A MULTI-AGENT LLM FRAMEWORK FOR SUSTAINABLE DESIGN CONCEPT GENERATION

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ABSTRACT
Incorporating sustainability principles into early product design phases presents significant challenges due to the complex, interconnected nature of product lifecycles. While Large Language Models (LLMs) demonstrate considerable potential for design ideation, their current application in sustainable design relies predominantly on unstructured, single-shot prompting approaches that inadequately address holistic lifecycle considerations. This study presents a novel multi-agent LLM framework for early-stage sustainable concept generation. The proposed architecture employs specialized LLM-powered agents distributed across four product lifecycle phases: Material, Production, Use, and End-of-Life. By employing Chain-of-Thought (CoT) reasoning protocols at each stage, the system generates comprehensive product design specifications for sustainable design exploration. These specifications can then be processed by a textual summarization agent, which transforms technical requirements into descriptive prompts for visual concept generation via a text-to-image generation agent. The framework's potential is demonstrated through a case study on a sustainable hair dryer concept development. Results demonstrate successful integration of lifecycle considerations into the design processes, producing concepts exhibiting both innovation and sustainability. This research establishes a foundation for leveraging AI in systematic sustainable design exploration, offering a structured alternative to conventional single-agent, single-shot prompting, enabling more rigorous and comprehensive sustainable design ideation.

Keywords: Large language model, Sustainable design, Concept generation, Multi-agent system, Chain-of-thought reasoning

1 INTRODUCTION

The conceptual design stage is widely recognized as the most critical phase for establishing sustainable product outcomes, as decisions made regarding product architecture, materials, and working principles become embedded during these early stages [1, 2]. Research demonstrates that early design choices determine approximately 80% of environmental impact across the entire product lifecycle [3, 4]. Consequently, effective sustainability integration requires comprehensive circularity and lifecycle thinking throughout all design phases [2]. However, designers face substantial cognitive limitations when simultaneously addressing functional requirements, economic constraints, and the complex, often contradictory sustainability demands spanning from material extraction to end-of-life disposal [5, 6]. This complexity highlights the urgent need for systematic tools that support sustainable design concept generation during periods of maximum design flexibility and environmental impact potential.

Recent advances in Large Language Models (LLMs) offer promising opportunities for augmenting creative and analytical capabilities during conceptual design [7]. These systems excel at processing and synthesizing extensive information, enabling comprehensive assistance across diverse design tasks, including brainstorming, ideation, and knowledge indexing and retrieval [8]. LLMs can function as collaborative partners, rapidly generating diverse initial concepts from minimal prompts while substantially expanding designers' solution exploration space [9]. The integration of such generative AI tools into design workflows demonstrates significant potential for accelerating innovation and enhancing decision-making during critical early-stage processes [10].

For complex design challenges that often require multi-step reasoning, Chain-of-Thought (CoT) methodologies have proven particularly effective [11]. This prompting technique guides LLMs to decompose complex queries into sequential logical steps rather than generating immediate responses. In design applications, CoT provides essential transparency by enabling examination of the underlying

rationale for specific recommendations, establishing trust and enabling validation of AI-generated concepts [12, 13].
While individual LLMs demonstrate considerable capabilities, sustainable design's multifaceted nature benefits from collaborative and specialized approaches [14]. A single-agent LLM, when tasked with designing a sustainable product, must simultaneously embody expertise across material science, manufacturing engineering, and sustainability principles, potentially producing overly generic and superficial outputs. Multi-agent systems distribute cognitive workload among specialized agents that interact collaboratively, mirroring human design teams where diverse expertise convergence produces robust outcomes [15]. Research indicates that multi-agent frameworks are essential for addressing complex design challenges requiring varied specialized expertise [16].
This paper proposes a multi-agent LLM framework specifically engineered to support sustainable concept generation at the early stages of product design. The framework integrates product life cycle thinking by assigning specialist LLM agents to its four critical stages: Material, Production, Use, and End-of-Life. Guided by Chain-of-Thought (CoT) reasoning, these agents collaboratively explore the design space initiated by a simple design task (e.g., "hair dryer"). The output is a comprehensive product design specification that offers design insight, potentially leading to a product concept image generated by employing a text-to-image generation agent.

2 RELATED WORK

2.1 Sustainability integration in the early stage of design

Sustainable design has evolved from broad integration of environmental, social, and economic considerations into design processes toward more sophisticated approaches emphasizing ethical responsibility and life-cycle thinking [17, 18]. Recent studies highlight the conceptual design stage as the most critical phase for achieving sustainable outcomes, as decisions made during this period fundamentally determine material use, energy performance, and end-of-life impacts. While life-cycle assessment (LCA) remains a dominant evaluation tool, researchers argue that its application occurs too late in the design process to meaningfully influence outcomes, leading to the development of lightweight evaluation metrics, search-tree protocols, and trade-off visualization tools for early design exploration [4, 19, 20].
Recent advances in computational design have enabled the emergence of integrated early-stage modelling environments that support real-time evaluation of carbon footprints, material impacts, and energy trade-offs throughout concept development phases. Early-stage optimization models for buildings and infrastructure demonstrate how parametric tools can embed sustainability considerations directly into the design space [21]. Metrics-based frameworks now enable sustainability quantification across material, production, use, and end-of-life dimensions before detailed designs exist [4]. Simultaneously, generative design and optimization approaches have gained traction for exploring concept spaces, enabling designers to evaluate thousands of alternatives while embedding sustainability constraints [22]. These developments collectively represent a paradigm shift from treating sustainability as a late-stage retrofit consideration toward positioning it as a fundamental creative design driver.

2.2 Large language models and Chain-of-Thought reasoning

Recent advances in artificial intelligence, particularly large language models (LLMs), have created new opportunities for design applications. Initial explorations demonstrated LLMs' capabilities in generating design concepts from natural language inputs [10]. Subsequently, LLMs have been applied to support diverse design activities, particularly in concept generation [23-26] and detailed design [27-29]. While AI-based optimization and generative tools are increasingly common in design, LLM applications for sustainability-focused ideation remain unexplored. Several studies have begun addressing sustainable design applications. Li*et al.* [30] demonstrated generative AI's capabilities in assisting novice designers with sustainable concept development, while Grandi*et al.* [31] evaluated LLMs for material selection to improve sustainability outcomes. However, these investigations suggest that while LLMs can function as co-pilots in sustainable design, their integration remains fragmented and exploratory [32, 33].
Sustainable design constitutes a wicked problem characterized by complex interdependencies and conflicting objectives [32], suggesting that inherent LLM capabilities may prove insufficient without enhanced reasoning frameworks. Chain-of-Thought (CoT) reasoning has emerged as a promising technique for improving LLM performance on complex tasks [11]. Rather than generating immediate

solutions, CoT prompting requires agents to articulate reasoning processes through intermediate logical steps, demonstrating improved performance on complex analytical tasks.

CoT reasoning has been successfully applied to conceptual generation contexts. Chang and Li [34] developed GPS, an LLM-augmented framework for enhanced ideation creativity during brainstorming activities. Similarly, Lee*et al.* [35] demonstrated that CoT application enabled students to generate more insightful responses. More recently, Ge*et al.* [13] integrated CoT with retrieval-augmented generation (RAG) techniques to facilitate concept generation. Despite growing interest in CoT-augmented LLM applications for concept generation, its application in sustainable design contexts remains unexplored, representing a significant research gap.

2.3 Multi-agent LLMs for design

While CoT reasoning enhances single LLM logical depth, its linear, monolithic nature struggles to address sustainable design's fundamental complexity. Sustainable design represents not a singular problem but a multi-objective system of competing priorities requiring negotiation and trade-offs [36]. Multi-agent LLM applications in design represent an emerging research field focused on leveraging collective AI intelligence for complex, multifaceted problem-solving [14].

Recent developments demonstrate the potential of multi-agent frameworks across various design domains. DesignGPT [37] pioneered multi-agent design collaboration by enabling designers to work with AI agents during conceptual design stages. Erikstad [38] advanced this approach by combining multi-agent LLMs with Model-Based Systems Engineering (MBSE), proposing frameworks that use specialized AI agent "crews" to translate design narratives into formal optimization models and executable code. Mushtaq*et al.* [14] further demonstrated how collaborative multi-agent capabilities enable engagement with multiple perspectives and simulation of trade-offs in globalized engineering contexts. Most relevantly, Tseng and Chang [16] showed that multi-agent LLM frameworks can enhance creativity, understanding, and synthesis in sustainable design contexts, providing a scalable foundation for AI-supported design in sustainability domains.

These multi-agent frameworks reshape design processes by distributing specialized tasks across coordinated LLMs, with agents simulating distinct roles as designers, evaluators, or domain experts. This distributed approach demonstrates improved coordination and problem-solving capabilities for complex engineering challenges. However, current applications remain limited in their integration of lifecycle thinking and structured reasoning processes specifically tailored for sustainable design generation, representing a significant research gap.

3 THE MULTI-AGENT LLM FRAMEWORK

To address the inherent limitations of single-shot, unstructured LLM applications in complex sustainable design tasks, this study proposes a novel multi-agent LLM framework (see Figure 1). The framework leverages the proven effectiveness of task decomposition in multi-agent systems, integrating lifecycle thinking principles with the CoT reasoning capabilities of contemporary LLMs. The proposed architecture comprises two primary phases.

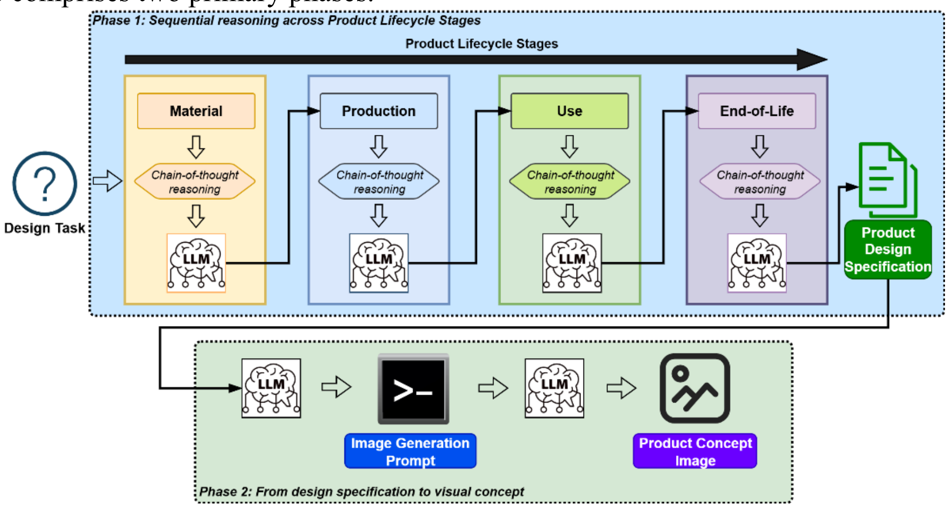

Figure 1. A multi-agent LLM framework for sustainable design concept generation

Phase 1: Sequential reasoning across Product Lifecycle Stages – Product design specification
The phase initiates with the core design task (e.g., "hair dryer", "bicycle", "electric scooter"). Rather than employing a monolithic LLM approach for concept generation, the framework decomposes the design task into four critical product lifecycle stages: Material, Production, Use, and End-of-Life. This sequential process ensures comprehensive sustainability analysis throughout the concept development process. Each lifecycle stage employs a dedicated LLM agent utilizing Chain-of-Thought (CoT) reasoning steps to generate structured responses through systematic step-by-step guidance derived from [4]. The output from each preceding stage serves as contextual input for the subsequent agent, establishing a cumulative and contextually aware design process. To facilitate seamless inter-agent communication, all responses are constrained to JSON format.
Table 1 presents the key CoT prompt elements, i.e. the guiding questions derived from [4], for each lifecycle stage. Subsequent stages incorporate additional prompts to integrate outputs from previous stages, exemplified by the Production stage prompt: "*...From the Material stage you have the following information available: {Material_output}... Please now focus on the Production stage, by thinking step-by-step...*"

Table 1. CoT reasoning prompt elements used for all lifecycle stages, derived from [4].

Lifecycle Stages	CoT prompt elements
Material	**Material origin** - Where the materials, used in the components and parts of a product, are originally sourced? - Are these materials originated from non-renewable or renewable resources? **Material property** - What about the toxicity, recyclability, and biodegradability of the materials? **Use of material** - What about the volume/weight of materials? - What about the number of types of materials involved?
Production	**Balance between number of parts and their complexity** - How to minimise the number of parts in a practical manner without adding too much complexity? **Part standardisation** - How to use more standardised parts/components and fewer unique parts/components? **Parts design for assembly** - How to design parts for ease of assembly involves better presentation, easy handling, mistake proofing, and efficient insertion. **Suitable fabrication method** - How to identify the most appropriate technology/process?
Use	**Product use time/lifetime** - How to balance between the product's lifetime and use time to minimise the negative environmental impacts of products? **Energy consumption during use** - How to reduce the product's resource or energy consumption? **Robustness, reliability, and maintenance** - How the design be more robust, reliable, and easy to maintain, avoid causing negative environmental impact due to malfunctioning and servicing?
End-of-Life	**Reuse** - How the component and part be design to allow easy reuse without the need for remanufacturing? **Recycling, remanufacturing, and repair** - How the component and part be designed to allow easy recycling, remanufacturing and repair? **Disposal** - How to minimise the environmental impact caused by disposal? **Ease of disassembly** - How the component and part be designed so that they are easy to disassemble at its end of life?

This phase generates structured JSON outputs containing key product components. For each component, the multi-agent architecture provides comprehensive ideas and justifications spanning all four lifecycle stages. These structured responses are subsequently synthesized into a detailed product design specification, encompassing key design features alongside the rationale and trade-offs considered throughout the entire lifecycle, thereby providing valuable design insights for practitioners during conceptual development phases.

Phase 2: From design specification to visual concept – Product concept image

The second phase transforms the comprehensive product design specification into visual concept representations through a dual-agent approach: one for textual summarization based on the detailed specification, and another for text-to-image generation.

Initially, the comprehensive design specification is processed by the first LLM instance, which functions as a specialized prompt engineering agent. This agent translates technical, functional, and sustainability attributes from the specification into rich, descriptive prompts optimized for the text-to-image model input. The resulting output constitutes an image generation prompt that encapsulates the essential features of the product design specification.

Subsequently, the image generation prompt is processed by an image generation agent, which produces a product concept image. This visual output goes beyond mere artistic representation, serving as a direct indication of lifecycle-based reasoning conducted in the preceding phase. The generated visual concept maintains fidelity to the sustainability considerations and technical specifications established through the multi-agent lifecycle analysis.

4 CASE STUDY

To demonstrate the practical application of the proposed framework, a case study was conducted using a hair dryer as the design task. Hair dryers represent a well-established product category with significant opportunities for sustainable design improvements, particularly in energy efficiency and material selection. For implementation purposes, Google's "gemini-2.5-flash" model served as the underlying language model for each individual agent within the multi-agent architecture. Phase 1 yielded a comprehensive product design specification, organized according to the product's primary components and their corresponding lifecycle considerations across the four stages. A representative extract focusing on the "Casing/Body" component is presented in Figure 2, with the complete specification documented in reference [39].

Component 1: Casing/Body

Materials

- Utilizes a blend of **post-consumer recycled (PCR) polycarbonate and ABS** to reduce reliance on virgin resources and divert waste from landfills.
- This blend provides excellent **heat resistance**, **impact strength**, and **durability**, essential for a hair dryer casing.
- While not biodegradable, the material choice prioritizes **future recyclability** to minimize environmental impact.

Production

- **Injection molding** is the chosen process, enabling complex geometries and a minimal two-part shell design.
- Design incorporates **snap-fit mechanisms** and clear alignment guides to ensure **quick, mistake-proof assembly**.
- **Standardized screw bosses** will accommodate various internal components, reducing unique part tooling and **streamlining production**.

Use

- The durable **PCR PC/ABS casing** is designed for **easy disassembly**, extending product life through facilitated **repair** and end-of-life recycling.
- An **aerodynamic form** optimizes airflow, indirectly contributing to reduced **fan energy consumption**.
- **Smooth surfaces** ensure the product is **easy to clean**, maintaining performance and preventing dust-related malfunctions.

End-of-life

- Features **tool-free disassembly** using snap-fits and standardized screws, allowing for quick **repair** and component replacement.
- Includes **clear material labeling** (e.g., ISO 7) to facilitate efficient sorting for **high-value recycling** of the PCR PC/ABS blend.
- The product's **modularity** supports **remanufacturing** into refurbished units, minimizing waste.

Figure 2. Product Design Specification for component Casing/body.

Following the generation of the product design specification in Phase 1, an image generation prompt was formulated by Gemini and then processed through Google's Nano Banana, i.e. "gemini-2.5-flash-image-preview", to produce visual concept representations. The prompt explicitly requested an exploded view diagram, a standardized visualization methodology prevalent in industrial design practice. This approach aligns with established engineering communication protocols and delivers actionable insights for design practitioners. The component identification and corresponding technical annotations were automatically generated by the agent to ensure comprehensive documentation of design elements. The resulting visualization is presented in Figure 3, demonstrating the framework's capability to transform complex, multi-dimensional design specifications into coherent visual representations. For comparative analysis, a baseline output generated from a conventional single-prompt approach, "*generate a concept of a sustainable hair dryer*", was also included to illustrate the enhanced detail and systematic organization achieved through the multi-agent framework.

Figure 3. Hair dryer concept images: (a) Single-prompt method, (b) Proposed method

5 DISCUSSION

The proposed framework contributes to both theoretical advancement and practical implementation in sustainable design. From a theoretical perspective, the approach successfully integrates lifecycle thinking within a generative artificial intelligence workflow, addressing the fundamental challenge of decomposing cognitively complex sustainability considerations into manageable, sequential analytical processes. The integration of Chain-of-Thought (CoT) reasoning technique addresses the critical requirement for transparent decision-making mechanisms in sustainable design applications, establishing an auditable documentation trail for each design decision. This positions LLMs as sophisticated design reasoning partners rather than conventional content generation tools, aligning with recent advances in explainable artificial intelligence systems.

The framework also addresses several implementation challenges within industrial practice. The structured JSON output format facilitates seamless integration with existing Computer-Aided Design (CAD) and Product Lifecycle Management (PLM) systems, thereby reducing technological adoption barriers for organizations. The automated generation of technical documentation and visualization capabilities substantially reduces the temporal and expertise requirements traditionally associated with comprehensive sustainability analysis, enhancing accessibility, particularly for small and medium-sized enterprises with limited specialized resources. Additionally, the automated visualization component effectively bridges the communication gap between complex technical sustainability data and stakeholder comprehension, enabling more efficient design review processes and informed decision-making.

However, several limitations necessitate future research considerations. The framework's dependence on static knowledge embedded within pre-trained language models presents challenges as sustainability standards and material technologies continue to evolve rapidly. Future implementations should incorporate dynamic integration with real-time sustainability databases, e.g. retrieval-augmented generation techniques, to maintain accuracy and relevance of recommendations. The sequential agent architecture, while ensuring systematic analysis coverage, may not adequately capture the inherently iterative and non-linear characteristics of design processes. Future research should investigate more flexible agent communication architectures, including bidirectional feedback mechanisms and parallel processing capabilities. Third, the aesthetic quality of the generated visuals may require refinement, and broader validation across diverse product categories and user studies with designers is necessary.

5 CONCLUSION

This research addresses a critical gap at the intersection of generative AI and sustainable design by introducing a multi-agent LLM framework that embeds product lifecycle thinking into the ideation process. The hairdryer case study demonstrated that this structured approach produces design specifications and visual concepts of greater depth and coherence than conventional, single-shot prompting methods. The framework contributes a novel methodology for integrating sustainability principles, enhancing design transparency through CoT reasoning, and bridging the communication gap between technical analysis and design practice. Its modular architecture and structured outputs facilitate integration with existing industry workflows, democratizing access to advanced sustainability assessment. While limitations such as static model knowledge and process linearity exist, they highlight clear directions for future research, including the development of iterative agent architectures and integration with real-time data. In conclusion, this study establishes a foundational approach for leveraging multi-agent systems to tackle complex sustainability design challenges, pointing toward a future where AI-assisted tools are integral to designing a more sustainable world.

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