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What's in this LCA Report? A Case Study on Harnessing Large Language Models to Support Designers in Understanding Life Cycle Reports

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Abstract

Life cycle assessment (LCA) is a well-established approach and benchmark for design for sustainability efforts, in which detailed reports are produced that can serve as decision-making guides for developing new products. However, LCA reports are typically dense and technically complex, making it difficult for many engineering design project stakeholders to appropriately leverage the information found within them. Our work seeks to understand and improve the transfer of knowledge from LCA reports during the early stages of the design process, specifically leveraging the natural language capabilities of large language models (LLMs). In this paper, we investigate how four LCA- and sustainability-centric prompting frameworks can extract relevant design knowledge from LCA reports, demonstrated through a case study where an LLM (ChatGPT) is prompted on a provided electric toothbrush LCA report. Key findings illustrate the prompting frameworks can establish high-level summaries and identify life-cycle specific information, but the development of specific and design-focused sub-prompts will allow for richer understanding. We envision designers can use these proposed frameworks to query an LLM to gain context and insights from relevant LCA reports. The proposed techniques serve as a basis for automatic knowledge extraction from life cycle documents, creating accessible information in a user-friendly manner for designers who look to develop life-cycle-informed products.

Keywords: sustainable design; life cycle reports; document understanding; knowledge management; large language models

1. Introduction

Life cycle experts play a crucial role on design teams, taking on responsibilities as sustainability interpreters and providing critical data and design strategies to help focus and inspire different design options [6]. They are often responsible for translating life cycle data into more accessible and intuitive formats for engineering design project stakeholders - referred to here as "designers" for brevity - playing a pivotal role in steering sustainable design decisions. However, the presence of life cycle experts in design teams is rare, presenting a significant challenge in integrating their product knowledge into designers' unique context.

Previous work has explored using ontology and knowledge graph-based methods to enable the linking and retrieval of knowledge [31, 27, 29]. In this work, we utilize a new technique - large language models (LLMs) - to help bridge the knowledge gap between the life cycle knowledge available in reports and designers' mental models of the information.

LLMs' ability to interpret context and natural languages provide a novel approach to bridge this gap. These models offer accessible and adaptable interaction modes compared to ontology-based methods. Designers can teach LLMs domain specific information and ask the model to explain answers they do not understand. When LLMs are combined with visual models, they can help designers interpret important data from diagrams, a common and vital component of life cycle reports.

In this work, we aim to understand the capabilities and limitations of using current large language models to facilitate knowledge transfer from life cycle reports. We compare four approaches (**Fig. 1**), with each approach incorporating literature-based strategies for effective LLMs prompting [24], including structured instruction, context, input, and output indicators (see details in Section 3.1). The four prompting approaches explored are: 1) **No report**, testing baseline LLM capabilities without a raw data input 2) **Report summary**, to generally learn more about the report, 3) **Life-Cycle stages**, to nav-

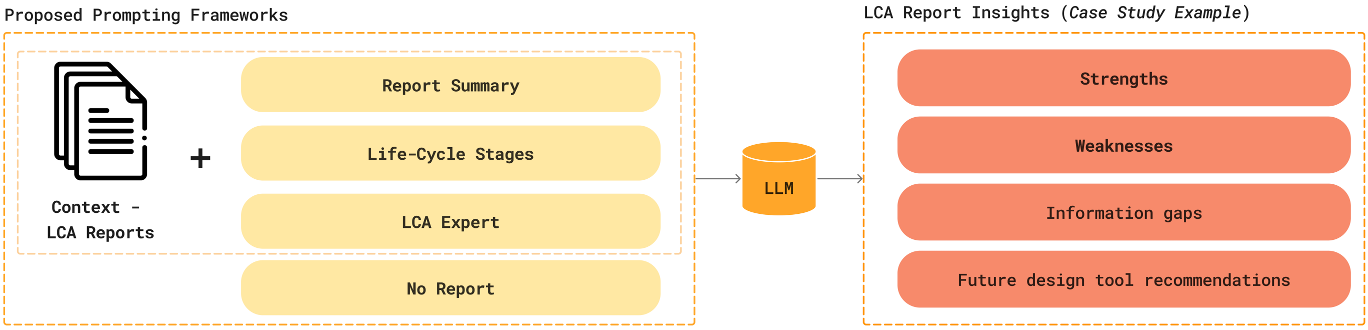

Fig. 1: Overview. We investigate how varying LCA- and sustainability-centric prompting frameworks (left) create accessible information from LCA reports. A case study highlights strengths and weaknesses of LLMs in analyzing LCA reports and proposes how future work can address gaps and opportunities in the space (right).

igate the report by life cycle stage and 4) **LCA expert queries**, to replicate practitioners' strategies in this task.

In this work, we position LLMs as a promising technique to extract and transfer life cycle knowledge. The primary contribution of this work is the introduction of four literature and empirically-driven approaches for using LLMs to interpret LCA reports, analyzing their strengths and weaknesses in a case study to guide future sustainable tool development in this area.

2. Related Work

2.1. LCA Reports

LCA is considered a benchmark approach for analyzing the environmental impact of a product, service, or system, and is considered a strong tool to guide decision-making [8]. However, many challenges exist for both creating an LCA (data sourcing, transparency, scaling, uncertainty) [9] and subsequently interpreting the results of an LCA, which can be highly technical, complex, and lengthy [7, 17]. This poses a significant problem for certain populations, like product designers, marketing departments, and policy makers, who may find the information in LCA reports to be useful, but who are unable to properly navigate the document. Despite LCA's prevalence, little work has investigated how key project stakeholders such as engineers, industrial designers, product managers, and other decision-makers in early-stage design use LCA and other reports of existing products to improve their own designs. Indeed, many outputs of LCA are not easily transferred to design decision-making or even applied to the design process as a whole [20]. This work builds on existing research on LCA documents to support facilitating knowledge transfer of sustainability information from these sources and thereby lowering the barrier to sustainability information access that designers face.

2.2. Large Language Models in Document Interpretation

Pre-trained large language models (LLMs) have demonstrated exceptional proficiency in engaging with, synthesizing, and contextualizing natural language inputs. Recent innovations have even extended their capabilities to include multi-modal inputs, such as images, further broadening their applicability [16]. LLMs have particularly revolutionized the field of document interpretation, making it possible to extract valuable insights and information from text-based content, which is crucial for informed, data-driven decision-making. This transformative ability has been applied across various domains, yielding promising results in tasks such as summarizing medical evidence [26], generating ideas for journalistic angles [19], and predicting consensus in legal documents [28].

Notably, LLMs excel in both summarization and creative idea generation [13, 14]. This capability positions them as powerful tools in overcoming many challenges associated with interpreting LCA reports. In this work, we aim to harness the automated potential of LLMs to enhance accessibility of LCA data through structured, life cycle-centric prompting.

3. Methods and Proposed Frameworks

We propose using the automated natural language capabilities of LLMs to intuitively extract information from LCA reports. Specifically, we propose a novel framework based on an interview study conducted in [6] with LCA experts across a variety of consumer product companies. This interview study resulted in a 5-topic codebook (Table 1), with each topic representing a key information area that LCA experts seek when parsing through an LCA document themselves.

LLMs can be sensitive to their inputs, with variations in prompts creating large differences in outputs [33]. Thus, we explore alternative prompting frameworks, namely (1) **no report queries** (akin to zero-shot prompting), whose purpose are to explore the baseline capabilities of the model with no LCA report as input, (2) **report summary queries** whose purpose are to learn more about the LCA report, and (3) **life-cycle stage queries** whose purpose are to learn more about each life cycle stage analyzed in the report. In doing so, we look to compare our proposed framework against 2 general LLM prompting techniques (Sections 3.1.1 and 3.1.2) and a well-established sustainability lens (Section 3.1.3). This approach is exemplified in a case study (Section 4) analyzing the life cycle report of an electric toothbrush using GPT-4 (the state-of-the-art model from OpenAI at the time of submission).

Table 1: Guiding framework proposed in [6] for navigating an LCA document, based on interview data with LCA experts. Each topic represents a key information area that LCA experts seek when parsing through an LCA document.

Topic	Description
Scope of Analysis	*Establishing the boundaries of what the life cycle assessment encompasses.*
Priority Areas	*Components and sub-assemblies of the product that are critical or highly important to the product's functionality or appearance.*
Eco Hotspots	*Life cycle phases with high environmental impacts. Phases can include material extraction, manufacturing, transportation/ distribution, use, end of life, etc.*
Key Metrics	*Numbers associated with high environmental impacts. This can include carbon emissions, energy, land use, etc.*
Design Strategies	*Overarching methods for minimizing or addressing environmental impact.*

3.1. *Proposed prompt templates*

Though prompt engineering remains a large challenge as the field of LLMs grows exponentially [32], we develop query templates that can be used across a variety of LCA report styles and customized as needed. By creating LCA- and sustainability-specific prompting frameworks, data extraction from the reports can help the LLM become focused and guided in its process.

A prompt's core elements include any or all of: [24]:

1. **Instruction**: a specific task or instruction you want the model to perform
2. **Context**: external information or additional context that can steer the model to better responses
3. **Input**: the input or question of interest for a response.
4. **Output indicator**: the type or format of the output.

In this work, the same **instruction** is used across all frameworks: *I'm designing a new [product of interest] and want to make it environmentally sustainable*. Any uploaded LCA reports are considered as the **context**. The primary focus of this work is the **input**, which is varied across the different proposed frameworks, as detailed in Sections 3.1.1 to 3.1.4 . Finally, the **output indicator** is not included, as this work is exploratory in nature. An example prompt is seen in Fig. 2.

An overview of the proposed prompting frameworks can be found in Table 2. We select these four categories as initial exploratory frameworks to provide a foundation for this field of research and anticipate this work as a first step toward using LLMs in an LCA interpretation setting.

3.1.1. *No Report Queries*

Zero-shot prompting is defined around giving a language model instructions regarding a task without inputting any examples, and has been shown to produce high-performing results [12]. We use this technique to establish an information baseline from the model and to explore how the design context is established without explicitly providing LCA report data as an input.

Instruction **Context** **Input**

I'm designing a new *[product of interest]* and want to make it more environmentally sustainable. Here is an LCA report of a *[product of interest]*. Identify the priority areas of this report. The definition of priority areas are components and sub-assemblies of the product that are critical or highly important to the product itself.

Fig. 2: An example query template with core prompt elements highlighted. This paper proposes different frameworks for use as **inputs** (highlighted orange).

With the intent of being used within the design process and improving future iterations of a product, the model is prompted (without any raw LCA reports being used, or no **context**) with the following example queries:

```
What are the important components of the
product of interest to consider? OR
What are the important life cycle phases of
the product of interest to consider?
```

3.1.2. *Report Summary Queries*

LLMs are well-known for their summarization abilities, as discussed in Section 2.2, which can be a valuable tool in situating the information of a report and priming a reader at a high-level. In this paper, we explore how general, high-level queries can summarize an LCA report and highlight relevant features. These insights help identify where further information must be explicitly probed, leveraging model summarization in future sustainable design tools. An example query is shown below, emphasizing model reasoning [12]:

```
Going step-by-step, summarize this document.
```

3.1.3. *Life Cycle Stage Queries*

Life cycle stages (raw material extraction, manufacturing, distribution, use, and disposal) provide an established structure for considering the environmental sustainability of a product. While some LCAs may only analyze a portion of these stages (cradle-to-gate, gate-to-gate), this framework is used as a sustainability baseline, with an example query shown below:

```
Identify information about the life cycle
stage phase of this LCA. OR Identify the
life cycle stage with the highest
environmental impact.
```

3.1.4. *LCA Expert Queries*

Previous work by the authors [6] built a framework around how LCA experts seek information when handling LCA reports, and how these techniques can be leveraged to support non-experts in interacting with LCA reports. We translate each category area of this framework (Table 1) into a query using the following template, with an example in Fig. 2.:

`Identify the category. The definition of category is description.`

Table 2: Overview of different prompting frameworks being proposed for interacting with existing LCA reports.

Prompt Category	Description
No Report	Establishing a baseline design context without any LCA data as input.
Report Summary	Learning about the report as a whole with unstructured queries.
Life-Cycle Stages	Learning about each life cycle stage of the product.
LCA Expert	Probing the report similar to how an LCA expert would, as seen in Table 1.

4. Case Study: Electric Toothbrush LCA

To evaluate the advantages and limitations of the proposed framework, a case study was carried out analyzing the LCA report of an Oral-B electric toothbrush [25]. This report was selected for the report's limited length (8 pages), providing for a suitable pilot task. To query the report, GPT-4 (latest model at the time of writing) was used via OpenAI's ChatGPT interface, in an effort to replicate an easily accessible task that a designer could undertake and to leverage its document upload capabilities. We additionally leverage ChatGPT's multimodal input abilities, which can take graphical components of the LCA as image inputs [16].

To explore the capabilities of LLMs in extracting information from LCA reports, the four query areas described in Section 3 are evaluated. We highlight strengths and weaknesses of each category, summarized in Fig. 3, and suggest directions for future work in this area.

4.1. Sustainable design querying with no LCA report can generate creative design suggestions, but will not be ground in specific, quantitative data.

Here, we explore how the LLM responds without any raw data as input.

Strengths: Without an LCA report to ground the queries, the LLM is open to propose novel, creative ideas. This generative capability can be a strong tool for creating design suggestions for a product re-design. For example, when prompted for new design strategies for an electric toothbrush, the LLM proposed features like *"an automatic shut-off"*, *"solar charging option"*, and a *"disassembly guide"*. This design idea generation capability is an emerging field of research itself, and one of the major strengths to be leveraged from this tool [5, 14, 15].

Weaknesses: There is no quantitative or data-rich support here, which is one of the primary advantages of this computational tool. This leads to problems around feasibility of proposed ideas and results in generic, product-agnostic results when asked about life-cycles and components of interest (ex: *"Consider the environmental impact of sourcing the materials. Opt for materials that are sourced sustainably."*). Here, we confirm the motivation for this work in exploring prompting frameworks for interacting with LCA reports, as this input is necessary for providing designers with specific LCA data to make future data-driven decisions. Additionally, LLMs are prone to producing hallucinations, information that is inaccurate or nonsense, a problem which can be mitigated by adding additional context to input queries [21], in this case LCA reports or more formulated prompts.

4.2. Report summary queries provide a strong starting point, but are constrained by existing document structure.

Strengths: When providing general queries as a prompt, the LLM can effectively begin breaking down and reading the document (ex: *"The provided infographic provides an in-depth analysis of an Oral-B electric toothbrush in terms of its environmental impact, materials, components, and manufacturing processes. Here's a summary of the key information presented:"*). By providing a concise summary of each section, the prompter can choose data of interest and continue to query within that area. Additionally, the data sources that were used are highlighted (ex: *"Data sources include the Cambridge Engineering Selector (CES) Eco Audit Tool."*), which is an important aspect of building trust and transparency when sharing these reports. Overall, future tools can leverage this query type as an introductory overview to the document.

Weaknesses: The LLM response is organized into the same sections as the LCA report itself, which may present a constraint for certain report styles, and will lead to overwhelmingly long summaries for certain reports. Additionally, while the summary for each section contained accurate information, it was often vague (ex: *"The main materials and components are shown."*) and would require further prompting. Here, there's an opportunity to organize query results for increased concision and clarity by 1) adding an **output indicator** constraining the length of the presented summary and 2) using queries from other proposed frameworks to dig deeper into the document.

4.3. Life cycle stage queries can identify detailed information about each stage but lacks a design lens and focus.

Strengths: Because life cycle stages are well-established and defined, the LLM can effectively identify relevant, accurate information with minimal additional prompting (ex: disposal phase - *"The materials are not compostable, and some materials required some careful attention for safe disposal such as toxic chemicals in the battery and heavy metals in the electronics. The manufacturer does not provide any type of end-of-life collection or recycling scheme for the product. "*). This is especially useful when considering how to improve a product's environmental impact, where process-oriented interventions (considering a single life cycle stage at a time) are easier to implement than product-oriented design interventions [10].

Weaknesses: Though effective at identifying life-cycle specific information, this framework lacks a specific design lens or focus, which may provide challenges for designers looking to translate this information into actionable design strategies. This indicates an area of opportunity to supplement these queries, perhaps leveraging the generative design strengths of base LLMs/ no report queries.

4.4. LCA expert queries can identify high importance areas, like components or carbon footprint.

Strengths: The LLM can identify the various priority components of the toothbrush and indicate which are of vital function and importance, even providing explanatory information not originally present in the report (ex: *"NiMH rechargeable battery is crucial for powering the electric toothbrush. Without it, the toothbrush would not function."*, *"Rubber Rings and Seals: Ensure that the toothbrush remains waterproof, allowing for safe use in wet environments like bathrooms."*). Like breaking the report down by life cycles (Section 4.3), this approach supports designers in thinking about the product by subsection for increased comprehension and navigation [6, 18]. Future work could investigate this component identification ability as product complexity scales.

With focused prompting, the LLM can also interpret graphs and present the high-level results, which was a major challenge previously faced by non-experts when analyzing LCA reports [6] (ex: *"The element with the highest CO2 footprint in the electric toothbrush, as depicted in the [relevant graph], is the Electronic components. They significantly surpass other components in terms of CO2 footprint."*). Finally, the response is not framed in specific life-cycle jargon (i.e. cradle-to-grave) which may detract from its credibility but provide support for non-experts, increasing the understandability of the output.

Weaknesses: There is a large opportunity within this area to provide more detailed sub-queries that explore common themes within each topic in Table 1 to provide even further support for non-experts. Future work could develop these sub-queries in a focused manner by incorporating common questions and challenges faced in this field (i.e. material selection, data transparency, component footprints, etc. [1, 2, 3, 6]), creating a thorough framework that allows user to probe for further details.

5. Future Work and Takeaways

Recommendations for using language models to help non-experts with LCA report interpretation and usage are derived from the case study. Namely,

- **LLMs summarization capabilities** should be leveraged for priming readers to the main points a report contains
- **Use established terminology** (like life cycle stage definitions) to identify key information from these reports in a focused manner [11]
- LLMs generative capabilities can be used for proposing **novel sustainable design suggestions** during ideation
- **Provide logical sub-queries** that walk a reader through the report methodically by incrementally adding details to follow-up prompts

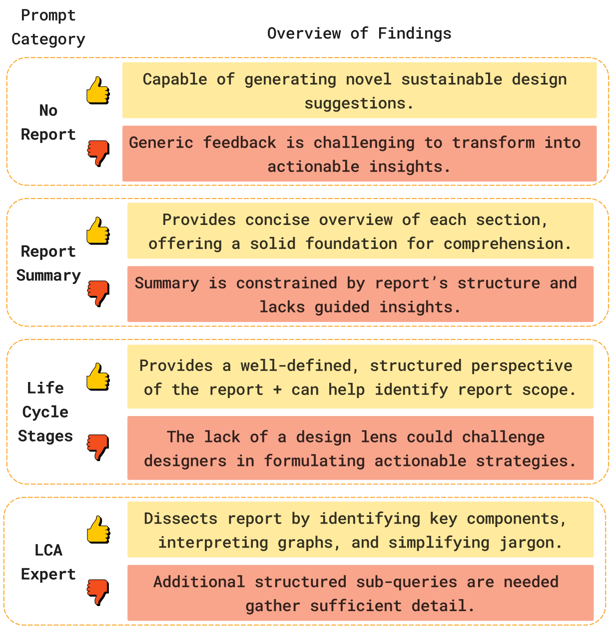

Fig. 3: Overview of strengths and weaknesses for each prompting category.

The proposed frameworks provide a foundation for future work around LCA document interpretation using LLMs and other natural language processing techniques, and can be expanded in many ways. First, the frameworks should be tested with a variety of LCA reports to examine efficiency across domains and report styles, as well as to provide comparison from multiple input reports [4]. Introducing additional forms of sustainability reports, like product passports [22], as data sources could provide further opportunity for supporting designers with life cycle information. Second, additional sustainable design frameworks (i.e. 9R framework, circular economy principles, etc.) can be implemented to explore their abilities [23, 30]. Third, each framework's responses should be evaluated for accuracy, clarity, and relevance in their content and presentation. Finally, future work can explore how combining various frameworks could provide a more holistic interpretation of the reports themselves. A major limitation in LCA interpretation remains however, given an expert's role in identifying the accuracy and validity of an LCA report. While LLMs may not be able to discern poor modelling skills, the ability to quickly probe a report and compare amongst multiple reports may provide a route for facilitating this task for experts and non-experts alike.

6. Conclusion

In this work, we present a novel application of LLMs to make life cycle information from LCA reports accessible to non-experts. Through a case study analyzing four distinct prompting frameworks, we identify strengths and weaknesses of each technique. Prompting an LLM without an LCA report as input can leverage the generative design features of language models to suggest novel design ideas; however, it may output generic feedback that is challenging to transform into actionable insights. When using LCA reports as input data, LLMs can concisely summarize the document, offering a solid foundation for comprehension, though the summary is constrained by the document's format and lacks structured insights. Examining the document with a life-cycle stage lens provides a defined, structured approach to extract information, but it needs more support in incorporating a design perspective. Finally, approaching the report from an LCA expert viewpoint helps dissect it by identifying key components, interpreting graphs, and simplifying jargon, though the creation of structured, detailed sub-queries could enhance this process. This work aims to enhance sustainable design tools using emerging technologies for greater accessibility of LCA reports to non-experts.

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