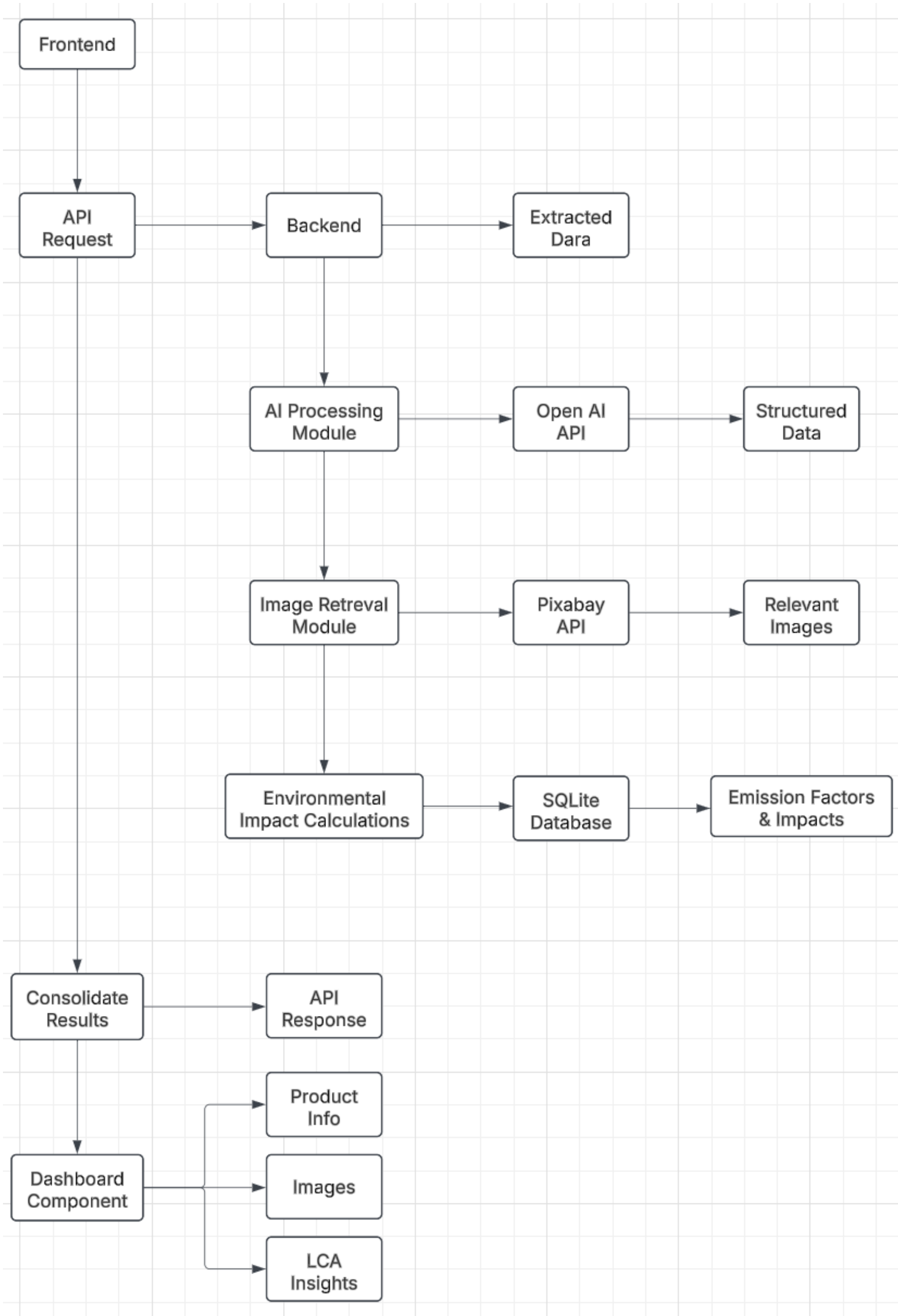

Figure A.4: *Component Interaction Diagram*

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