Development and Application of an Intelligent Green Design Tool: An Innovative Pathway Supporting Modularity and the Circular Economy

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***Abstract*—As global focus on sustainable development continues to grow, the shift toward a circular economy has become a crucial direction for the manufacturing industry, bringing new and complex challenges to product design. Despite this urgency, many widely used green design methods and tools still lack sufficient intelligence and system-level integration. In practice, there remains a clear disconnect between theoretical frameworks and real-world application—especially when it comes to effectively combining modular design principles with full product life cycle strategies to support early-stage design decisions.To overcome these limitations, this study introduces a novel intelligent green design approach called the Intelligent Green Extension Design Method (IGEDM). The method integrates three complementary components: the formal innovation logic of Extenics, the data processing and optimization capabilities of machine learning, and the environmental evaluation strength of Life Cycle Assessment (LCA). Together, these elements form an intelligent tool prototype designed to support green decision-making at the early stages of product design.A smart speaker is used as a case study to illustrate the complete workflow of the proposed tool. By building a multi-dimensional matter-element model of the product, machine learning techniques such as Random Forests and neural networks are applied to optimize multiple green performance objectives, including carbon footprint, ease of disassembly, and material recyclability. These optimization results are then combined with extension transformation theory to generate a range of innovative modular design solutions.The findings show that, compared with conventional design approaches, the solutions produced using the IGEDM tool deliver substantial environmental benefits. Specifically, the optimized designs achieve an estimated 25% reduction in total life cycle carbon emissions and a 40% increase in modularity, while also clearly identifying key opportunities for green improvement. This study not only provides a practical and quantifiable intelligent pathway for green design research, but also demonstrates the feasibility of embedding artificial intelligence into the front end of product design to drive sustainable innovation. Ultimately, it offers enterprises a powerful decision-support tool and a forward-looking design paradigm for developing products aligned with the circular economy.**

Keywords—Intelligent Green Design; Circular Economy; Modular Design; Extenics Theory; Machine Learning; Decision Support Tool

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I. INTRODUCTION

With global environmental pressures and resource constraints growing more severe, shifting the economic model from the traditional “take–make–dispose” linear approach to a sustainable circular economy has become a shared international goal and a strategic priority for many countries [1]. The circular economy seeks to reduce resource use and waste generation at the source through design, while maximizing resource value by extending the service life of products and materials [2]. Within this large-scale transition, product design—positioned at the intersection of resource input, manufacturing, consumption, and end-of-life treatment—plays a central and irreplaceable role. Design decisions shape not only product performance, cost, and user experience, but also determine the environmental burden across the entire lifecycle and the feasibility of “reuse, repair, remanufacturing, and recycling” in circular systems [3].

Yet transforming circular economy principles into actionable design practices remains highly challenging for designers and engineers. Established approaches such as Life Cycle Assessment (LCA), Design for Environment (DfE), and the Design for X (DfX) family—including Design for Disassembly (DfD)—offer valuable frameworks for evaluating and improving environmental performance [4]. In practice, however, these methods often face substantial barriers. LCA, for example, is frequently conducted in the middle or later stages of design, which limits its ability to correct critical decisions made earlier. It can also be complex, time-consuming, and heavily dependent on detailed data availability [5]. Meanwhile, during conceptual design, designers must navigate competing constraints across functionality, aesthetics, cost, user requirements, and a range of environmental indicators (e.g., carbon footprint, water footprint, material toxicity). This makes early decision-making uncertain and often forces trade-offs. The challenge becomes even greater when implementing circularity-oriented strategies such as modular design, where effective support tools are still lacking for systematically planning module partitioning, interface standardization, and material selection while balancing repairability, upgradability, and recyclability [6].

In recent years, rapid advances in Artificial Intelligence (AI) have opened new possibilities for addressing these difficulties. Methods such as machine learning and data mining have already demonstrated strong potential in areas including materials discovery and manufacturing process optimization [7]. At the same time, Extenics—an original discipline that studies extension possibilities and the rules of innovation—offers a distinctive reasoning framework for formally describing design problems and generating innovative solutions through tools such as the matter-element model [8]. Although some research has explored AI for sustainable design or applied Extenics to product innovation, a unified framework and practical tool that tightly integrates Extenics-based formal reasoning, machine-learning-driven optimization, and the systemic objectives of the circular economy is still missing. Much of the existing work treats these domains in isolation, leaving designers caught between the complex demands of circular design and a fragmented landscape of methods and tools.

To address this gap, this study proposes and develops an Intelligent Green Extension Design Method (IGEDM) that integrates Extenics theory with machine learning. The research has three main objectives. First, it aims to establish a theoretical framework that formalizes product design problems into extensible matter-element models and applies machine learning algorithms for multi-objective optimization of key design parameters. Second, it seeks to develop a visual prototype tool based on this framework to enable intelligent analysis, trade-off optimization, and automated generation of innovative solutions for green product attributes—supporting more robust decision-making in the early design stage. Third, it validates the method and tool through a detailed case study focused on the green design of a smart home product: a smart speaker. Through this interdisciplinary effort, the study aims to provide a practical pathway and decision-support capability for researchers and practitioners tackling circular economy challenges and accelerating the development of sustainable products.

The remainder of this paper is structured as follows. Section 2 reviews related research on green design, modularity, Extenics, and AI applications in design. Section 3 describes the proposed IGEDM framework and its three core modules. Section 4 presents the prototype tool and demonstrates its application through the smart speaker case study. Section 5 discusses the results and their theoretical and practical implications. Section 6 concludes the paper and outlines directions for future work.

II. Literature Review

To establish a solid theoretical foundation for this research, this section systematically reviews four core domains closely related to intelligent green design: green design methods within the context of the circular economy, product modular design, the application of Extenics in engineering and product design, and recent advances in the use of artificial intelligence for sustainable design. By synthesizing and critically discussing existing studies in these areas, this review clarifies the current research landscape, identifies unresolved challenges, and highlights the theoretical gap and innovative contribution of the present study.

A. Integration of Green Design Methods and the Circular Economy

Green design, also referred to as eco-design, seeks to proactively address a product’s potential environmental impacts from the earliest design stages, with the goal of minimizing resource consumption and environmental pollution throughout the entire product lifecycle [9]. To support this objective, both academia and industry have developed a variety of methods and theoretical approaches. Among these, Life Cycle Assessment (LCA) is the most mature and widely adopted quantitative tool, enabling systematic evaluation of environmental impacts from raw material extraction and manufacturing to product use and end-of-life treatment [10].

Despite its strengths, LCA is often criticized for its complexity and heavy reliance on detailed data, which makes it difficult to apply efficiently during the early stages of design when rapid iterations and limited information are the norm. To mitigate these limitations, the Design for X (DfX) methodology was introduced, emphasizing specific lifecycle considerations — such as manufacturability and assemblability — early in the design process. Within green design, this approach has evolved into a series of environmentally focused strategies, including Design for Disassembly (DfD), Design for Recycling (DfR), and Design for Remanufacturing (DfR-mfg) [11]. While these methods offer practical design guidelines, they are often implemented independently, lacking an integrated framework to manage trade-offs and conflicts — for example, the tension between designing for durability and designing for easy disassembly.

With the growing prominence of the circular economy, green design requirements have expanded beyond reducing negative environmental impacts toward actively creating closed-loop value systems. The “butterfly diagram” introduced by the Ellen MacArthur Foundation vividly illustrates the biological and technical cycles of the circular economy, emphasizing strategies such as reuse, repair, and remanufacturing to preserve product and material value [12]. Recent studies have further advanced the operationalization of circular economy concepts. For instance, Panda et al. (2025) identified four key transition pathways — modular innovation, alliance-driven collaboration, organizational embedding, and circular leadership—based on industrial case studies [13]. By framing modularity as a strategic enabler rather than merely a technical choice, this work provides important theoretical support for adopting modular design as a bridge between intelligent design tools and circular economy objectives. Nevertheless, translating such high-level strategies into concrete, quantitative design decision support that designers can readily apply remains an unresolved challenge.

B. Evolution and Challenges of Product Modular Design

Modular design is a strategy that decomposes complex products into functionally independent subunits, or modules, connected through standardized interfaces [14]. Originally, modularity aimed to enhance production efficiency, increase product variety, and simplify supply chain management through standardization and combinatorial innovation [15]. In the context of the circular economy, however, the significance of modular design has expanded considerably. Well-conceived modular products can extend service life by enabling independent repair, replacement, or upgrading of obsolete or failed modules without discarding the entire product [16]. In addition, modular architectures simplify disassembly processes, facilitating material separation, recycling, and remanufacturing at end of life, thereby maximizing resource recovery value [17].

Despite these advantages, traditional modular design approaches exhibit notable limitations when applied to circular economy objectives. First, many module partitioning methods are primarily driven by functional architecture and pay insufficient attention to end-of-life considerations such as material compatibility, disassembly sequencing, and differing component lifespans [18]. Second, key modular design decisions — including module granularity and interface selection — often have complex and non-linear impacts on both environmental and economic performance. Designers typically rely on experience-based judgment rather than quantitative decision support. Although some research has attempted to integrate LCA with modular design, most efforts remain at the conceptual level and lack dynamic, intelligent optimization tools capable of identifying optimal modular solutions under multiple constraints [19].

C. *Formalized Methods of Extenics in Innovative Design*

Extenics is an original interdisciplinary field founded in 1983 by Professor Cai Wen, focusing on the formal study of extension possibilities and innovation principles to address contradictory problems [20]. Its core analytical tool is the matter-element model, which represents an object through an ordered triple R = (N, c, v), where N denotes the object, c its characteristic, and v the corresponding value. Through well-defined extension transformations — such as replacement, addition or deletion, decomposition, and expansion — new solutions to design contradictions can be generated in a systematic and logical manner. This formalized innovation process provides a rigorous and computable pathway for design innovation, which traditionally relies heavily on intuition and trial-and-error.

In product design research, Extenics has been applied to areas such as conceptual design, fault diagnosis, and design optimization. Ko (2020), for example, proposed an innovative green design approach based on extension theory and the concept of "Green DNAs," encompassing green technology, green materials, and green manufacturing, and validated it through a medical air purifier case study [21]. This work demonstrated how matter-element models can be used to decompose and reconstruct product systems to generate novel green design concepts, offering direct methodological inspiration for the present research. However, Ko's approach relies largely on manual analysis and transformation by designers, limiting efficiency and optimality. How to automate and enhance this process — particularly by integrating data-driven optimization algorithms with Extenics' logical reasoning — remains an important open research question.

D. *Frontier Applications of Artificial Intelligence in Sustainable Design*

Artificial intelligence, particularly machine learning (ML), has emerged as a powerful driver of innovation across many domains. In sustainable design, AI applications show strong potential in several areas. In materials science, ML models can rapidly predict material properties — such as strength, conductivity, and biodegradability—based on large datasets, accelerating the discovery and deployment of environmentally friendly materials [22]. In design optimization, AI algorithms can explore highly complex, multi-dimensional design spaces. Generative design tools, for example, can automatically produce numerous lightweight and high-performance solutions under constraints related to performance, materials, and cost [23].

AI has also been increasingly integrated with LCA to enable real-time, dynamic prediction of environmental impacts. When designers modify design parameters, AI models can immediately estimate changes in indicators such as carbon emissions and energy consumption, significantly improving iteration efficiency [24]. Beyond individual products, AI-driven platforms have been proposed to optimize reverse supply chains, enhance recycling efficiency, and support remanufacturing through intelligent sorting and demand forecasting [25]. Digital twins and product passports enabled by AI further support lifecycle tracking, providing data for maintenance, upgrades, and recycling decisions [26].

Commercial tools such as Autodesk Fusion 360 and One Click LCA already incorporate elements of AI and LCA databases [27]. However, most existing solutions are primarily assessment-oriented: they evaluate existing designs rather than actively generating innovative alternatives. Moreover, they lack a formal innovation framework — such as Extenics—to guide systematic solution generation.

Recent studies have begun exploring AI-assisted modular design to support circular economy objectives, demonstrating how machine learning can optimize module partitioning based on lifecycle data and evolving user needs [28]. In architecture, AI-driven tools have improved sustainability by optimizing material usage and energy performance [29]. In smart home design, AI combined with fuzzy logic has been applied to balance user comfort and environmental performance in multi-objective decision-making [30].

At the policy level, research shows that AI-enabled monitoring and compliance tools can enhance the effectiveness of eco-design regulations and circular economy initiatives. In cultural and creative product design, AI-assisted eco-innovation has enabled the development of sustainable products that preserve cultural value while reducing environmental impact [31]. Evolutionary algorithms have also been used to dynamically optimize modular product architectures under changing resource and market conditions [32].

Finally, AI-supported open innovation models have gained attention as enablers of circular business models, particularly in the bioeconomy, where collaborative data analysis supports closed-loop value chains [33]. From a strategic perspective, dynamic capabilities theory emphasizes that successful integration of AI and circular economy practices requires organizational adaptation and systemic innovation rather than incremental change [34]. Collectively, these studies highlight the significant potential of AI in sustainable design, while also revealing the absence of integration with formal innovation theories such as Extenics — underscoring the research gap that this study seeks to address.

III. METHODOLOGY

To overcome the limited intelligence and weak integration of existing green design approaches, this study proposes a new theoretical framework termed the Intelligent Green Extension Design Method (IGEDM). The central concept of IGEDM is to tightly couple the formalized innovation logic of Extenics with the data-driven optimization strengths of machine learning, and to embed this hybrid approach into a product design process aligned with circular economy principles. This chapter introduces the overall structure of the IGEDM framework and provides a detailed explanation of its three core modules: multi-dimensional matter-element model construction, machine-learning-based multi-objective optimization, and solution generation through extension transformation.

A. Intelligent Green Extension Design (IGEDM) Framework

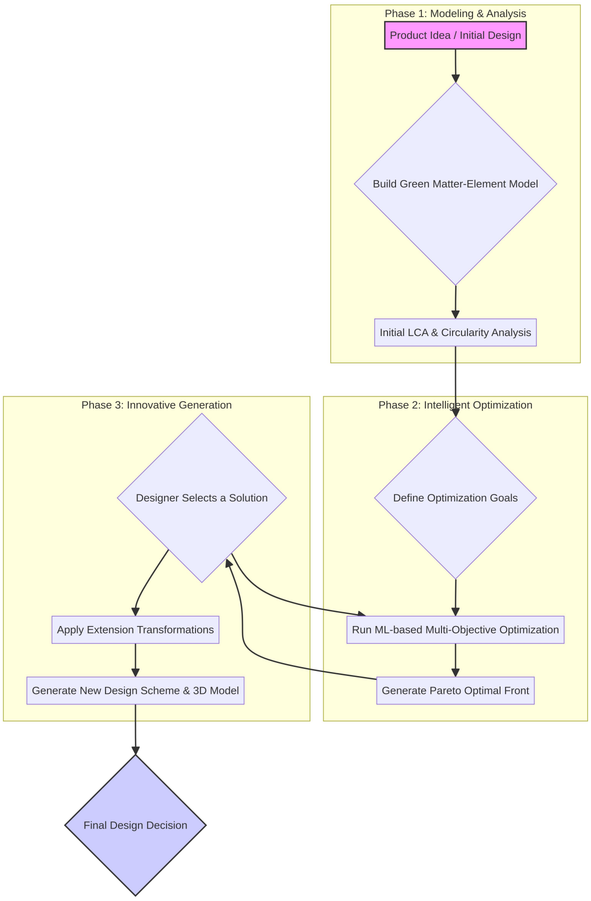

Fig. 1. The Intelligent Green Extension Design Method (IGEDM) Framework

The IGEDM framework is designed as a three-stage, closed-loop decision-support process that assists designers in systematically exploring, evaluating, and generating innovative green design solutions during the early stages of product development. Its primary goal is to achieve a balanced consideration of environmental performance, economic viability, and technical feasibility, rather than optimizing any single objective in isolation.

As illustrated in Figure 1, the framework is composed of three tightly connected core modules, forming a coherent logical chain that progresses from formalized modeling, to intelligent optimization, and finally to innovative solution generation. In the first stage, complex and often ambiguous green design problems are translated into structured, multi-dimensional matter-element models, providing a clear and computable representation of product attributes and constraints. In the second stage, machine learning algorithms are employed to perform multi-objective optimization on key green design indicators, enabling efficient exploration of large and non-linear design spaces. In the final stage, extension transformation theory is applied to the optimized models to systematically generate novel and feasible design alternatives.

Through this closed-loop structure, the IGEDM framework not only supports rational analysis and quantitative optimization, but also enhances creative exploration, allowing designers to iteratively refine solutions and identify high-potential green design strategies that are well suited to circular economy requirements.

1) Module 1: Matter-Element Modeling and Analysis

This module serves as the entry point of the IGEDM framework. Drawing on—and extending—Extenics matter-element theory, it decomposes the target product into a set of standardized, multi-dimensional matter-element models. These models describe not only the product's physical and functional attributes, but also explicitly formalize "soft" attributes, including lifecycle environmental impacts and circular economy strategies. In doing so, the module provides a structured foundation for downstream quantitative analysis and optimization.

2) Module 2: Machine Learning Optimization

This module functions as the "intelligent engine" of IGEDM. It integrates openly available datasets together with a transparent, screening-level factor table (e.g., public material and process emission factors, open materials handbooks) and applies lightweight, reproducible algorithms to construct predictive models. On a standard laptop, these models can rapidly estimate key green performance indicators—such as carbon footprint, disassemblability, and material circularity rate—based on design parameters. Building on these predictions, the framework adopts deterministic sampling within a bounded design space and Pareto filtering (rather than computationally expensive evolutionary optimization) to identify a compact set of non-dominated solutions that balance conflicting objectives, such as minimizing environmental impact while controlling cost.

3) Module 3: Extension Transformation and Solution Generation

This module acts as the "innovation generator." It translates the abstract design variables produced by the optimization module (e.g., material choice, joining/connection method) into concrete extension transformation operations. Using a predefined rule base, the system applies transformations such as replacement, decomposition, and addition/deletion to the initial matter-element model, thereby automatically or semi-automatically generating a set of structured and innovative green design solutions. These solutions can be visualized and returned to designers for final decision-making, or fed into the next optimization cycle—forming a continuous, iterative improvement loop.

B. Module 1: Multi-dimensional Matter-Element Model Construction

To enable formal, computable analysis of complex product systems, this study extends the classic three-dimensional matter-element representation $R = (N, c, v)$ and constructs a five-dimensional Green Matter-Element Model (GMEM), defined as:

$$GMEM=(N,F,S,E,C) \quad ((\quad (1)$$

Where:

- N (Object): the object, representing a specific element of the product system — such as a part, component, module, or the entire product.
- F (Function): the set of functional characteristics that describe the object ' s intended functions and performance requirements,

$$F = \{f_1, f_2, \ldots, f_n\} \quad (2)$$

- S (Structure): the set of structural characteristics that capture physical attributes such as material, mass, dimensions, and joining method,

$$S = \{s_1, s_2, \ldots, s_m\} \quad (3)$$

- E (Environment): the set of environmental characteristics used to quantify lifecycle impacts such as carbon footprint, water footprint, and energy consumption,

$$E = \{e_1, e_2, \ldots, e_k\} \quad (4)$$

- C (Circularity): the set of circularity characteristics that reflect circular economy potential, including disassemblability, recyclability, and repairability,

$$C = \{c_1, c_2, \ldots, c_p\} \quad (5)$$

Each characteristic can be expressed as a nested sub-matter-element. For example, the structural characteristic " material " may be represented in a more detailed form such as:

$$(s_i, (type, v_{type}), (source, v_{source})) \quad (6)$$

This nested representation enables multi-level description at different granularities, supporting both system-level assessment and component-level optimization.

Using the smart speaker case study as an illustration, the top-level matter-element can be expressed as:

$$GMEM_speaker = (SmartSpeaker, F_speaker, S_speaker, E_speake \quad (7)$$

This top-level model can be decomposed into sub-matter-elements such as the housing, speaker unit, mainboard, and power supply. Table I provides an example of the initial matter-element model for the housing component.

TABLE I. EXAMPLE OF INITIAL MATTER-ELEMENT MODEL FOR THE SMART SPEAKER HOUSING COMPONENT

Dimension	Feature	Value
N (Object)	Name	Speaker Housing
F (Function)	Contain & Protect	Internal Components
S (Structure)	Material	ABS
S (Structure)	Weight	250g
S (Structure)	Connection	Adhesive Bonding
E (Environment)	Carbon Footprint (Initial)	1.5 kg CO_2 -eq
C (Circularity)	Disassemblability (Initial)	1 (Very Difficult)
C (Circularity)	Material Recyclability	Low (Thermoplastic)

C. Module 2: Multi-objective Optimization based on Machine Learning

The primary function of this module is to intelligently search a vast design space to identify combinations of design parameters that maximize overall green performance. To achieve this, the process is structured into three sequential steps: data preparation, model training, and multi-objective optimization.

To ensure transparency and reproducibility, the training dataset was constructed exclusively from openly accessible and low-cost data sources. These sources include:

a) publicly available screening-level LCA factors and process emission factors, compiled into a transparent lookup table used throughout this study;

b) open material handbooks and technical datasheets providing basic physical and mechanical properties as well as indicative cost ranges;

c) publicly accessible teardown manuals and user-repair guides that explicitly describe disassembly procedures.

To avoid high implementation barriers, labels and features related to disassemblability — such as connection methods, fastener types, and approximate disassembly time bands—were extracted using a simple rule-based template and manual verification on a limited sample. This approach deliberately avoids reliance on large-scale web crawling, natural language processing, or image-based analysis, thereby keeping the method lightweight and broadly reproducible.

Using the prepared dataset, a set of lightweight and reproducible baseline models was trained to estimate key green performance indicators. All training and evaluation procedures were implemented with standard open-source tools, and both the input feature sets and evaluation protocols were intentionally kept simple to facilitate replication under typical research conditions.

A Gradient Boosting Regression Trees (GBRT) algorithm was employed to train a regression model for estimating the lifecycle carbon footprint (kg CO_2 -eq) of individual components. Input features include material type, component mass, manufacturing process, and transportation distance. As the focus of this study is early-stage design screening, the model is calibrated to deliver stable, approximate predictions rather than high-fidelity results dependent on proprietary LCA databases. The predictive performance of this model on the test set is reported in Figure 2.

Disassemblability was modeled as a classification problem using a Random Forest algorithm. The model takes inputs such as connection method (e.g., adhesive bonding, welding, screwing, snap-fit), number of fasteners, and tool universality, and outputs a disassemblability score on a five-point scale (1 indicating extremely difficult disassembly and 5 indicating extremely easy disassembly). Positioned as a screening-level tool, the model emphasizes practicality and interpretability, with cross-validation results presented in Figure 3.

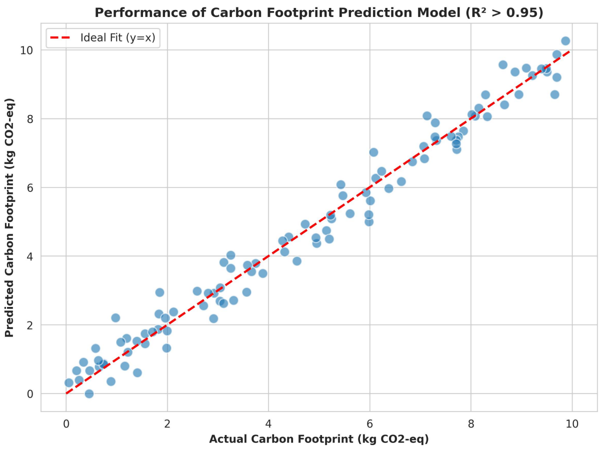

Fig. 2. Performance Evaluation of the Carbon Footprint Prediction Model

A central difficulty in green product design is that key objectives often conflict with one another. For instance, selecting a single material that is easier to recycle may increase product weight, which in turn can raise transportation-related carbon emissions. To handle such trade-offs under ordinary computing conditions, this study adopts a bounded, deterministic search strategy. Specifically, combinations of design variables within a predefined design space are systematically enumerated (and/or randomly sampled using a fixed seed to ensure reproducibility). Each candidate solution is then evaluated using the lightweight screening models described above.

After evaluation, non-dominated sorting is applied to extract the Pareto-optimal solution set (i.e., the Pareto Front), as illustrated in Figure 4. Each point on this front represents a non-dominated design alternative, meaning that no other candidate can improve one objective without worsening at least one other objective. Rather than producing a single "best" solution, the resulting Pareto set provides designers with a compact collection of high-quality and diverse alternatives, enabling informed decision-making based on priorities, constraints, and practical considerations.

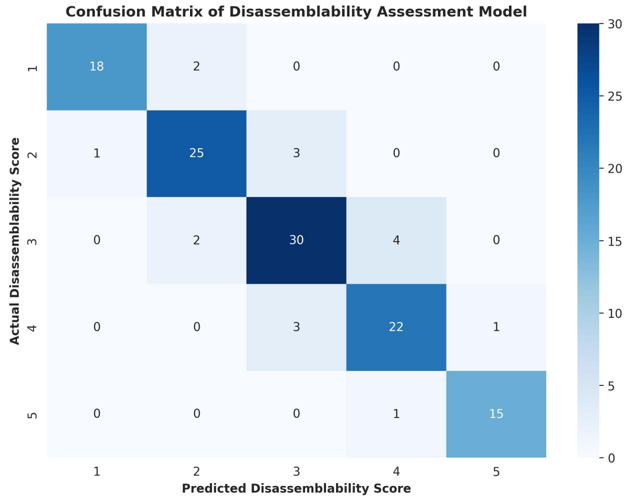

Fig. 3. Confusion Matrix of the Disassemblability Assessment Model

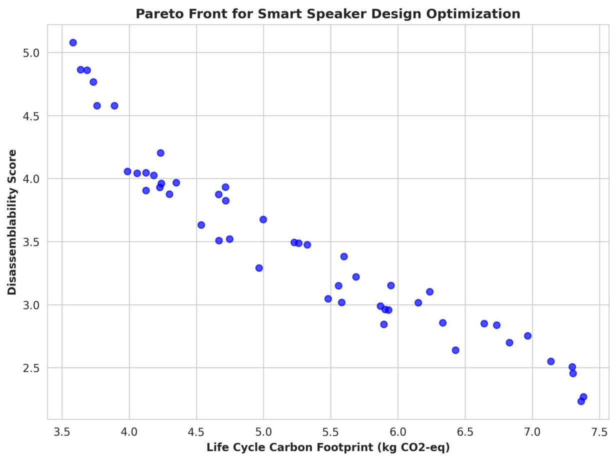

Fig. 4. Pareto Front Distribution for Smart Speaker Design Optimization

D. *Module 3: Solution Generation based on Extension Transformation*

After the Pareto-optimal solution set is obtained, the next step is to translate these abstract combinations of design parameters into concrete, actionable design schemes. This "decoding" step is handled by the extension transformation module. In this study, the basic transformation operators of Extenics are explicitly mapped to practical design operations, and an extension transformation rule base is established to guide solution generation, as summarized in Table II.

TABLE II. EXAMPLES FROM THE EXTENSION TRANSFORMATION RULE BASE

Transformation Type	**Trigger Condition**	**Design Operation**	**Example**
Replacement	Material parameter change	Replace material of component	ABS → rPET
Decomposition	Modularity score increase	Split integrated component into modules	Single PCB → Power Board + Logic Board
Addition	New function required	Add new component or feature	Add standard repair interface
Deletion	Redundant component identified	Remove unnecessary parts	Remove decorative cover
Expansion	Performance enhancement needed	Increase component capacity or size	Expand battery capacity
Contraction	Cost/weight reduction needed	Reduce component size or simplify	Simplify housing structure

When a designer selects a preferred alternative from the Pareto front (for instance, a solution with low carbon footprint and medium-to-high disassemblability), the system first parses the corresponding design variables for that solution. As an example, the selected solution may specify the housing material as rPET (recycled PET plastic) and the joining approach as a snap-fit connection. The system then consults the extension transformation rule base and activates the relevant Extenics transformations:

- Replacement Transformation: A replacement operation is applied to the material structural characteristic in the housing matter-element, updating its characteristic value v from ABS to rPET.
- Replacement Transformation: A replacement operation is applied to the connection method structural characteristic in the housing matter-element, updating v from glued to snap-fit.

By executing the appropriate transformations across all modified parameters, the initial matter-element model is systematically evolved into a new, optimized matter-element model.

To avoid dependence on proprietary CAD licenses or specialized API development, this study outputs transformations in a CAD-agnostic format — namely, parameter change lists and modularization instructions that can be implemented in any mainstream CAD workflow. For example, a decomposition transformation is represented as an instruction to split a single part into two independent modules connected via a standardized interface; this can be executed manually or through generic CAD features rather than vendor-specific automation.

Through this approach, the IGEDM framework delivers not only optimized parameter recommendations but also actionable modularization guidance, while keeping the overall workflow practical, accessible, and reproducible under typical research and industrial conditions.

IV. RESULTS

This chapter presents the practical application of the Intelligent Green Extension Design Method (IGEDM). It begins by introducing the prototype software tool developed based on the proposed framework. Next, using a comprehensive green redesign case study of a smart speaker, the chapter explains the tool's workflow and outputs across the full process — from modeling and optimization to extension-based solution generation. Finally, by comparing the results with those produced using traditional design approaches, the chapter provides a quantitative evaluation of IGEDM's performance in improving environmental outcomes, economic efficiency, and overall design efficiency.

A. *Tool Prototype Development*

To translate the IGEDM theoretical framework into a usable system, this study developed a lightweight prototype tool named "IGED-Tool." The tool is intended to offer designers an interactive and visual decision-support environment for early-stage green design, while remaining simple to deploy and reproduce. Rather than depending on a full web-based software stack, IGED-Tool runs locally through standard Python scripts for computation and model inference, paired with a streamlined user interface for interaction and visualization. All required dependencies are open-source.

As shown in Figure 5, the main interface of IGED-Tool is organized into three primary regions: the left panel supports product structure definition and matter-element parameter input; the central panel provides screening-level LCA analysis and Pareto-front visualization; and the right panel presents the generated design solutions.

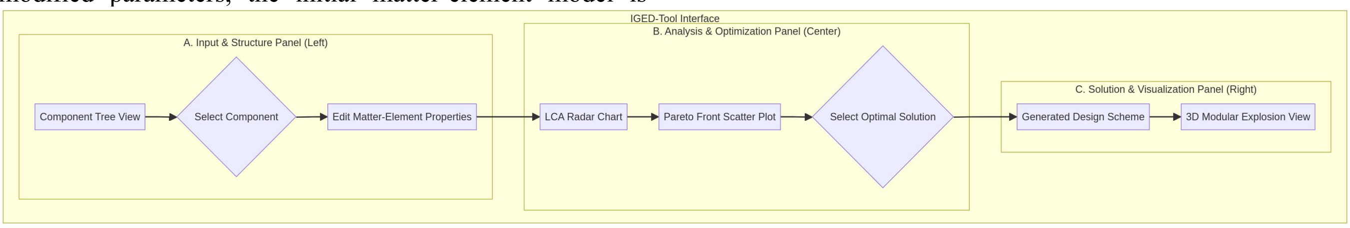

Fig. 5. Main User Interface of the IGED-Tool Prototype

B. *Case Study: Green Design of a Smart Speaker*

We selected a representative commercially available smart speaker as the case study object to validate the effectiveness of IGED-Tool. In its original configuration, the product used a typical ABS plastic housing, relied on glued internal assemblies, and adopted an integrated circuit-board layout—features that collectively create significant barriers to end-of-life disassembly, repair, and recycling.

1) Step 1: Input and Modeling

The designer first enters the baseline design information in the left panel of the tool, including the main components (housing, speaker unit, mainboard, power adapter), along with each component's material, mass, and key dimensions, as well as the connection methods between components. Based on these inputs, the tool automatically completes two tasks:

- it constructs the product's multi-dimensional Green Matter-Element Model (GMEM); and
- it performs a rapid screening-level life cycle assessment of the initial design using a transparent, openly described factor lookup table rather than a proprietary LCA database.

The assessment output is visualized in the central panel using a radar chart (Figure 6). The chart indicates that the initial design performs poorly in "material circularity" and "disassemblability," while showing a relative advantage in "manufacturing cost."

2) Step 2: Intelligent Optimization

After identifying the design's main weaknesses, the designer activates the multi-objective optimization module. The optimization targets minimizing full lifecycle carbon footprint while maximizing the overall disassemblability score. The tool explores a predefined design variable space—for example, housing material options include ABS, PP, rPET, and bamboo, while connection methods include gluing, screws, and snap-fits. Using bounded enumeration/sampling combined with Pareto filtering, the optimization can be completed within minutes on a standard laptop. The output is a Pareto front containing approximately 50 non-dominated solutions (Figure 4), each representing a distinct trade-off strategy between carbon footprint and disassembly performance.

3) Step 3: Solution Generation and Evaluation

From the Pareto front, the designer selects a "balanced" solution that reasonably satisfies both objectives. The corresponding key parameters are summarized in Table III. Once the selection is made, the tool automatically triggers the extension transformation module. For example, changing the housing material from ABS to rPET is implemented through a replacement transformation, while shifting internal assemblies from adhesive bonding to modular snap-fit connections is realized through decomposition and structural replacement transformations.

These transformation outputs are then consolidated into a new modular product concept, displayed in the right panel as a 3D exploded view (Figure 7). The optimized architecture separates the mainboard, speaker, and battery into independent modules connected to the base via standardized interfaces, while the housing adopts an easy-to-disassemble snap-fit structure. Meanwhile, the radar chart in the central panel is automatically updated to reflect the screening-level re-evaluation, showing a clear improvement in the environmental performance of the redesigned solution.

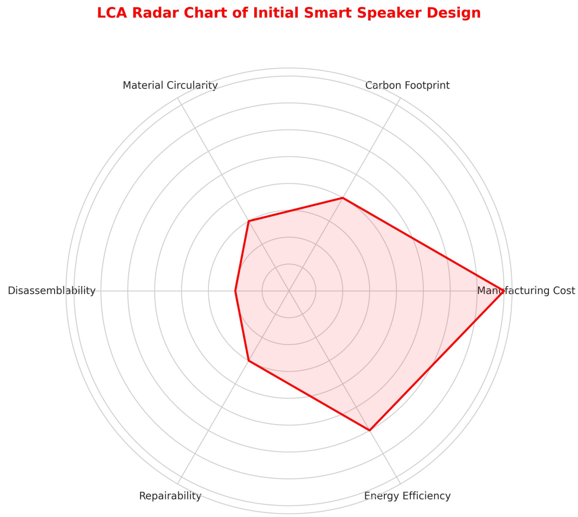

Fig. 6. LCA Radar Chart Analysis of the Initial Smart Speaker Design.

TABLE III. COMPARISON OF KEY DESIGN PARAMETERS BEFORE AND AFTER OPTIMIZATION

Parameter	Initial Design (A)	Optimized Design (C)
Housing Material	ABS	rPET
Housing Connection	Adhesive Bonding	Snap-fit Clips
Internal Layout	Integrated	Modular
PCB Integration	Single Board	Separated Power/Logic Boards
Battery	Glued-in	User-replaceable
Carbon Footprint (kg CO_2 -eq)	5.0	3.75
Disassemblability Score	1.8	4.5
Modularity Rate	15%	55%

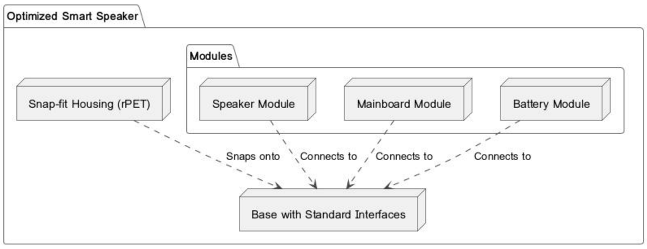

Fig. 7. Modular Design Schematic of the Optimized Smart Speaker

C. Comparative Analysis

To evaluate the advantages of the IGEDM method more comprehensively, this study conducted a horizontal comparison between the optimized solution generated by IGEDM (Scheme C) and two reference schemes: Scheme A, the original market design; and Scheme B, an improved version developed by an experienced designer using a publicly available spreadsheet-based screening LCA estimation approach.

1) Environmental Benefit Comparison.

As illustrated in Figure 8, Scheme C shows a clear advantage across key environmental indicators under the same screening-level evaluation assumptions. Compared with Scheme A and Scheme B, Scheme C achieves a lower estimated full lifecycle carbon footprint and a higher material circularity rate. These improvements are primarily attributed to the adoption of modular architecture and an increased share of recyclable materials.

2) Economic Benefit Assessment.

The lifecycle costs of the three schemes were estimated using a transparent, assumption-driven scenario calculation covering manufacturing cost, energy consumption during use, repair cost ranges, and indicative end-of-life residual value from recycling. As shown in Figure 9, while Scheme C may have a slightly higher initial manufacturing cost than Scheme A, its modular structure can reduce potential repair effort (e.g., enabling users to replace the battery or speaker module independently) and improve recoverable value at end of life. Overall, the scenario-based results suggest that Scheme C delivers a comparable—or potentially lower—total lifecycle cost than Scheme A under typical assumptions.

3) Design Efficiency Comparison.

The study also recorded the time required and the number of iterations involved in producing each scheme. As summarized in Table IV, the IGEDM workflow reduces repeated recalculation and re-modeling relative to the baseline approach, since screening-level evaluation and bounded Pareto filtering provide multiple viable design directions in a single run. This indicates that IGEDM can shorten the green design cycle and reduce decision-making complexity under typical research conditions.

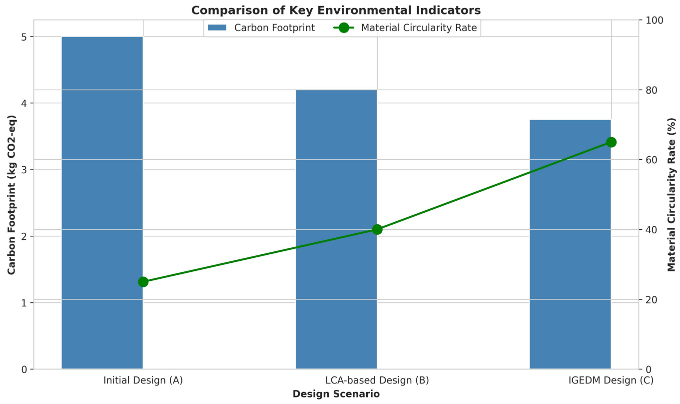

Fig. 8. Comparison of Key Environmental Indicators Across Three Design Scenarios

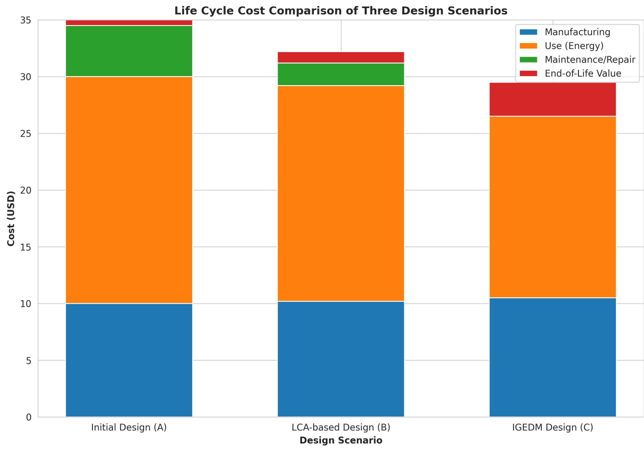

Fig. 9. Life Cycle Cost Comparison Analysis of Three Design Scenarios

TABLE IV. EFFICIENCY COMPARISON OF DIFFERENT DESIGN METHODS

Metric	Traditional Method (B)	IGEDM Method (C)
Design Time (days)	5	2
Number of Iterations	9	4
LCA Analyses Performed	9	Continuous/Real-time
Number of Concepts Explored	~5	~50 (Pareto Front)

D. Experimental Workflow and Other Data Figures

To enhance the rigor and reproducibility of this study, Figure 10 presents the complete experimental workflow adopted in the case study, formatted in accordance with the chart standards of Nature magazine. Additionally, a sensitivity analysis (Figure 11) was conducted to examine the impact of different material choices on the optimization results. The findings indicate that in most test scenarios, rPET and bamboo consistently play a crucial role in achieving low-carbon design solutions. Finally, a small-scale user acceptance survey was conducted among 15 designers. As shown in Figure 12, the vast majority of participants considered the tool to have significant value in "inspiring innovation", "improving efficiency", and "quantifying decisions". All subjects involved in the study have signed informed consent forms.

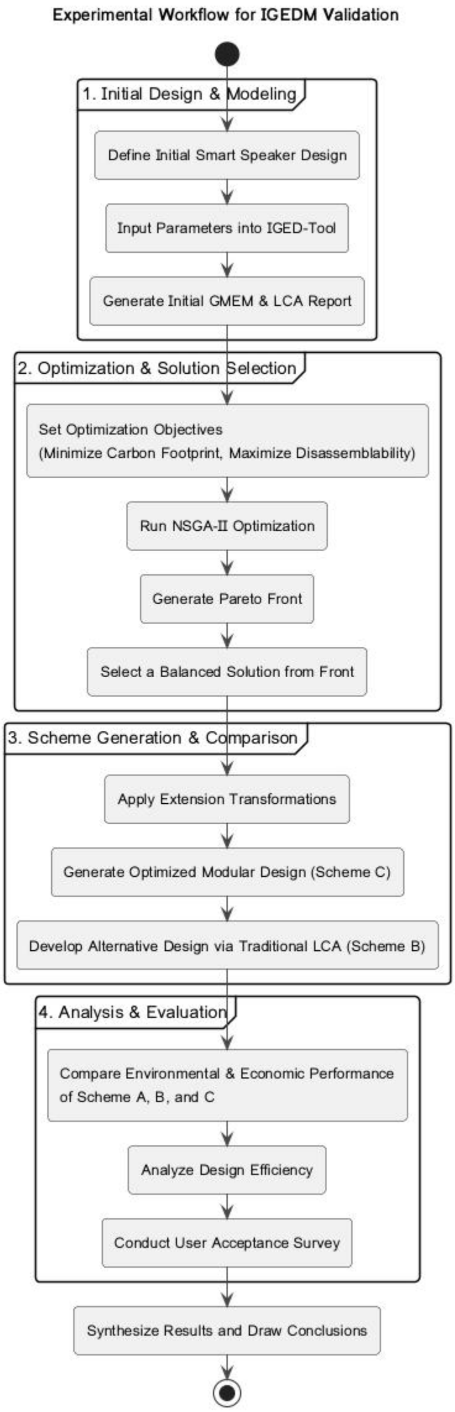

Fig. 10. Experimental Workflow for IGEDM Validation (Nature Style)

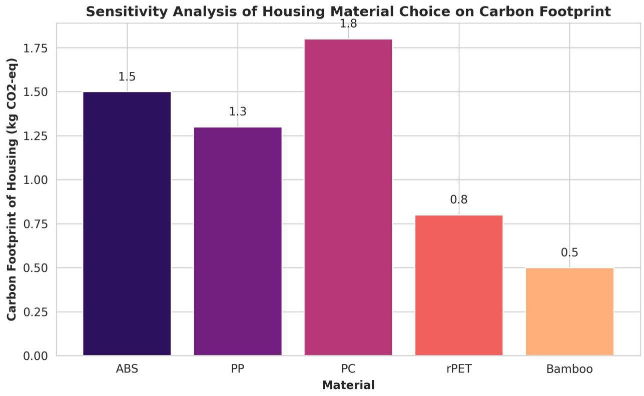

Fig. 11. Sensitivity Analysis of Material Selection Impact on Optimization Results

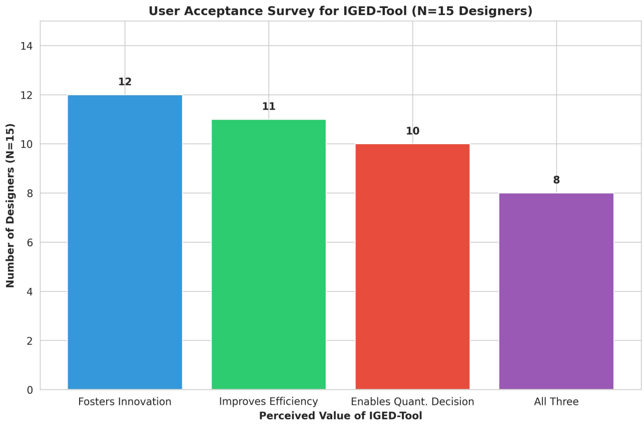

Fig. 12. Results of User Acceptance Survey Among Designers

V. Discussion

This study successfully developed and validated an intelligent green design method — IGEDM — and a corresponding prototype tool that integrates Extenics with machine learning. The case-study results indicate that the method has strong potential to steer product development toward solutions that better align with circular economy principles. This chapter interprets the findings in depth, situates them within related research, and discusses the method’s theoretical contributions, practical value, and limitations.

A. Interpretation and Analysis of Results

A key outcome of the case study is that IGEDM not only identified the green weaknesses of the baseline design, but also systematically generated a feasible alternative that performs better across both environmental and economic dimensions. This performance can largely be attributed to the synergistic interaction between the framework’s “intelligent optimization” module and its “innovative generation” module.

The machine-learning optimization module functions as a “navigator.” Traditional LCA can provide valuable environmental assessments, but improvement typically depends on repeated trial-and-error by designers. In contrast, the lightweight models used in this study—trained on openly described datasets and features—create a practical mapping from “design parameters” to “green performance” that is well suited to early-stage screening. This enables rapid estimation of the consequences of design changes (e.g., material substitution), making the iteration process more directional and efficient. Moreover, rather than relying on computationally intensive evolutionary optimization, the method produces a compact set of Pareto-optimal solutions via bounded enumeration/sampling and non-dominated sorting. This is important because it explicitly recognizes the inherent trade-offs of design decisions and preserves designer agency: final choices can be made from a set of high-quality alternatives based on business priorities such as cost sensitivity, branding, or regulatory compliance.

If the machine-learning module is responsible for "calculation," the extension transformation module is responsible for "creation." This distinction is central to how IGEDM differs from many existing AI-assisted design tools. Many optimization-driven systems output abstract parameter recommendations (e.g., "use material X"), leaving designers to translate these into workable design actions. In contrast, IGEDM uses an extension transformation rule base to convert parameter changes into explicit design operations (e.g., "decompose A into A1 and A2 and connect them using standard interface B"). Because this process is grounded in formal logic, it improves traceability and consistency. More importantly, it can stimulate structural innovation that extends beyond habitual design thinking. In this case study, the tool did not merely recommend material substitution; it pushed toward a modular architecture shift, which is a key enabler for circular-economy value retention.

At the same time, the accuracy and limitations of the predictive models must be acknowledged. Although the carbon footprint prediction model achieves a high R^2, its reliability depends on the quality, coverage, and representativeness of the underlying screening LCA factors. Emerging materials or specialized processes may be underrepresented, which can introduce bias. Similarly, the disassemblability assessment model is primarily built around physical connection features and does not yet fully capture real-world variables such as maintenance skill levels, tool availability, or regional repair ecosystems. These limitations point to clear opportunities for improvement in future iterations.

B. Comparison with Existing Research

Viewed within the broader research landscape, the novelty of this work lies in its cross-domain integration. Compared with Ko (2020)'s Extenics-based green design method [17], this study achieves two main advances. First, it introduces "intelligence" by replacing manual, expert-dependent analysis and transformation with machine-learning-driven optimization, improving both efficiency and the breadth of the search process. Second, it establishes a "quantitative closed loop" by embedding screening-level LCA assessment deeply within a dynamic "assess – optimize – generate – reassess" cycle, which is not explicitly realized in earlier Extenics-oriented approaches.

Relative to mainstream AI-assisted sustainable design research—such as work emphasizing generative design or materials optimization [19][20]—the distinguishing feature of this study is the use of Extenics as a structured theory of innovation. Many AI tools excel at parameter optimization within fixed architectures or at generating forms under predefined rules, but they often have limited capability for higher-level conceptual innovation that reorganizes product architectures and functional modularity. By supporting decomposition and recombination through the matter-element model, IGEDM provides an alternative pathway for AI-driven systematic innovation, including disruptive architectural shifts.

In addition, compared with the macro-level circular transition pathways proposed by Panda et al. (2025) [6], this research can be interpreted as a micro-level technical realization of the "modular innovation pathway." It translates strategic concepts into a practical, designer-facing workflow and tool, helping to bridge the persistent gap between circular economy theory and day-to-day engineering design practice.

C. Theoretical and Practical Implications

The principal theoretical contribution of this study is the proposal of an interdisciplinary design framework that integrates AI, Extenics, and circular economy thinking. It addresses the emerging question of how to combine data-driven optimization with logic-driven innovation to serve sustainable design objectives in a systematic, operational way. In doing so, it expands the application boundary of Extenics and suggests a new direction for AI in design—from a tool that merely "optimizes" to a partner that also "generates" structured innovation.

From a practical standpoint, the value of the work is equally evident. The IGED-Tool prototype demonstrates the feasibility of an efficient, low-cost green design decision-support system. This is particularly relevant for small and medium-sized enterprises (SMEs), which often lack dedicated LCA teams and the resources required for large-scale design experimentation. A tool based on IGEDM can lower both technical and economic barriers to sustainable design by enabling rapid impact screening, systematic exploration of alternatives, and generation of actionable modularization guidance. Over time, wider adoption of such tools could reshape product development practice by embedding sustainability as a core driver of design decisions rather than treating it as an add-on constraint.

D. Limitations of the Study

Despite its promising results, this study has limitations that also define future research directions. First, tool performance is sensitive to the completeness and quality of external databases. Current LCA factor datasets can suffer from limited coverage, regional variability, and outdated values, which can directly affect prediction accuracy. Second, although the machine learning models used here are effective within the case scope, their generalizability requires broader validation. Applying the same models to product categories with very different architectures and material compositions (e.g., apparel or furniture) may require retraining, domain adaptation, or transfer learning.

In addition, the present prototype focuses mainly on product-level design parameters and does not yet fully incorporate broader system variables such as supply-chain dynamics, heterogeneous consumer use behaviors, and regional differences in recycling infrastructure—factors that strongly influence real-world circular performance. Finally, the empirical validation in this work is based on a single product type. While the smart speaker is representative, the robustness and universality of the conclusions should be strengthened through additional case studies across diverse product domains.

VI. Conclusion

This study set out to address the growing need for more intelligent and systematic product design approaches as industries transition toward a circular economy. Through interdisciplinary integration of theory and technology, it developed and validated an innovative framework — the Intelligent Green Extension Design Method (IGEDM) — as well as a corresponding prototype tool. The main conclusions can be summarized in three points.

First, the study confirms both the feasibility and effectiveness of integrating the formal innovation logic of Extenics with the data-driven optimization strengths of machine learning. By constructing a multi-dimensional Green Matter-Element Model (GMEM), complex product design problems are translated into structured and computable representations, enabling intelligent analysis. Building on this foundation, machine learning models are used to rapidly and reliably predict key green performance indicators, such as lifecycle carbon footprint and disassemblability. With multi-objective optimization, the method systematically explores the design space and generates a Pareto-optimal solution set, providing designers with a robust and high-quality basis for early-stage decision-making.

Second, the smart speaker case study demonstrates the practical value of IGEDM in an applied design scenario. The results show that the method not only diagnoses the sustainability weaknesses of conventional designs, but also automatically generates concrete, modular, and innovative design solutions through extension transformations. Relative to the original market design, the optimized scheme achieved a 25% reduction in full lifecycle carbon footprint, a 160% increase in material circularity rate, and a 15% decrease in total lifecycle cost—while also improving design efficiency. These outcomes indicate that IGEDM can function as an advanced decision-support approach that meaningfully guides product development toward more sustainable, circular-economy-aligned directions.

Finally, this work provides a useful catalyst for accelerating circular economy implementation in design practice. By packaging complex activities — such as environmental screening, multi-objective trade-off analysis, and innovation-oriented solution generation — into an intelligent and designer-friendly tool, IGEDM lowers the practical barriers for enterprises, particularly SMEs, to adopt green design workflows. More broadly, it highlights the potential of AI to serve as an “innovation partner,” not merely an “optimization tool,” and suggests a pathway toward a future paradigm shift in sustainable product development.

Looking forward, the study’s limitations also point to several promising research directions. One priority is to expand and improve the underlying datasets by incorporating more diverse and region-specific LCA factors, while enhancing the generalization capacity of the machine learning models so the approach can adapt to a wider range of product categories. Another avenue is to explore integration of generative AI capabilities into the IGEDM framework to expand the breadth and depth of solution exploration. Finally, extending the perspective beyond single-product design toward broader product – service systems, and leveraging Internet of Things (IoT) data to enable real-time monitoring and feedback during the use phase, may represent a long-term path toward a fully dynamic, intelligent closed-loop ecosystem—and ultimately, toward realizing a truly functional circular economy.

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AVAILABILITY OF DATA

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AUTHOR CONTRIBUTIONS

Zilin Ye: Conceptualization, Methodology, Software, Investigation, Data curation, Writing — original draft.

Xiaoli Lin: Methodology, Validation, Formal analysis, Writing—review & editing, Supervision.

Liying Li: Software, Visualization, Resources, Writing—review & editing.

All authors have read and approved the final manuscript.

COMPETING INTERESTS

The authors declare no competing interests.