# Leveraging Generative AI for Integrated Design Optimization: A DfX Framework for Innovation and Efficiency

Aya El Montassir[1,3†], Maryam Benaida[2,3†], Ibtissam El Hassani[3,3†]

Contributing authors: a.elmontassir@edu.umi.ac.ma; m.benaida@ensam.ac.ma; i.elhassani@edu.umi.ac.ma;
†These authors contributed equally to this work.

**Abstract**

The integration of generative AI into product design offers a transformative approach to addressing the challenges of modern development processes, including the need for rapid innovation, cost efficiency, and sustainability. This paper presents a novel framework that combines generative AI with Design for X (DfX) principles to streamline and enhance product design workflows. The framework automates the generation of detailed object descriptions, explores innovative design alternatives, and provides tailored specifications for diverse design goals, such as manufacturability, usability, and reliability. A validation study using a wristwatch design demonstrates the framework's ability to reduce analysis time, optimize material usage, and generate actionable insights aligned with industry standards. The results highlight the potential of generative AI to redefine product development, enabling designers to achieve efficiency and innovation while addressing the demands of modern engineering and sustainability. This work establishes a foundation for further exploration of AI-driven tools in multidisciplinary design contexts.

**Keywords:** Generative AI, Product Design, Design for X (DfX), Automation

# 1 Introduction

Product design has never been an easy or linear process but one that involves striking a fine balance between innovation, functionality, cost-effectiveness, and sustainability. Older methods of design are typically highly dependent on manual expertise, which is valuable but slow and unscalable when dealing with complex challenges. With mounting pressures for quick development cycles, green solutions, and accuracy in engineering, there exists a crying need for sophisticated tools capable of improving and optimizing the design process.

Generative AI is a revolutionizing technology in this arena, delivering unprecedented capability in terms of creativity, optimization, and analysis. Employing machine learning models, designers can now automate exploration of design alternatives, integrate multiple Design for X (DfX) concepts, and generate actionable insights based on a particular goal. Not only does it accelerate the iterative nature of product development but also makes the designs manufacturable, usable, reliable, and sustainable right from the inception.

We propose a new paradigm that integrates generative AI with rigorous DfX principles to revolutionize product design workflows. By removing lengthy analysis and providing structured recommendations, the paradigm addresses some of the key issues faced by traditional methodologies. Through a validation study that uses a wristwatch design example, we demonstrate how the paradigm may be employed for generating detailed object descriptions, exploring novel alternatives, and tailoring specifications to cater to diverse design goals. This study finds the potential of generative artificial intelligence in transforming product design to enable designers to attain efficiency, stimulate innovation, and satisfy the demands of the new industry.

# 2 Literature review

## 2.1 Role in Ideation and Prompt Refinement

Generative AI is revolutionizing product design by enhancing ideation processes and empowering designers to create innovative and precise concepts. Acting as a co-creator, it helps designers explore alternatives, refine ideas, and craft targeted prompts. By leveraging machine learning to analyze extensive design datasets, it uncovers patterns, generates novel forms, and offers solutions beyond human intuition. Studies, such as [Designer-Generative AI Ideation Process][1], show that Generative AI improves ideation through iterative keyword testing, semantic analysis, and prompt optimization, enabling designers to align visuals with product goals.

Workshops validate its role in fostering creativity while reducing cognitive load. For instance, participants using AI tools in urban furniture design demonstrated higher creativity and lower mental effort than those without AI ([Can Artificial Intelligence Support Creativity in Early Design Processes?][2]). These tools streamline repetitive tasks like keyword categorization, allowing designers to focus on creative decisions and engage in reflective dialogue with the AI.

However, Generative AI has limitations, often requiring manual intervention for usability-focused innovations or functional details. This emphasizes the importance of prompt engineering and the designer's role in guiding AI. As AI continues to integrate into workflows, fostering collaboration between human creativity and AI capabilities will ensure its transformative potential is fully realized.

### 2.2 Simulating Team Dynamics with AI: The Impact of DesignGPT on Product Design Workflows

Generative AI frameworks like DesignGPT are transforming product design by simulating team dynamics through multi-agent systems. Unlike standalone AI tools, DesignGPT integrates multiple AI agents representing roles such as market analyst, product engineer, and design strategist, enabling designers to interact with them as if they were colleagues. These agents, equipped with domain-specific knowledge, facilitate natural language collaboration, allowing designers to ask questions, refine ideas, and receive specialized insights tailored to the design process.

Experimental validation highlights that DesignGPT outperforms single-agent tools by improving design task efficiency and quality. This iterative, dialogue-driven approach enhances workflows by offering diverse perspectives across technical, creative, and strategic domains, fostering faster decision-making and greater creativity. DesignGPT demonstrates how multi-agent systems can seamlessly integrate AI into design environments, empowering designers to harness collective expertise and optimize the design process in ways single-agent systems cannot [3].

### 2.3 The Role of Generative AI in Enhancing Creativity and Efficiency in Product Design

Generative AI is transforming product design by enhancing creativity and efficiency, acting as a collaborator that automates repetitive tasks and supports designers in creating innovative outputs. Frameworks like A Task-Oriented Framework for Generative AI in Design [4] and Generative Design: Reframing the Role of the Designer in Early-Stage Design Process [5] highlight the pivotal role of generative AI in three key forms of creativity: combinational, exploratory, and transformational. Combinational creativity enables AI to merge existing elements into novel concepts, exploratory creativity expands possibilities through variations, and transformational creativity reinterprets and reinvents design concepts, pushing beyond traditional boundaries.

By automating tasks such as rendering, 3D modeling, and trend analysis, generative AI allows designers to focus on groundbreaking innovations. For instance, turning sketches into detailed renders, generating real-time 3D models, and leveraging predictive analytics to anticipate trends empower designers to iterate quickly and make data-driven decisions. Studies, including A Study on the Practical Use of Generative Design in the Product Design Process [6], demonstrate how AI-driven tools streamline workflows by producing optimized, high-performing solutions based on constraints and input parameters. This approach enables deeper problem exploration and solution refinement while automating tasks like geometry adjustments and structural analysis.

Ultimately, generative AI fosters a collaborative, iterative design process, enhancing both the structural integrity and aesthetic quality of outputs. By freeing designers from routine tasks, these tools act as catalysts for transformational creativity and efficiency, driving innovation and advancing product design to unprecedented levels of sophistication.

### 2.4 Autodesk Generative Design: Enhancing Structural Optimization in Product Design

Autodesk's Generative Design, embedded within the Fusion 360 platform, stands as a key example of how generative AI can significantly enhance the product design process. As explored in the study Generative Design: An Explorative Study by Buonamici et al. [7], Autodesk's software enables designers to generate a range of optimized design solutions by inputting parameters such as material type, load constraints, and manufacturing methods. This AI-driven approach leverages algorithms to explore a multitude of potential designs, helping designers find the most efficient solutions in terms of performance, cost, and manufacturability. The study emphasizes the software's capacity to not only provide multiple alternative solutions but also to ensure that the generated designs are manufacturable, addressing a critical aspect of the design process. By automating structural optimization and exploring various design possibilities, Autodesk's Generative Design helps streamline workflows, allowing designers to focus on more complex and creative elements of product development. The software's ability to integrate with other CAD tools further enhances its utility, providing a cohesive platform for both design ideation and final product realization. Through practical case studies, Autodesk's Generative Design has been shown to significantly improve the efficiency and effectiveness of the design process, making it a valuable tool in the field of product design.

### 2.5 Generative AI Tools in Product Design: Autodesk and Siemens NX

Generative AI tools such as Autodesk's Generative Design and Siemens NX highlight the transformative impact of AI in product design. Autodesk's tool, integrated within Fusion 360, facilitates structural optimization by generating multiple design solutions based on input parameters like material type, load constraints, and manufacturing methods. As shown by Buonamici et al. [7], it enhances efficiency by ensuring manufacturability and streamlining workflows, allowing designers to focus on creative tasks.

Similarly, Siemens NX leverages AI-driven generative design through its Algorithmic Feature, a visual programming tool that simplifies complex design creation for non-programmers. As Rawat and Tiwari [8] highlight, this tool empowers designers to explore diverse, optimized design alternatives while maintaining workflow efficiency through features like associativity and customizability. Both tools exemplify how generative AI supports innovation and efficiency, offering practical solutions for design challenges and pushing the boundaries of creativity in product development.

## 2.6 Design for X (DFX): A Systematic Review

The concept of Design for X (DFX) offers a versatile framework for optimizing various product characteristics, where "X" represents attributes such as assembly, ergonomics, reliability, cost, and safety. The article "A Systematic Review About Design For X" [9] provides a detailed analysis of the methodology's historical context, current state, and research gaps. Through a systematic literature review of 5,842 articles, the authors identified 18 key studies, revealing a notable lack of tools and methods to assist designers in selecting the appropriate "X" during product development.

The study highlights DFX's potential to enhance product quality, reliability, and cost-effectiveness by integrating these considerations from the early design stages to the end of the product lifecycle. However, it emphasizes the need for further research to develop methodologies that support informed decision-making for optimizing specific product attributes. This review is a valuable resource for advancing DFX practices, providing insights into existing challenges and areas for future exploration in product development.

# 3 Framework

## 3.1 Pipeline

The proposed framework for integrating generative AI into product design provides a structured and systematic approach, ensuring each stage of the process contributes effectively to the overall design optimization. This framework is divided into six essential steps, which collectively transform raw design inputs into actionable insights aligned with DFx (Design for X) principles:

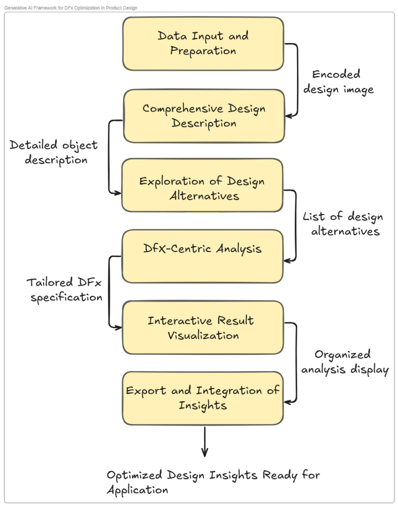


**Fig. 1** Generative AI pipeline for DFx Optimization in Product Design

1. **Data Input and Preparation** The process begins with the upload of a design image or file. This data is standardized and formatted to ensure compatibility with AI-driven analysis tools. Proper preparation at this stage ensures smooth processing and accurate outputs.
2. **Comprehensive Design Description** At this stage, the system analyzes the input data to generate a detailed description of the object. This includes identifying components, estimating dimensions, determining material properties, and outlining the key features and intended uses. This serves as the foundation for subsequent design evaluations.
3. **Exploration of Design Alternatives** Using the initial description as a base, the system explores alternative design options. These include modifications to components, substitutions for materials, ergonomic improvements, and innovative ideas. The system also identifies trade-offs between options, balancing factors like cost, performance, and sustainability.
4. **DfX-Centric Analysis** The framework focuses on specific DFx objectives, such as manufacturability, reliability, usability, and sustainability. For each selected category, the system generates detailed specifications, requirements, constraints, and recommendations tailored to the product's goals and operational context.
5. **Interactive Result Visualization** To ensure the analysis results are easy to interpret, the framework presents them in a clear, organized format. Users can navigate through different sections, such as design descriptions, alternatives, and DFx analysis, to gain a comprehensive understanding of the insights.
6. **Export and Integration of Insights** Finally, the framework consolidates all analysis outputs into a structured format, typically as a downloadable report or file. This enables seamless integration of the insights into further design, production, or review processes.

## 3.2 Proof of concept

The proof of concept demonstrates the practical application of the proposed framework to validate its effectiveness in leveraging generative AI for product design optimization. This section explains how the methodology was implemented step-by-step, detailing the tools, processes, and results achieved during the validation phase. To validate the framework, a proof of concept was implemented using OpenAI's GPT-4 model. The model was chosen for its advanced capabilities in natural language understanding and generation, enabling it to analyze complex design data and generate actionable insights. The implementation followed these key steps:

1. Tools and Technologies
    - **Model:** GPT-4 powered the analysis, delivering detailed descriptions, alternative designs, and DFx specifications.
    - **Development Platform:** Python was utilized for data processing, model interaction, and application logic.
    - **Interface:** Streamlit provided a user-friendly platform for presenting analysis results interactively.

- **Data Format:** JSON was used to structure outputs, ensuring clarity and integration with external systems.

2. Workflow

    - **Data Preparation:** Design images were uploaded and encoded into Base64 format to ensure compatibility with GPT-4 inputs.
        - *Analysis:* GPT-4 processed the design data based on carefully designed prompts, generating detailed outputs:
        - *Object descriptions:* Components, dimensions, materials, and intended use.
        - *Design alternatives:* Material substitutions, ergonomic improvements, and innovative solutions.
        - *DFx specifications:* Requirements and recommendations for manufacturability, sustainability, and usability.
    - **Visualization:** Results were displayed in an interactive format, allowing users to explore the outputs through a structured interface.

3. Outcome The proof of concept successfully demonstrated the practical application of generative AI in product design. It automated critical stages of the process, provided structured insights tailored to DFx goals, and offered a user-centric platform for exploring results.

This implementation validated the framework's ability to transform raw design inputs into actionable insights, paving the way for efficient and innovative product design.

# 4 Results

The validation of the framework was conducted using a classic analog wristwatch design as the test case. This allowed the system to showcase its ability to analyze, optimize, and generate actionable insights tailored to specific Design for X (DfX) objectives, including cost and sustainability. Below, we present the results of this validation process.

## 4.1 Validation Setup

To test the framework, a design image of a wristwatch was uploaded. The chosen design exemplified simplicity and functionality, making it an ideal candidate for evaluating the system's capabilities.

**Fig. 2** Input Design Image: Classic Analog Wristwatch.

The analysis focused on two key DFx objectives:

- **Cost:** Ensuring affordability through material selection and streamlined manufacturing processes.
- **Sustainability:** Prioritizing environmentally conscious materials and design practices.

## 4.2 Object Description

The framework provided a detailed description of the wristwatch, extracting key attributes:

- **General Overview:** Identified as a minimalist analog wristwatch, combining simplicity with durability.
- **Components:** The system identified key elements such as the watch case, leather strap, adjustable buckle, crown, and hands.
- **Dimensions:** Approximate measurements included a length of 25 cm, width of 4 cm, and height of 1 cm.
- **Materials:** Suggested materials included stainless steel for the case, leather for comfort, and sapphire crystal for scratch resistance.
- **Use Case:** The design was positioned for daily wear, prioritizing comfort and reliability.

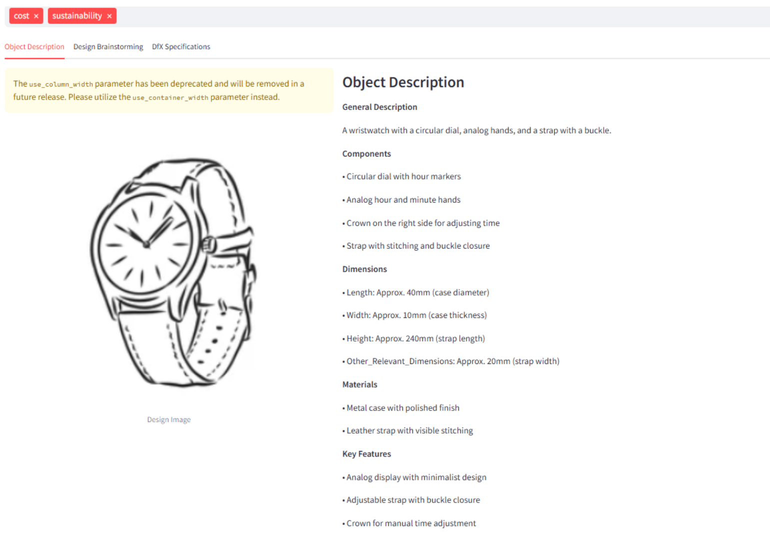


**Fig. 3** Object Description Output.

## 4.3 Exploration of Design Alternatives

The system proposed creative alternatives to enhance the design:

- **Component Modifications:** Suggestions included hybrid watch faces and digital displays for enhanced functionality.
- **Material Options:** Options such as ceramic cases and silicone straps offered trade-offs between cost and performance.
- **Ergonomic Improvements:** Larger, textured crowns were recommended for easier adjustments.
- **Innovation Opportunities:** Solar-powered mechanisms and eco-friendly materials were proposed for future upgrades.

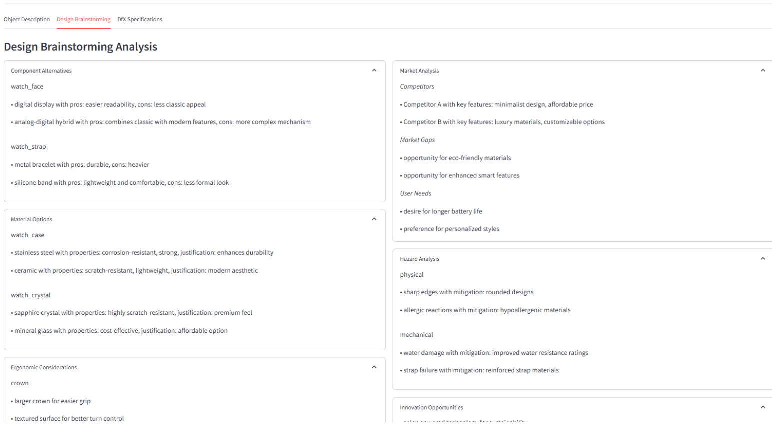


**Fig. 4** Design Brainstorming Output.

## 4.4 DfX-Centric Analysis

The analysis tailored its outputs to address the selected objectives of cost and sustainability:

### Cost Analysis

- **Specifications:** Material costs capped at \$10 per unit; assembly streamlined to under five steps.
- **Recommendations:** Use standardized parts and partner with competitive suppliers.

### Sustainability Analysis

- **Specifications:** Use 50% recycled materials, biodegradable packaging, and water-based adhesives.
- **Recommendations:** Promote energy-efficient manufacturing and explore local sourcing options.

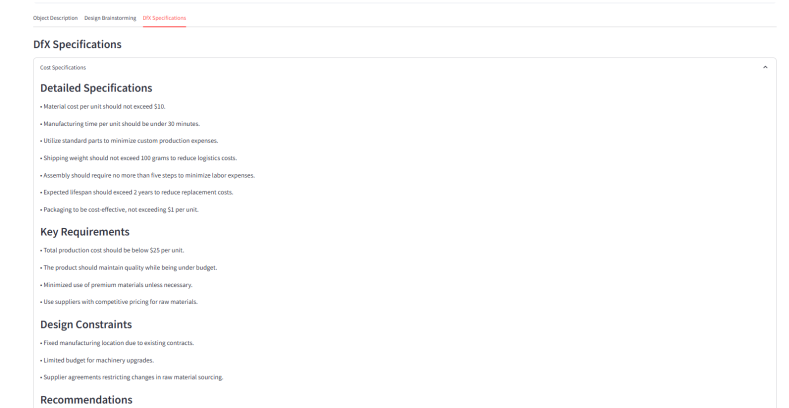


**Fig. 5** DfX Specifications Output for Cost and Sustainability.

## 4.5 Interactive Platform

The results were presented in an intuitive interface, with tabs for:

- **Object Description:** A detailed breakdown of the wristwatch design.
- **Design Brainstorming:** Alternatives and ergonomic improvements.
- **DfX Specifications:** Tailored outputs for cost and sustainability.

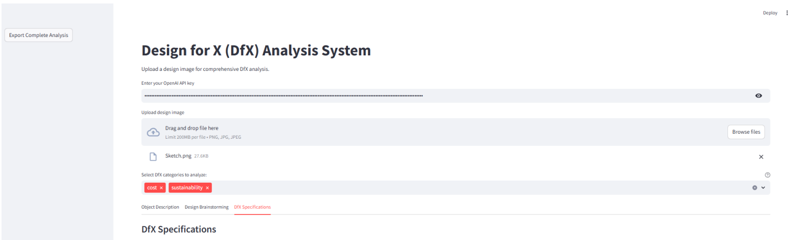


**Fig. 6** Interactive Streamlit Interface with Organized Tabs.

# 5 Discussion

The validation results demonstrate the framework's ability to effectively integrate generative AI into product design, providing detailed object descriptions, innovative design alternatives, and tailored DFx specifications. The outputs highlight the framework's capacity to address multiple dimensions of product development, including manufacturability, sustainability, usability, and reliability.

## 5.1 Key Strengths

The framework exhibits several notable strengths. Its scalability allows it to adapt seamlessly across diverse industries and product categories, making it a versatile tool for designers and engineers. The user-friendly interface ensures that results are presented in a clear and organized format, facilitating easy interpretation and informed decision-making. Additionally, by leveraging AI-powered brainstorming, the framework introduces innovative alternatives and trade-offs that enhance design flexibility and creative potential. Furthermore, the automation of detailed design analysis significantly accelerates iterative design cycles, reducing manual effort and saving time while maintaining a high level of accuracy.

## 5.2 Challenges and Limitations

Despite its strengths, certain challenges and limitations were observed during the validation process. The accuracy and relevance of outputs heavily depend on the quality and detail of the uploaded design images. This reliance on input quality can impact the effectiveness of the analysis, especially for less detailed or ambiguous designs. Additionally, while the system generates multiple alternatives, effectively balancing competing objectives, such as cost and sustainability, often requires additional context or user intervention. Finally, for highly specialized industries or regulated environments, the recommendations may need further refinement to align with specific requirements or compliance standards. Addressing these limitations in future iterations could enhance the framework's robustness and expand its applicability.

## 5.3 Broader Implications

The framework's integration of generative AI with DFx principles has significant implications for product design. By automating complex analyses and generating actionable insights, the system reduces the time required for iterative development, thereby accelerating design cycles. The brainstorming capabilities foster creative solutions that align with market demands and technological advancements, enhancing the innovative potential of the design process. Moreover, the inclusion of sustainability-focused recommendations supports global efforts toward environmentally conscious manufacturing and resource efficiency, contributing to more sustainable product development practices.

## 5.4 Future Directions

To further improve the framework, several areas of development are recommended. Integrating the system with real-time design tools, such as CAD or PLM platforms, could enable seamless optimization during the design process. Expanding the scope of the framework to include additional DFx categories, such as maintainability, scalability, and regulatory compliance, would enhance its versatility and utility. Leveraging more advanced AI models or incorporating domain-specific datasets could improve the precision and depth of the generated insights. Additionally, enabling multi-design comparisons would allow users to evaluate and select optimal solutions more effectively, further broadening the framework's applicability and impact.

# 6 Conclusion

The integration of generative AI into product design marks a transformative shift in addressing the challenges of modern development processes. By combining generative AI capabilities with Design for X (DFX) principles, this paper has demonstrated how innovative frameworks can streamline workflows, optimize design solutions, and enhance creativity. The validation study, using a wristwatch design, showcased the framework's potential to automate complex analyses, explore alternative designs, and tailor specifications for diverse objectives such as cost, sustainability, and usability.

While the results underscore the effectiveness of generative AI in accelerating iterative design cycles and improving efficiency, certain limitations, such as reliance on input quality and context-specific refinements, highlight areas for future improvement. Nevertheless, the proposed framework establishes a foundation for integrating AI-driven tools into multidisciplinary design contexts, paving the way for more sustainable, innovative, and efficient product development practices. Future exploration could focus on expanding DFX categories and enhancing system precision, further solidifying the role of generative AI as a catalyst for innovation in product design.

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