GENAI-DFX: An Integrated Generative AI and Design for X (DfX) Framework for Product Design

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Abstract

Context: The main problem in product design is the idea. Creating an innovative idea is not a very easy task to do, and so is bringing it into the real world... In order to use, for example: Midjourney, Vizcom, Prome AI...etc. Designers first have to go through Chatgpt to generate very well-coated prompts. All of that, of course, speeds up the task of product design ideating. The purpose of this paper is to study how can open-source models generate better images that are applicable and consider the DFX aspect. Find the best way to prompt those image generation models using a specific LLM. Make an application with simple UI/UX that is optimized containing both the image generation and the text prompting parts.
Methodology: The methodology used to create this application consists of combining multiple models depending on the use case, for example when needing to use only text to image, the user can select any model they want, and based on the paraphrasing of an LLM (mistral), the image gets generated with few enhancements. In the other hand, when using sketch to image, the image generation model is combined with another model, ControlNet, which is used for masking the sketch used. After the image gets generated the user gives his feedback based on the DFX aspect they want to follow and then the image either gets improved or keeps the details.
Conclusion : The GENAI-DFX application enhances creativity, improves design efficiency, and embeds critical DfX considerations early in the design process, thereby supporting the development of more manufacturable, sustainable, and serviceable products.

Keywords: Generative AI, Product Design, Industrial Design, Image Generation, Ideation, Design Optimization, LLM (Large Language Models), Human-AI Collaboration

1 Introduction

+ In today's industrial world, where companies are continuously challenged to reduce the time between product conception and production while not comprising the level of innovation, sustainability, and manufacturability built into a product. Early product design when key decisions on form, function, and feasibility are made, is plagued by slow iterations, expensive prototyping, and subjective judgments. While traditional methods, such as iterative prototyping, user-centered design, and design thinking, are consistent and prevalent practices, they can be time constrained and limit creative exploration as a result of cognitive biases or infrequent exposure to relevant feedback.

In this context, many organizations struggle to explore a wide range of design possibilities quickly while ensuring alignment with industrial constraints such as manufacturability (DFM), assembly efficiency (DFA), serviceability (DFS), and sustainability (DFSust). These constraints are rarely considered systematically in early ideation phases, leading to costly revisions or suboptimal solutions later in development.

This project addresses the challenge of improving early-stage product design by evaluating how generative methods can help industrial designers rapidly explore and refine product concepts while embedding Design for X (DfX) principles from the outset. The objective is to assess whether the integration of generative approaches into design ideation workflows can reduce development time, enhance design quality, and support decision-making aligned with industrial goals.

2 State of the Art

2.1 GenAI in Design Ideation and Concept Generation:

+ Generative AI tools, particularly text-to-image models like DALL-E, Midjourney, and Stable Diffusion, are increasingly used in the early stages of design for inspiration, mood board creation, and concept ideation (Bartlett and Camba, 2024; Takale et al., 2024). Kwon et al. (2024) propose a "Designer-Generative AI Product Design Ideation Process" that emphasizes prompt crafting and iterative image exploration to align AI-generated images with designer intent. Their work highlights the importance of structuring prompts and utilizing AI for keyword extraction and refinement, a concept partially mirrored in GENAI-DFX's 'DesignPromptGenerator' and its use of Mistral for prompt enhancement. Pariveda Solutions (2025) notes that current GenAI tools like Uizard and Figma plugins are already showcasing potential in creating visual assets from text prompts, marking a significant leap in design efficiency. The GENAI-DFX application builds on these ideas by providing structured inputs (category, focus, style) to guide prompt generation and offering iterative refinement capabilities. The ability of GenAI to generate numerous variations quickly can accelerate concept development timelines significantly (Qin, 2025).

2.2 Human-AI Collaboration in Design:

+ The consensus in recent literature is that AI will serve as a powerful partner for human designers, augmenting their capabilities rather than replacing them (Bartlett and Camba, 2024; El Montassir et al., 2024). EIMT (2025) describes GenAI transforming into a "partner or collaborator," where artists, writers, and designers engage with AI to expand creative boundaries. Frameworks are emerging to assess and optimize this collaboration. For instance, the Human-AI Augmentation Index framework focuses on how AI complements human capabilities, fostering innovation by allowing humans to concentrate on complex, creative challenges (Friends of Europe, 2025). While GENAI-DFX is not a multi-agent system, its interactive nature, allowing users to guide the AI through prompts, settings, and iterative feedback (scoring), fosters a collaborative environment aligned with these emerging co-creative models.

2.3 Existing Generative Design Tools and Trends:

+ Commercial tools like Autodesk Generative Design (within Fusion 360) and Siemens NX already leverage AI for structural optimization and exploring design alternatives based on engineering constraints (Buonamici et al., 2020; Rawat and Tiwari, 2023, as cited in El Montassir et al., 2024). These tools often focus on generating 3D geometry. GENAI-DFX, while also aiming for design optimization, primarily focuses on 2D concept visualization and DfX textual analysis in the earlier stages. The trend is towards more democratized AI tools (EIMT, 2025; Pariveda Solutions, 2025), and GENAI-DFX's use of open-source models and Streamlit aligns with this, potentially making advanced capabilities more accessible. Codewave (2025) provides a guide on using GenAI in product design, emphasizing its role in generating multiple variations, reducing material waste, and enabling customization.

2.4 Gaps Addressed by GENAI-DFX:

+ GENAI-DFX attempts to provide an integrated environment that:

- Combines diverse image generation models with a text-based LLM for deeper, DfX-focused analysis. - Explicitly incorporates a DfX selection and reporting mechanism early in the visual concept generation phase. - Offers a sketch-to-image pipeline with ControlNet. - Provides an iterative design loop with user scoring to guide the AI towards DfX compliance and desired aesthetics, fostering a co-creative dynamic (EIMT, 2025).

The application aims to make DfX considerations more tangible from initial concept stages, leveraging AI for both creative exploration and practical optimization.

2.5 Current Issues and Potential Directions

+ The present context indicates that, in spite of the possible advantages, the use of generative AI in product design is met with various challenges. One major challenge revolves around interpretability because it is necessary for designers to ensure the AI-produced outputs conform to desired goals and follow applied guidelines within the industry. Moreover, even though AI shows proficiency in creating a large variety of design options, choosing the most suitable option often calls for human judgment and hence highlights the need for collaborative human-AI coordination (Torabi, April 10, 2024). Other challenges include ethical issues such as concerns regarding data anonymity and the embedded prejudices found in AI-designed solutions (Addepto, June 18, 2024). Future studies need to focus on real-time use of design tools, the development of metrics to measure AI's influence on creativity and sustainability, and besides this, the strategies that will counteract the ethical issues.

3 Methodology

3.1 Framework

3.1.1 AI integration

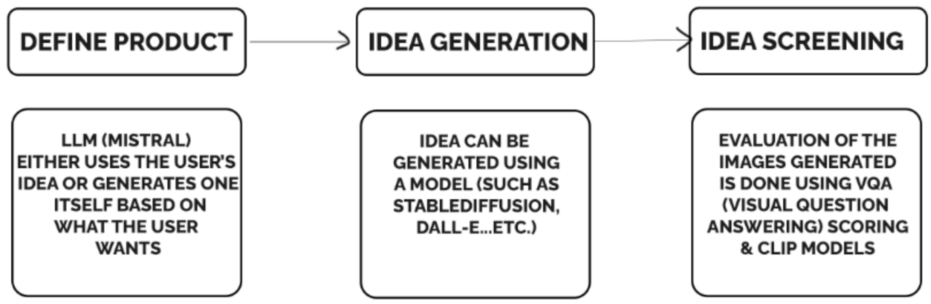

Fig. 1: Generative AI in product design framework

This paper aims to integrate Generative AI within the 3 first steps :

1. The Definition of the product.
2. The Generation of an idea of how that product should be (aesthetically, physically ...etc.).
3. The Screening of that idea (evaluation).

For the first step, designers need only to have an idea of what item or product they want to design. By having an idea of what the product is, identifying what the customer needs and what's trending in the market, they can easily decide what's required in the product in order for it to be successful. And that is where the idea generation takes place, after defining what is needed. Designers traditionally start making different sketches of how the product can look like. But using generative Ai, in this step, you can only specify the shape and what exactly is needed in the product and it will generate a corresponding prompt for you to use and generate images. If the designer struggles with defining a product, it could suggest ones itself.

Having the idea generated and its visualization, designers need to know if it corresponds to what they want. There are multiple ways to evaluate the image generated by an AI model:

1. User's feedback
2. VQA metrics: They are designed to assess how well a model answers questions about images. By asking a model if the image matches the description (prompt) given.
3. CLIP: a model developed by OpenAI that learns to align image and text representations using contrastive learning on a massive dataset of image-text pairs

In this application we're only using the user's feedback for simplicity. The GENAI-DFX application is a Streamlit-based web application designed to assist product designers by integrating generative AI for concept visualization and DfX analysis. Its framework is built around a user-centric workflow that allows for design brief generation, image synthesis from text or sketches, and DfX-focused evaluation.

3.1.2 Application Architecture:

The application follows a typical client-server architecture facilitated by Streamlit:

- **Frontend (Client-Side):** User interface built with Streamlit components (select boxes, text areas, sliders, buttons, file uploaders). Users interact with these components to define design parameters, upload sketches, and view generated outputs.

- **Backend (Server-Side):** Python script ('GENAI-DFX.py') processes user inputs, manages AI model loading and execution, and generates results. It utilizes:

- **Hugging Face Diffusers Library:** For loading and running various Stable Diffusion models (SD 1.5, SD 2.1, SDXL, SDXL-Turbo, OpenJourney) for image generation.

- **ControlNet:** Integrated with Stable Diffusion models for sketch-to-image generation.

- **Ollama with Mistral:** For natural language processing tasks, including design brief generation and DfX report generation.

- **Pillow (PIL):** For image processing tasks, such as sketch manipulation and analysis for image descriptions.

- **PyTorch:** As the underlying deep learning framework for the diffusion models.

3.1.3 Pipeline:

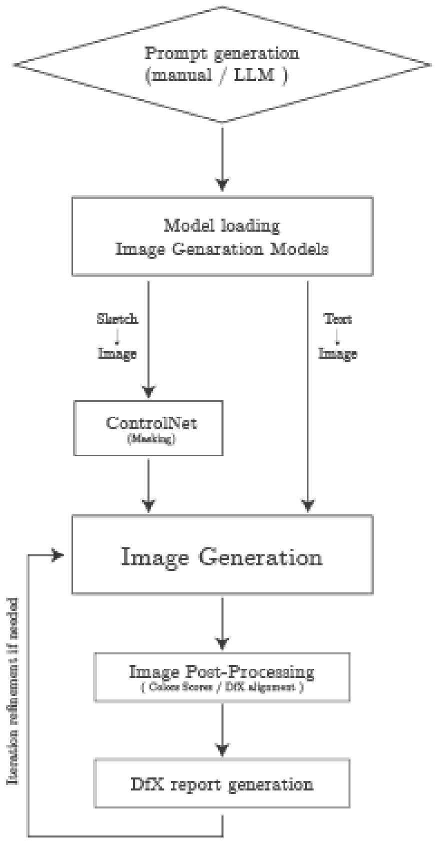

Fig. 2: Pipeline

1. Prompt generation: Create a textual prompt manually or using mistral.
2. Model loading: Load the appropriate image generation model based on the task and resources.
3. ControlNet (optional): Guides the image generation with additional inputs like sketch or hint images.
4. Image Generation: Generate an image from the prompt and any guiding inputs.
5. Image Post-Processing: Refine the generated image.
6. DFX report generation: Based on the images generated and the DFX aspect chosen, Mistral generates a report containing the caracteristics of the product generated.

3.2 Models

In this study, there were multiple models used differently. The models used for image generation:

- Stable Diffusion v1.5
- Stable Diffusion v2.1
- Stable Diffusion XL
- OpenJouerney v4
- ControlNet (for input images mask)

The model used for prompting the image generation models :

- Mistral

3.3 Tools

The tools used are :

- Python
- Streamlit
- Transformers
- Diffusers
- Torch
- Pillow
- csv
- json
- pandas

3.4 Workflow

1. **Model Selection**
   At the top of the streamlit page, the user sees a header, a drop-down of the models, and the hardware status. They need to select a model that is appropriate for their hardware configuration.

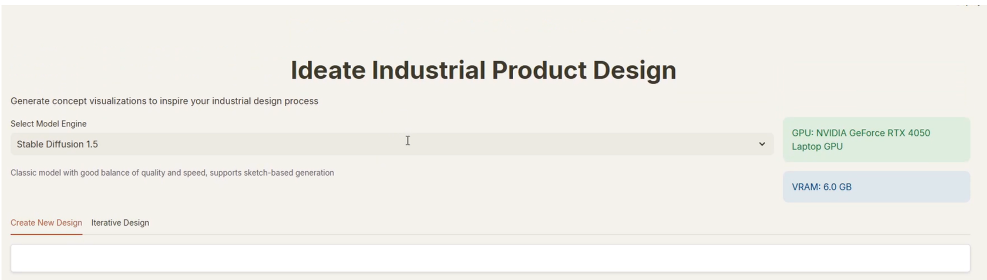

Fig. 3: Header of the page

2. **Design Inspiration Section**

The user selects options such as the product Category (e.g., "Furniture," "Ergonomics," "Minimalist"), The design focus and the design style. Text inputs can be optionally used if the user already has an idea of what item or product he exactly wants.

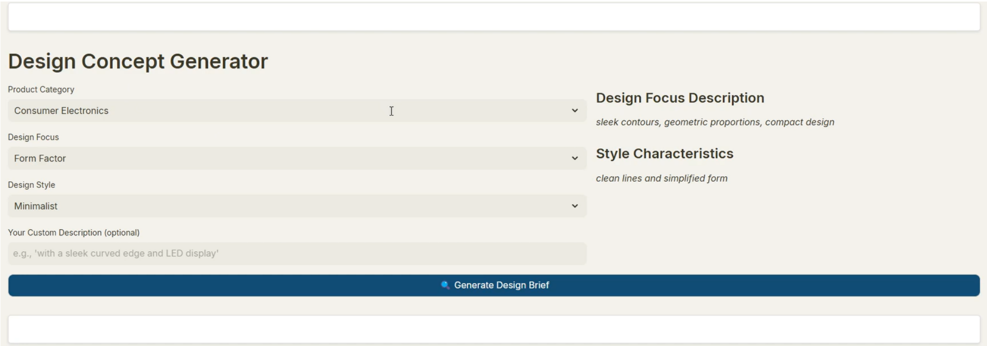

Fig. 4: Design inspiration section

After generating the prompt by an LLM. The user can choose or not to use the design brief.

3. **Design Brief Section**

   This section shows:

   - The mode the user wants to use (sketch -¿ image or text -¿ image).
   - the prompt that will be used directly with the text-to-image model.

Fig. 5: Design Brief Section

4. **Visualization Settings**

   The user adjusts settings such as : Viewpoint (e.g., "three-quarter view"), rendering style (e.g., "product photography"), and a suffix checkbox. Height/width sliders (model-specific ranges, e.g., 512x512). Advanced settings: negative prompt, quality (inference steps), low memory mode, guidance scale, and seed (random or fixed).

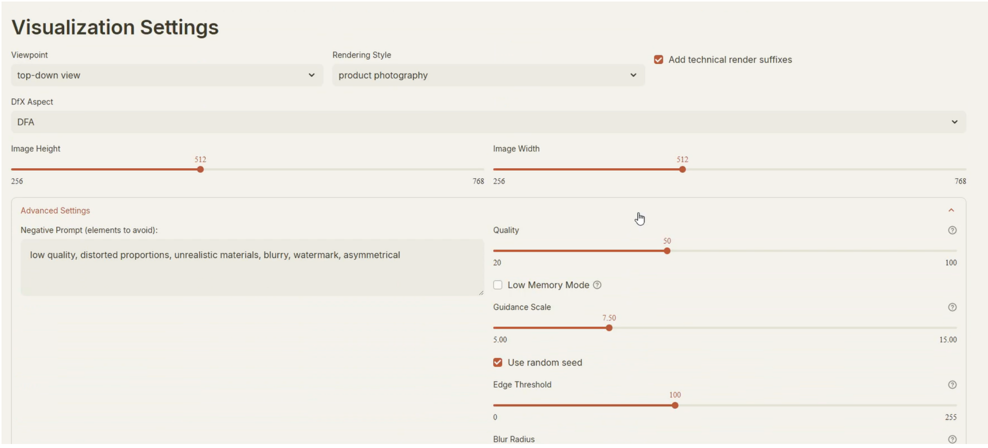

Fig. 6: Visualization Settings Section

5. **Image Generation**
   After clicking the "Generate Design Visualization" button, the model starts loading its components (the cache files containing weights ...etc.). Then starts generating the image while a progess bar is showing up. After the progress bar reaches the end, the image shows up.

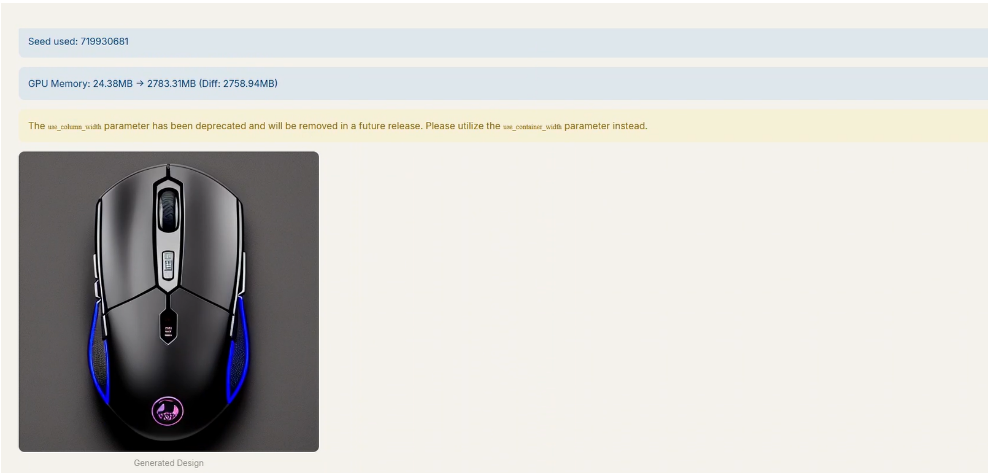

Fig. 7: Image Generation

6. **Scoring**
   After the image is finished generating, the user can either accept or not accept the image generated, he can also give a score relating to the respect of DFX aspect.

Fig. 8: Scoring

7. DfX Analysis and Reporting

   After an image is generated and accepted (in the "Create New Design" tab or for the best result in "Iterative Design"), the user can generate a DfX report. The user selects a DfX aspect (DFA, DFM, DFS, DFSust). The generated image is then analyzed (visually, if possible, for complexity/color) and gets combined with the DfX aspect, user prompt, category, and form. This rich description is then passed to generate text with mistral.

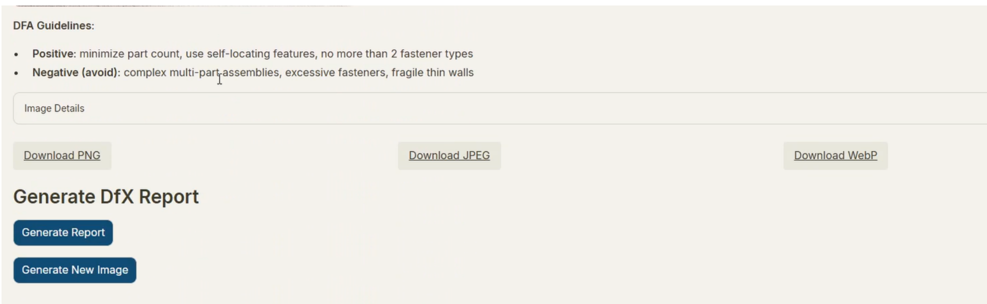

Fig. 9: DFX Report

4 Illustrative Example (Conceptual - Text-to-Image)

- **Prompt:** "an angular industrial speaker with a distinctive hexagonal prism design, marrying sleek contours with robust mechanical elements for a striking silhouette that defies traditional loudspeaker conventions., professional product visualization, studio lighting,high detail"
  - **Model: SDXL**
  - **Image generated:**

Fig. 10: Angular edges speaker

5 Illustrative Example (Conceptual - Sketch-to-Image)

- Sketch:

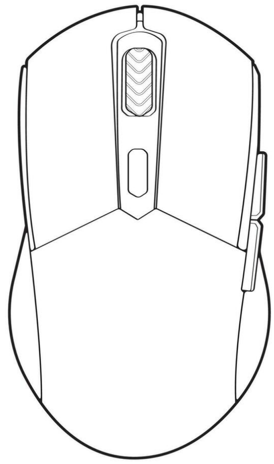

Fig. 11: Mouse Sketch

- **Prompt:** "A gaming mouse"
- **Model: Stable Diffusion 1.5 (with ControlNet)**
- **Image generated:**

Fig. 12: Mouse Generated

Model Selected	Expected Image Type / Characteristics	Sketch-to-Image Support
Stable Diffusion 1.5	Good balance of quality/speed, general purpose.	Yes (with ControlNet)
Stable Diffusion 2.1	Improved detail consistency over 1.5.	Yes (with ControlNet)
Stable Diffusion XL	High detail, excellent composition, photorealistic.	No (as per current code)
SDXL Turbo	Very fast generation, suitable for rapid iteration, potentially lower detail.	No (as per current code)
OpenJourney v4	Midjourney-like aesthetic, artistic, good for conceptual product design.	Yes (with ControlNet)

Table 1: Comparison of generative AI models for industrial design visualization

6 Discussion

The GENAI-DFX application represents a significant step towards integrating generative AI into the practical workflows of product designers, particularly by emphasizing Design for X (DfX) principles from the early conceptual stages. Its architecture and functionalities offer several strengths but also present limitations and raise important considerations.

6.1 Interpretation of Capabilities and Strengths

6.1.1 Enhanced Ideation and Exploration

By leveraging models like Stable Diffusion and a prompt generation system powered by Mistral, GENAI-DFX can significantly broaden the scope of initial design exploration (Kwon et al., 2024). The ability to quickly generate diverse visual concepts from text or sketches can help designers overcome creative blocks and explore unconventional ideas. As Qin (2025) notes, GenAI can supercharge design teams by rapidly generating numerous creative options, acting as a creative collaborator.

6.1.2 Early DfX Integration

A key strength is the explicit incorporation of DfX aspects (DFA, DFM, DFS, DFSust). With Mistral's ability to generate DfX reports, this allows designers to receive early feedback. This proactive approach aligns with El Montassir et al. (2024) and the trend of using AI for material optimization and performance analysis (Gembah, 2025).

6.1.3 Iterative Refinement with Feedback

The "Iterative Design" tab, with its user-scoring mechanism, introduces a feedback loop. This aligns with the concept of human-AI co-creation (EIMT, 2025) and frameworks assessing human-AI augmentation (Friends of Europe, 2025), where AI complements human judgment.

6.1.4 Flexibility with Multiple Models and Sketch Input

Offering a selection of image generation models and ControlNet for sketch-to-image bridges traditional practices with AI, enhancing versatility.

6.1.5 Limitations and Mitigation Strategies

- **Quality of AI Outputs:** Dependency on AI model capabilities remains.
  - Mitigation: Continued emphasis on detailed prompting and advanced settings.
  - Future: fine-tuning or more sophisticated prompt engineering.
  - **DfX Rule Depth and Context:** High-level DfX rules.
  - Mitigation: Frame DfX reports as initial guides.
  - Future: user-customizable rules or integration with detailed DfX knowledge bases.
  - **Ethical Concerns and Originality:** Inherent GenAI issues (Bartlett and Camba, 2024; Kanerika, 2025).
  - Mitigation: Disclaimers and user education. Human scoring can steer outputs.
  - Future: research into bias detection and originality checks.
  - **Computational Resources:** Intensive for local execution.
  - Mitigation: "Low Memory Mode."
  - Future: cloud options, optimized models.
  - **Sketch Interpretation:** Canny edge detection limitations.
  - Mitigation: User guidance.
  - Future: explore alternative ControlNet preprocessors.
  - **"Black Box" Nature:** Opaque AI decision-making.
  - Mitigation: A significant research challenge.
  - Future: LLM-based explanations of DfX reasoning.

6.1.6 Interval of Creativity and Innovation Potential

- GENAI-DFX can accelerate the initial design phase, freeing designers for strategic thinking (Qin, 2025; Pariveda Solutions, 2025). - Early DfX integration promotes robust product development. - Serendipitous AI outputs can spark novel design directions (Bartlett and Camba, 2024). - The iterative loop hints at a co-creative process where AI helps optimize based on defined criteria, aligning with the vision of humans and AI as co-creators (EIMT, 2025). The potential for AI to suggest material optimizations and perform design validation (Gembah, 2025) could be further explored.

6.1.7 Security and Data Privacy

The use of Ollama for local LLM inference is positive for data privacy. However, image models are from Hugging Face Hub. For sensitive IP, a fully private infrastructure would be needed.

In conclusion, GENAI-DFX thoughtfully combines GenAI's creative power with DfX necessities. It serves as a valuable framework within a human-led design process, aligning with current trends of AI-driven design acceleration and human-AI collaboration.

7 Conclusion

The GENAI-DFX application stands as a testament to the evolving landscape of product design, effectively demonstrating how Generative AI can be harnessed to augment the creative and analytical capabilities of designers. By providing an integrated platform for design brief generation, text-to-image and sketch-to-image visualization, and DfX-focused analysis.

The application addresses key challenges in modern product development, namely the need for rapid innovation, early consideration of lifecycle factors, and enhanced creative exploration.

The trends for 2025 and beyond indicate a deeper integration of AI into design workflows, focusing on AI as a collaborative partner, enhancing creativity, and optimizing designs for various objectives including sustainability and manufacturability.

8 Key Contributions

- ***Integrated Workflow:*** Successfully combines multiple AI functionalities into a cohesive application.

- ***DfX Emphasis:*** Explicitly integrates DfX principles into early-stage design, promoting holistic development.

- ***Iterative Design Support:*** Fosters collaborative interaction between designer and AI through guided refinement.

- ***Accessibility of Advanced AI:*** Leverages open-source models and Streamlit, making sophisticated GenAI tools more accessible, contributing to the democratization of design.

9 Significance

The application showcases GenAI's potential to accelerate design tasks and embed critical lifecycle thinking from inception. This aligns with industry observations where AI reduces concept development timelines and enhances innovation (Qin, 2025). For designers, tools like GENAI-DFX can act as powerful catalysts, augmenting their skills and allowing them to focus on higher-level problem-solving, shifting their role more towards strategic thinking and creativity (Pariveda Solutions, 2025).

References

- Bartlett, K. A., and Camba, J. D. (2024). Generative Artificial Intelligence in Product Design Education: Navigating Concerns of Originality and Ethics.

- International Journal of Interactive Multimedia and Artificial Intelligence, 8*(5), 55-64.

- Buonamici, F., Carfagni, M., Furferi, R., Volpe, Y., and Governi, L. (2020). Generative Design: An explorative study.

- Computer-Aided Design and Applications, 18*(1), 144-155. (Cited in El Montassir et al., 2024)

- Codewave. (2025, March 19).

- Using Generative AI in the Product Design Process: A Guide. Retrieved from Codewave Insights. (Conceptual citation based on search result 1.4)

- EIMT. (2025, March 31). The Future of Generative AI: Trends to Watch in 2025 and Beyond. Retrieved from EIMT Blog. (Conceptual citation based on search result 3.2)

- El Montassir, A., Benaida, M., and El Hassani, I. (2024). Leveraging Generative AI for Integrated Design Optimization: A DfX Framework for Innovation and Efficiency.

- Friends of Europe. (2025, February 6). Introducing a new method to assess the productivity of human-AI collaboration. Retrieved from Friends of Europe Insights. (Conceptual citation based on search result 2.1)

- Gembah. (2025). The Future of Industrial Design: Essential 2025 Trends and Predictions. Retrieved from Gembah Blog. (Conceptual citation based on search result 3.7)

- Kanerika. (2025, April 19). How to Address Key AI Ethical Concerns In 2025. Retrieved from Kanerika Blogs. (Conceptual citation based on search result 3.1)

- Kwon, J., Jung, E.-C., and Kim, J. (2024). Designer-Generative AI Ideation Process: Generating Images Aligned with Designer Intent in Early-Stage Concept Exploration in Product Design. Archives of Design Research, 37*(3), 7-23.

- Lazarev. Agency. (2025, May 20). AI Product Design in 2025: Tools and Strategies for Business Leaders. Retrieved from Lazarev.Agency Articles. (Conceptual citation based on search result 1.6)

- Montreal Ethics.AI. (2025, January 5). Mapping the Ethics of Generative AI: A Comprehensive Scoping Review. Retrieved from Montreal AI Ethics Institute. (Conceptual citation based on search result 3.5)

- Neural Concept. (2024). Revolutionizing Generative AI Product Design for Innovative Solutions. Retrieved from Neural Concept Blog. (Conceptual citation based on search result 1.1)

- Pariveda Solutions. (2025, April 8). The AI-driven revolution in product design: how generative AI is reshaping the future. Retrieved from Pariveda Perspectives. (Conceptual citation based on search result 1.2)

- Qin, H. (2025, March 17). Generative AI: The Next Evolution In Product Design And Marketing. Forbes. (Conceptual citation based on search result 1.5)

- Takale, D. G., Mahalle, P. N., and Sule, B. (2024). Advancements and Applications of Generative Artificial Intelligence. Journal of Information Technology and Sciences, 10*(1), 20-27.

- Taylor and Francis. (2025). Human-AI Collaboration for Generative Intelligent Design [Special Issue Call]. (Conceptual citation based on search result 2.2)

- The American Journal of Engineering and Technology. (2025, March 5). Human-AI Collaboration in IT Systems Design: A Comprehensive Framework for Intelligent Co-Creation. (Conceptual citation based on search result 2.5)