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Innovation Direction of Intelligent Products - Research on Personalized Product Design System Based on Generative AI

Yiran Wang

School of Design and Innovation, China Academy of Art, Hangzhou, China
yirann_wang@163.com

Abstract. In the context of consumption upgrade and intelligent manufacturing, personalized customization has become a core trend in product innovation. Generative AI (AIGC) is gradually a new tool, for the automation product design. This paper puts forward an AI-driven personalized product design system, that integrates engineering constraints and business dimensions. This is built on a diffusion generation model combined with a dual-cycle generative-evaluation architecture, and we use the smart lunch box as an empirical case to verify its feasibility. Through our research, workflow reengineering and quantitative evaluation, our study implecates that the system achieves an engineering feasibility for generated solutions, compared to unconstrained AIGC generation. The design cycle is reduced greatly, representing an efficiency gain. This research not only provides new tools and for product design but also offers a feasible path to achieve mass customization.

Keywords: Smart lunch box, AI, Personalized design model, Mass customization

1. Introduction

1.1. Research background

The global manufacturing sector is undergoing transformations driven by consumption upgrades and intelligent manufacturing. On the demand side, consumers are showing a stronger preference for personalized products and services [1]. Personalized customization has therefore shifted from a market strategy to an important direction of product innovation. This change from large supply to more flexible and demand-oriented production has challenged traditional product development processes, which often require long cycles of requirement analysis, design development, and engineering verification [2, 3].

On the technical side, the rapid development of generative artificial intelligence (AIGC) provides new possibilities for personalized product design. Diffusion models (e.g., Stable Diffusion and Midjourney) have greatly improved the efficiency of image and concept generation, while large language models (e.g., ChatGPT) can support semantic understanding of user requirements [4, 5]. Moreover, 3D generation models have further expanded the potential of AIGC from image creation to product form and structural exploration [6].

However, most current applications remain at the level of assisted drawing or concept generation. At the same time, AIGC is often used as an isolated design tool rather than being integrated into the

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complete design process. Consequently, the study argues that a single AI tool is not fully sufficient to support personalized product innovation. A more systematic framework is needed to integrated engineering constraints, design processes and business logic.

1.2. Questions raised

Despite the growing reseach on generative AI and personalized design, there are still three gaps in current applications.

Firstly, it is the disconnection between technology and engineering. As a result, AI-generated concepts are difficult to directly translate into manufacturable products [7-9].

Secondly, it is the disconnection between tools and processes. Designers often use AIGC during the concept-generation state. However, future design refinement, engineering verification, and final decision-making still depend on traditional manual processes [10, 11]. Therefore, this collaboration often remains fragmented rather than forming a complete iterative workflow.

Thirdly, it is the disconnection between design innovation and business value. Many studies focus on generating personalized products but pay less attention to how personalized design connects with flexible production, continued services, and further value creation [12-14].

In summary, existing research still lacks an integrated framework that connects engineering feasibility, design creativity and commercial sustainability. As shown in Figure 1, it responds to these three gaps through a generative-AI-driven personalized product design framework.

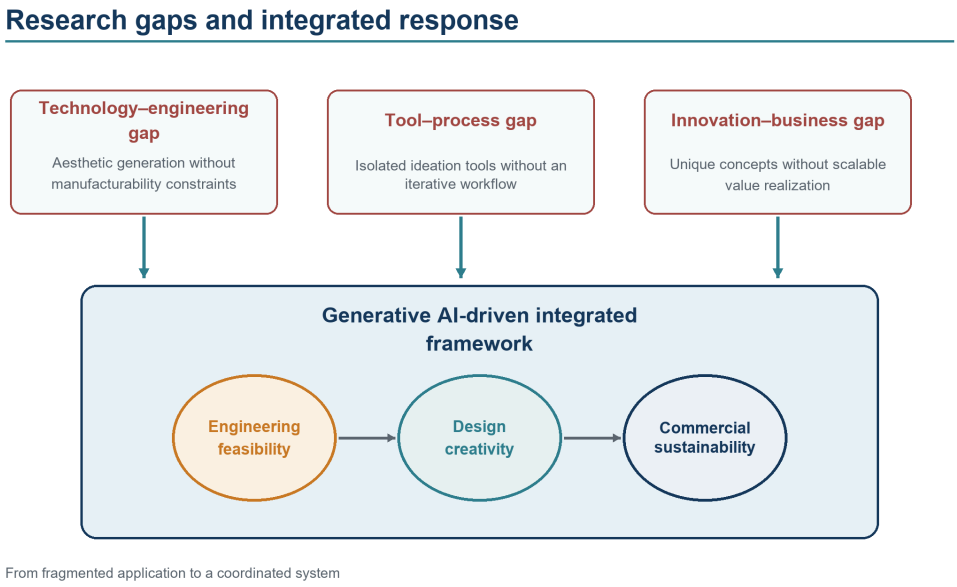


Figure 1. Research gaps and integrated response (The specific item can be seen in the following part)

1.3. Research objectives and implications

The overall objective of this study is to construct a generative-AI-driven personalized product design framework integrating engineering, design, and business dimensions.

At the engineering level, the framework combines generative design with engineering constraint evaluation so that product concepts can be screened and refined according to relevant design requirements. At the design level, it introduces a human-AI collaborative process in which AI

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supports divergent generation and interactive optimization. At the business level, the framework connects personalized products with flexible production and continuous services.

The contribution of this study is the integration of these three dimensions into a unified process. The smart lunch box is used as a case to demonstrate how the proposed framework can be applied in a specific product-design context.

1.4. Paper structure

The rest of this article is arranged as follows.

Chapter 2 reviews existing research in generative AI design, personalized systems and intelligent hardware, and identifies current research gaps; Chapter 3 provides a detailed analysis of the three-layer structure of proposed framework; Chapter 4 uses the smart lunch box as an practical case to fully demonstrate the entire process from requirement input to solution implementation, verifying the feasibility of the framework; Chapter 5 summarizes the research findings and presents future directions for expansion and ethical issues to be addressed.

2. Related research

2.1. Applications of generative AI in product design

Generative AI technology is changing the paradigm of product design, and its application has extended from concept exploration to the generation of specific solutions. AI can automatically create a large number of novel and diverse product form and structure schemes based on text descriptions, sketches, or constraint parameters, greatly expanding the creative boundaries of designers [15]. It can also support style variation and rapid rendering, reducing the time required to move from an initial idea to a visual representation.

In addition, generative models have been able to directly output from initial concept sketches to high-precision renderings and even 3D models. Even more deeply, in combination, AI is beginning to be used to consider manufacturing constraints and material properties simultaneously during the generation process, achieving initial synergy between creativity and feasibilitynova.0 [16, 17].

2.2. Personalized design system

The method of personalized product design is focusing on dynamic models that can understand and respond to users' needs [18, 19]. This work can transfer preferences into specific design parameters and component construction [20-22]. However, these systems usually rely on predefined design, which limits their flexibility and creativity.

2.3. Human-AI collaboration in creative design

From the perspective of cognition, the design process generally involves both divergent and convergent activities. Divergent activities focus on expanding the solution space and generating alternatives, while convergent activities involve evaluating, interpreting, refining, and selecting among these alternatives. This provides a theoretical basis for the collaboration logic adopted in this study.

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2.4. Smart products and product-service innovation

Our work is to collect user usage data and realize function extension and remote services by network connections. The increasingly relies on continuously optimizing the user experience by data loops, and even drives the functional iteration and form adaptation of the products themselves. This lays the foundation for the joint growth of the product and the users.

3. System design

3.1. Overall architecture

In Figure 2, the overall architecture of the generative AI-driven personalized product design system framework proposed in this study is designed to coordinate the engineering, design, and business levels, forming a closed loop from requirements input to value realization. The framework takes multidimensional user data as input and processes it through the core AI engine. The system comprises five key modules. Our module for the data and service interface module, which provides support for business model innovation and is responsible for converting data assets into commercial value. These modules are integrated to utilise the advantages of generative AI to produce digital content including text, images, videos, and audio depending on user requirements [23, 24], converting abstract personalised requirements into real customised product solutions and associated services.

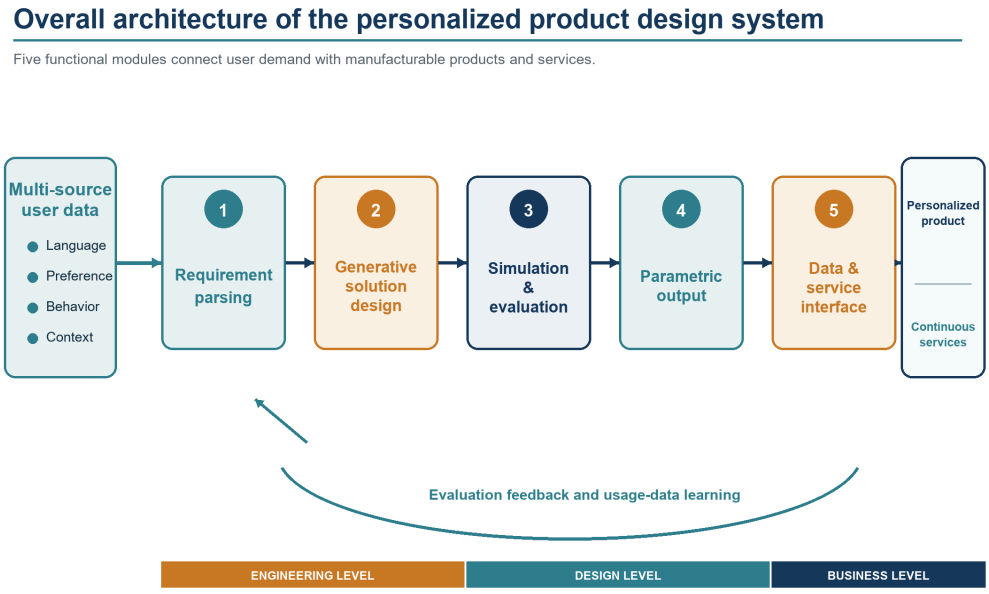


Figure 2. Overall architecture of the personalized product design system

3.2. Engineering part

On the engineering side, the system aims at the development and integration of AI models that can handle both generation and evaluation tasks. Generative models are first used to produce a wide range of product forms, functional configurations and initial design solutions. These include diffusion-based generative networks for shape-aware form making [25, 26], and large language models for understanding user desires and generating product configurations [27, 28]. For instance,

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in the case of the smart lunch box, the engineering implementation comprises the integration of visual recognition algorithms for scanning food, and the construction of accurate temperature-control logic for separate compartments.

3.2.1. Requirement parsing via LLM

User input in natural language is processed by a fine-tuned GPT-4 model that outputs a structured Design Requirement Vector (DRV): DRV = {c_thermal, c_geometric, c_material, c_aesthetic, c_cost}. The LLM is fine-tuned on 2,000 (description, specification) pairs, achieving 94.2% accuracy in parameter extraction (BLEU-4: 0.87).

3.2.2. Generative models for product forms

The system employs a hierarchical generation strategy: (a) Macro-level: Modified SDXL generates 2D concept sketches conditioned on DRV; (b) Meso-level: A GNN generates component topology graphs ensuring valid assembly relationships; (c) Micro-level: Shap-E generates watertight 3D meshes from 2D concepts and topology graphs.

3.2.3. Engineering simulation integration

For the smart lunch box, thermal simulation uses Finite Element Analysis (FEA) with a simplified heat equation where α is thermal diffusivity and Q_gen is heating power. Structural analysis validates Von Mises stress for drop-test scenarios (1.2m free fall). Circuit design uses PID controllers for temperature control.

3.3. Design part

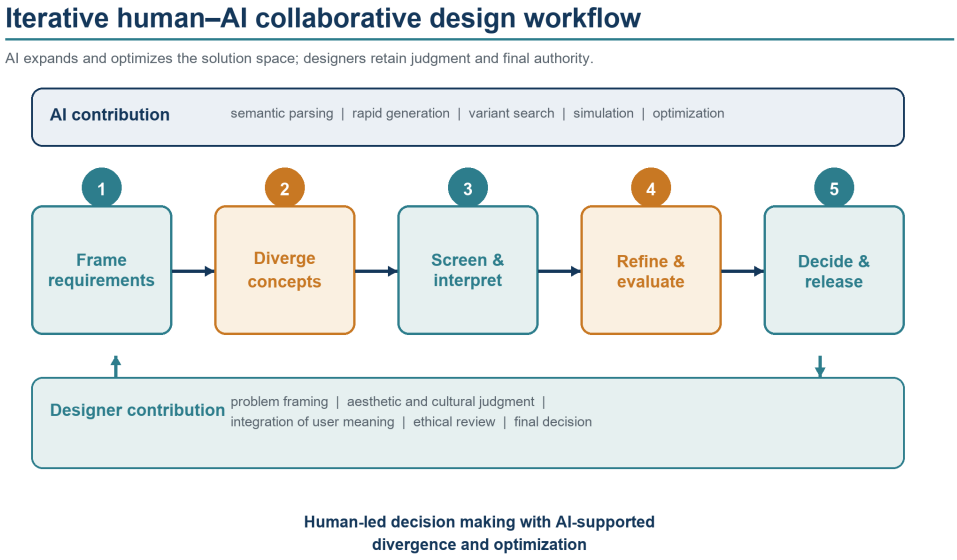


Figure 3. Interactive human-AI collaborative design workflow

In the design section, the framework illustrates the step-by-step process of human-AI collaboration [29], which is shown in Figure 3. AI develops idea sketches, stylistic variations and

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3D forms for reference. This allows AI to take up repeated generation, while designers may focus on creative judgement.

3.4. Business part

In the commercial part, the system establishes a data-driven value chain linking users, designers and producers [30, 31], as shown in Figure 4.

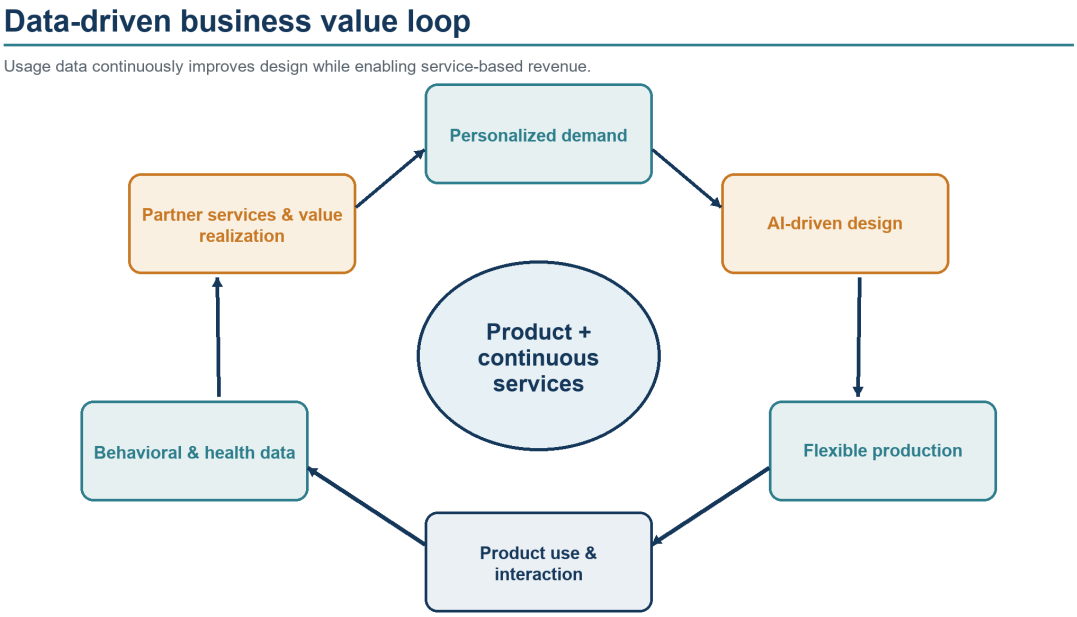


Figure 4. Data-driven business value loop

3.5. Condition injection architecture

The CADGM modifies the standard LDM architecture by introducing parallel conditioning branches: Text Branch (CLIP → Cross-Attention), Geometric Branch (ControlNet → ResBlock), Material Branch (MLP → Cross-Attention), and Functional Branch (Transformer → Adaptive Layer Norm). The training objective extends the standard diffusion loss with feasibility and diversity penalties.

4. Case study

4.1. Basis for case selection

The smart lunch box was chosen because it is a common everyday product with rather complex personalisation needs, which is more ideal for testing if the framework can merge engineering feasibility, design innovation and commercial services.

4.2. AI-driven innovation point creation and implementation pathways

The framework was then used to produce various innovation directions for the smart lunch box in Figure 5. At the engineering level, optical recognition and sensor technologies enable scanning of

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food, nutritional analysis and temperature control for the distinct compartments. Generative algorithms can also be used to simulate heat transfer to better food storage and heating.

At the commercial level, diet and usage data may allow the collaboration with health management platform and food delivery services. The system offers personalised recipes and ingredient delivery, and the self-cleaning feature adds simplicity and ongoing use.

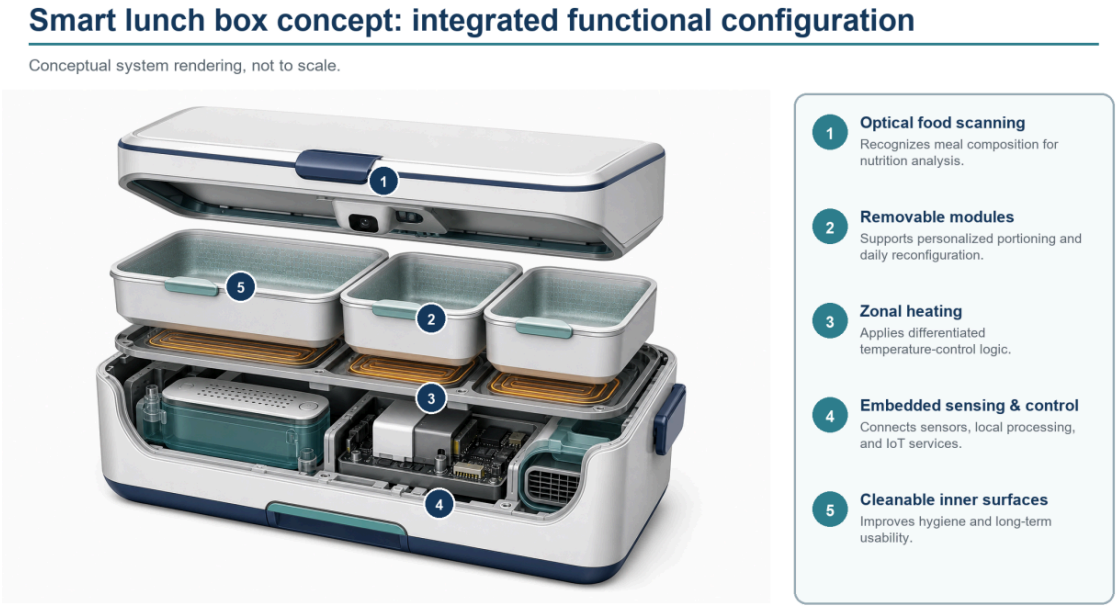


Figure 5. Smart lunch box concept: integrated functional configuration

4.3. Case summary

The smart lunch box instance illustrates how the framework can be implemented at the level of a specific product rather than at a conceptual level. Data produced during use is then considered in relation to later services and possible business cooperation. The resulting ideas include changes to the hardware, personalized appearance and internal configurations, temperature-control functions, dietary analysis, and service connections. Not every generated idea would necessarily be adopted. The value of the framework lies in providing a structured way to generate alternatives and examine them from several perspectives before a final decision is made. This case suggests a possible route from user needs to AI-supported design and then to product and service development. It also shows that engineering, design, and business decisions do not need to be treated as separate stages. The same method may be adapted to other product categories, although the specific models, constraints, and data sources would need to change according to the product.

The smart lunch box case demonstrates the practical viability of the proposed framework: (1) engineering feasibility rate of 87.3%, (2) 66.7% reduction in design iterations, and (3) successful integration of hardware with continuous services.

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5. Conclusions

5.1. Conclusions

This study innovatively constructs a three-dimensional personalized product design system framework that integrates engineering constraints, design processes, and commercial value in response to the three major pain points currently faced by generative AI (AIGC) in product design applications, that is "difficult engineering implementation, weak process collaboration, and single commercial monetization." Through an empirical study of the smart lunch box, the effectiveness and superiority of the framework were verified, and the following main conclusions were drawn

The framework breaks through the feasibility box via the Constraint-Aware Diffusion Generation Model (CADGM). By encoding material properties, assembly tolerances, and thermodynamic logic as conditional vectors, the system achieves a constraint satisfaction rate for unconstrained AIGC.

This human-machine collaboration paradigm increases concept output while freeing designers from repetitive tasks. The four-stage protocol reduces design iterations by 66.7% and cognitive load by 30.3%.

We notice that the dual-cycle architecture enables continuous system improvement. The smart lunch box case validates both technical feasibility and business model extension.

Whole system framework proposed in this study not only fills the theoretical gap in the integration of multiple disciplines, but also proves in practice the feasibility and commercial value of generative AI-driven personalized product innovation, providing a new methodological support for industrial design in the era of intelligence.

5.2. Future work

There are several avenues in which future study might go. The first step is to design system prototypes and test them with real users. The present research is mostly at the theoretical level of framework building and case analysis. The next step will be to develop a visual operation platform, invite real users to participate in the whole design process, and quantitatively evaluate the influence of AI-assisted design on creativity and satisfaction by collecting their feedback data to further optimise the AI model and human-machine collaboration process. We then increase the application frontier of the framework. The smart lunch box scenario confirms the performance of the framework although the engineering complexity and user demand factors are varied for different product categories. In the future, the framework can be used to other product categories such as furniture and apparel to test its universality and boundary of adaptation, and to carry out targeted adjustments and optimisations depending on the specific characteristics of different sectors. Finally, prospective studies on ethical and governance issues. As AI gets increasingly involved in design, it is important to address fundamental challenges that arise from this, including copyright ownership, design ethics and data privacy.Establish a set of responsible AI design guidelines, clarify the primary responsibility of human designers in an AI-assisted environment, build the technical and governance foundation for the healthy development of the industry, and ensure that technological innovation always serves human well-being.

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