Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 128 (2024) 905–910

www.elsevier.com/locate/procedia

34th CIRP Design Conference

Digital Twin and Generative AI for Product Development

Riddhi Kasar[a,b], Tarun Kumar[c]*

[a]Department of Design, PES University, Bangalore, India
[b]Graduate School of Design, Harvard University, Cambridge, USA
[c]Centre for Product Design and Manufacturing, Indian Institute of Science, Bangalore, India

* Corresponding author. Tel.: +91 9483742547; *E-mail address:* tarunkumar@iisc.ac.in

Abstract

Optimisation of the product design and development cycle is crucial for maintaining product quality and ensuring lower production costs. It is necessary to intervene at early stages to prevent future expenses. Leveraging rapid digitalisation to achieve the desired goals and bringing in 'smart manufacturing' will benefit industries with large-scale productions. This paper proposes a novel approach to enhance 'design for manufacturability (DfM)' paradigm. Integrating digital twins and generative artificial intelligence (AI), a software is proposed that not only simulates real-world environments for testing and visualisation of potential processes but also provides designs to optimise the manufacturing process, maintain cost, and enhance the product's appeal to the target market. The proposed model uses sensors to replicate the product in a digital environment to run a simulation. Meanwhile, a generative AI model embedded in the software provides creative and effective solutions based on user requirements and market data. When incorporated into the product development cycle, this process will ensure cost efficiency and improve the time required to develop quality products, enabling quicker launches. Thus, combining these emerging technologies yields a powerful, innovative model that enhances design for manufacturability.

Keywords: Smart Manufacturing, Design for Manufacturability, Digital Twin, Generative AI

1. Introduction

Artificial intelligence is the theory and method used to build intelligent machines [1]. A subset of AI is machine learning (ML), where the model is trained from input data. Deep learning (DL) is a subset of ML. Deep learning uses neural networks inspired by the human brain to process complex patterns [2]. Generative artificial intelligence falls under deep learning. It is a type of AI that can generate various types of content [3]. The nested model of AI/ML is presented in Fig. 1.

Nomenclature

AI	Artificial intelligence
ML	Machine learning
DT	Digital twin
DfM	Design for manufacturability

With upcoming models utilising generative artificial intelligence, the workload in various fields has been reduced. These large language models can generate new content in the form of different kinds of output—such as audio, imagery, text, natural language and so on—using labelled and unlabelled data inputs [4]. These generative AI models learn the patterns in the language, make predictions, and generate new media using it.

Another aspect of artificial intelligence is digital twins. A digital twin is a virtual model of a physical object. It uses real-time data from the sensors on the physical object to simulate the behaviour and monitor operations [5]. Digital twins help improve the product's performance and identify and address problems efficiently. They enable remote monitoring and thus improve the product development time. Digital twins have been

2212-8271 © 2024 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2024.06.043

applied in various industries, such as the construction industry to design better plans for infrastructure projects, manufacturing industries to monitor product performance, and the energy sector to optimise performance and lifecycle. The automotive industry uses digital twins for testing. A digital twin plays a crucial role in the pharmaceutical industry supply chain case study [6]. It models and analyses various operating scenarios related to supply, manufacturing, inventory, and product distribution. By uploading key data such as customer insights, demand data, and inventory policies, the digital twin enables predictive analytics and better collaboration among stakeholders. When disruptive events occur, the digital twin adapts the original planning, helping redefine the global operations strategy in a resilient manner. Further case studies on digital twins shed light on their abilities and effectiveness. Modelling and simulation are common practices in system development that aid in designing tasks and validating system

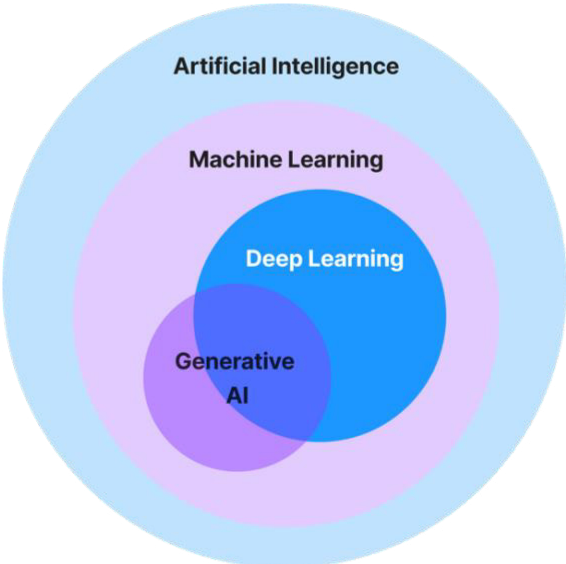

Fig. 1. Nested model of AI/ML.

properties. When applied in this context, digital twins assist in optimising operations and forecasting failures, thus helping users manage the complexity of mechatronic systems [7].

It should be noted that although digital twins are prevalent in the manufacturing industry, their use in the product development process and the product lifecycle is still nascent [8]. Product lifecycle monitoring is crucial for cost-effective, sustainable manufacturing. Furthermore, there are growing complexities when it comes to manufacturing processes. In today's fiercely competitive and ever-changing business landscape, the manufacturing sector confronts fresh challenges necessitating a comprehensive approach to the four key manufacturing aspects: cost, time, quality, and flexibility [9]. Manufacturing firms must generate cutting-edge products with cost efficiency and a shortened time-to-market. Moreover, although the use of digital twins and generative AI has been applied separately in the product design process, applying both technologies together for an optimised system is novel. This paper proposes using digital twins and generative artificial intelligence in the product lifecycle to improve design for manufacturing.

2. Methodology

A five-step methodology is followed to reach the desired objective. As depicted in Fig. 2, the first step is conducting a literature review of related works to gauge existing solutions and their limitations. The second step involves validating the problem and identifying user needs and requirements using surveys. The third step is framework generation and solution proposal, where the system workflow is detailed. The fourth step comprises technical integration, software development,

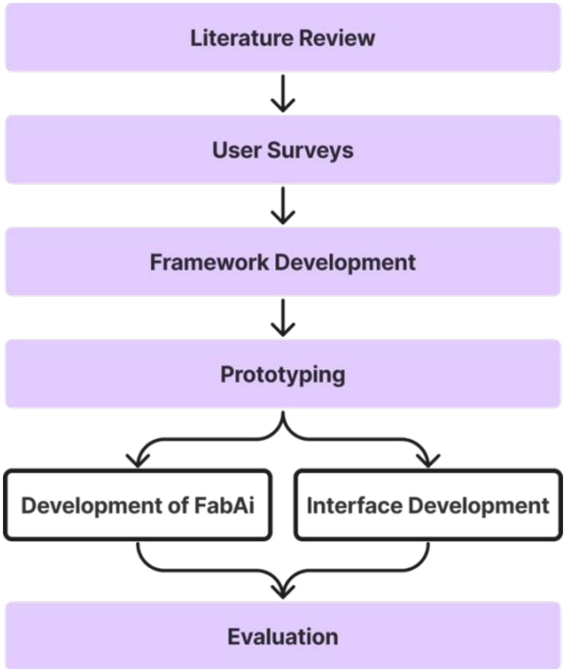

Fig. 2. Methodology adopted in this paper.

and interface prototyping. The final step is the evaluation of the system and user assessment. This method provides an end-to-end solution and thoroughly explains the process followed.

2.1. User survey

A user survey is carried out to validate the problem identified concerning the product design and development process. Twenty stakeholders who have worked and engaged in product development were surveyed. Restrictions faced when designing for manufacturability are investigated, and requirements are generated to address them.

2.2. Framework development

A conceptual framework is proposed that will address the problems around the product design and development process. Hindrances pertaining to market unpredictability, design complexity, material unavailability and production costs are addressed. The proposed concept leverages technologies for optimising the product design and development process. A digital system is developed that incorporates a generative artificial intelligence model and a digital twin model to aid in designing for manufacturability. The framework is named *FabAi*, short for 'Fabricating Artificial Intelligence', as the technologies for fabricating and manufacturing optimisation have been used.

2.3. Prototyping

A digital prototype of the software is made to validate the framework of FabAi and the system. Prototyping consisted of two parts, namely technical integration and interface development. The system was assembled using Unity and Autodesk Fusion 360. Arduino platform and multiple sensors were used for data collection to develop a digital twin of the product. A circuit diagram was created using the TinkerCad software, and a simulation was conducted to test it. A model of generative AI was also developed using Python and TensorFlow. Furthermore, Figma was used to facilitate interface development. To guarantee optimal performance and simplicity of use, attention was given to the arrangement and positioning of the components on the display. Several rules and guidelines were applied to determine the most optimal layout. The design choices have been backed by reasoning and testing to assess their effectiveness. Additionally, the software's branding has also been considered. The finalised *FabAi* logo, colour schemes, palettes, and typefaces were chosen to complement the application's general theme and the stakeholders involved.

2.4. Evaluation and User Assessment

Testing was carried out on users from the product design and development field to validate the proposed solution system. They were explained the solution and shown the prototype. After user testing, the results were evaluated.

3. Results

This study aims to understand concepts that help optimise the product design and development process and aid in designing for manufacturability. Firstly, insights from user surveys are generated and presented. A framework is then developed that tackles the problems at hand. The solution is detailed, and a workflow is fabricated. The next section elaborates on the prototype and the development of the system. Finally, evaluation is looked into, and the system is validated.

3.1. Insights from user surveys

A user survey was carried out with 20 stakeholders to validate the problem. The targeted stakeholders were people who had engaged in and actively participated in product design and development. This survey gave prominent insights into users' views regarding designing for manufacturability. The factors and responses are depicted in Fig. 3 (a) and (b), respectively. It was found that design for manufacturability was an important parameter for designers regarding their design process. Users were asked to rate how much they prioritised DfM on a linear scale of 1-5, 1 being the least and five being the most, and 40% of the users surveyed rated 5, whereas 30% of the users chose 4 and 25% chose three on the scale. Only 5% of the stakeholders chose 2, whereas 0% chose 1, proving that DfM was an important parameter in the design process. When asked for the reasoning behind their ratings, it was found that users who prioritised manufacturability did so because they felt that if the feasibility of production is unattainable, the rationale behind an impressive design becomes questionable. Moreover, improving product sales and reducing fabrication costs were the main reasons for a high rating. Users who rated three stated that although DfM was important, they sought a balance between aesthetics and manufacturability. Moreover, the profession played an important role in this survey. It was understood that for design students, considerations regarding the manufacturability aspect of a design might not be of primary concern unless engaged in a project that necessitates such considerations since their projects are conceptually based and don't end up being manufactured in most cases. However, the students stated that these skills were necessary for working in an industry where DfM plays an important role. Furthermore, the major hindrances that forced users to deviate from manufacturability were analysed. 55% of the users stated that the complexity of their designs was the primary reason, along with a focus on other factors in the design process. 40% of the users indicated that market requirements, along with preference given to quality, were the reasons that caused them

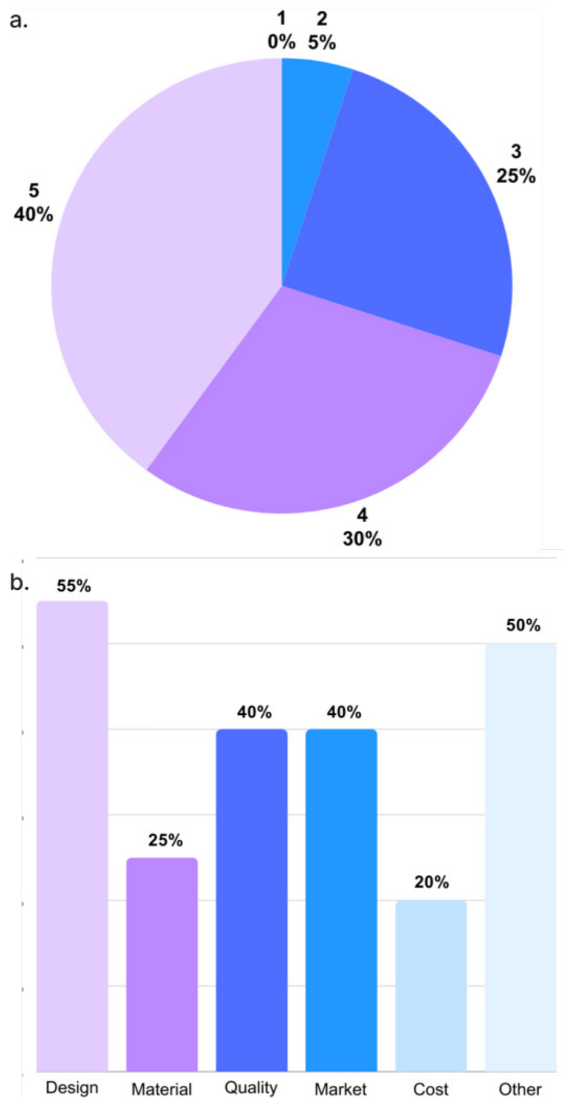

Fig. 3. (a) Priority rating of DFM; (b) Problems faced in DFM.

to stray from making decisions solely based on manufacturability.

3.2. Framework development

An integrated framework (*FabAi*) is developed for optimising the fabrication and manufacturing process during the design stage of the product life cycle, as presented in Fig. 4. The three main components that facilitated the framework are generative AI, digital twin, and design intervention. The proposed framework seeks to aid in DfM.

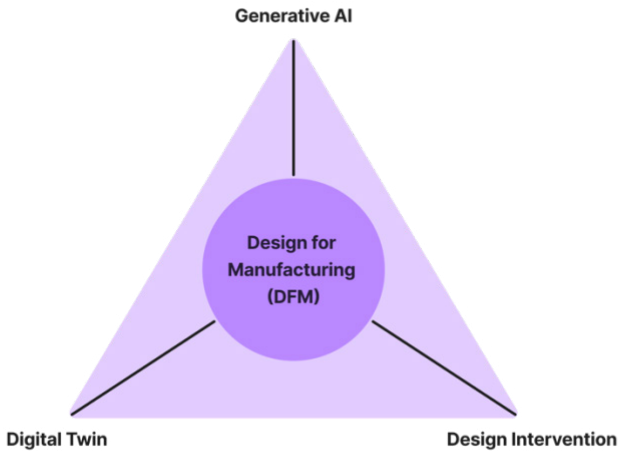

Fig. 4. *FabAi* integrated framework.

Utilising the framework, a software application is proposed that takes user requirements and product details as input and provides design solutions and manufacturing processes that are optimal and cost-effective. The system comprises two components: a generative AI model and a digital twin aspect. The solution system diagram is shown in Fig. 5. The first component, the generative AI model, goes over the input and provides designs and prompts that satisfy the parameters. Market trends, cost-effectiveness, ease of manufacturing and other parameters are considered when providing prompts. Moreover, the model is customisable and can provide a full-fledged product design and designs for components and elements of the product based on user needs. Specifics of the product are investigated, and solutions are provided. The second component of the software is a digital twin. Simulation and monitoring of the proposed product are performed. The designs from the generative AI model are tested for their manufacturing process, durability, requirements satisfaction, and other parameters in this component. The system iterates between these two components of AI and DT until the most efficient design and manufacturing process is identified while satisfying all the requirements. The output provided by the system includes designs based on the testing carried out, a flowchart of the most efficient manufacturing process, and data on product performance. Thus, users can gauge through this information and make quick and effective decisions that will ease DfM without compromising the other parameters in the design process. The designs are validated since the system justifies the suggested preferences. Fig. 6 depicts the detailed flow of the software.

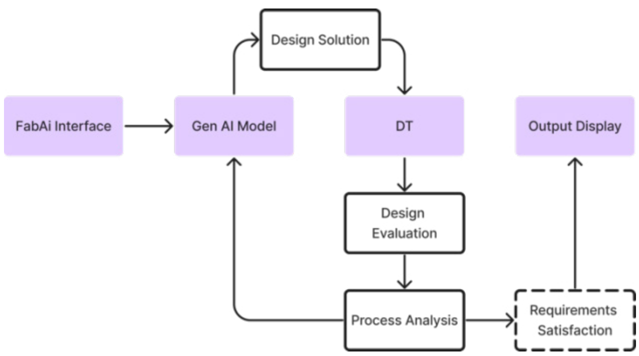

Fig. 5. *FabAi* system diagram.

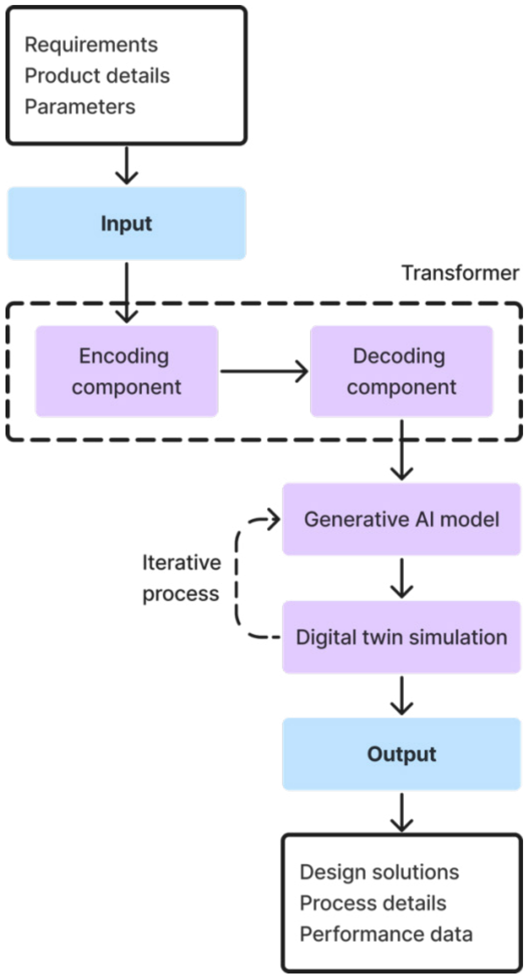

Fig. 6. Detailed workflow of the solution system.

3.3. Prototype development and technical integration.

Prototyping of all three components of the system—Generative AI model, digital twin, and user interface—was carried out. A sample generative AI model was developed using Python and TensorFlow. Prompt engineering was carried out to ensure an efficient use case, which involved training the model for domain-specific applications [10]. In deep learning, the semi-supervised model took unstructured data for a generation [11]. The basic equation followed by the generative model is depicted in Equation 1 [12].

$$y = f(x) \quad (1)$$

Where y is the output, function f is the required model, and x is the input data provided. This model can understand both text and image input. The output combines image (media) and text (natural language). The digital twin prototype was developed using 3D modelling and hardware integration. A test product, an X-Box controller, was taken to carry out the required development. A digital simulation of the test product was made using Autodesk Fusion 360, which was then imported to Unity for real-time visualisation. A snippet of the model is shown in Fig. 7. For hardware integration, an Arduino platform and multiple sensors were used. The sensors incorporated are load, position, motion, temperature, pressure, vibration, humidity, and proximity sensors. These sensors were applied as it was understood that these factors are necessary to aid in the manufacturing and design of a product [13]. Scripts were written in Unity to receive data and sensor readings, and the serial connection was applied to establish communication between Unity and Arduino. The last component of the system, the software interface, was designed on Figma. The interface includes buttons, commands, and displays to ensure a seamless user experience. Hick's and Fitt's laws were applied to the design to guarantee an accurate interface [14]. Thus, by following these procedures, an AI model and a digital twin were created, bridging the gap between the real and virtual worlds with an effective user interface.

The development of this model was to present a simulation of the proposed solution system. Hence, a non-extensive prototype was developed with a limited scope for representative purposes. The components included developing a realistic replica of the 3D object. Furthermore, real-time tracking of the factors on which the digital twin would depend was investigated.

Fig. 7. Unity model of the test product, an X-Box controller.

3.4. Testing and evaluation

Twenty stakeholders with experience in the product design and development process were explained the prototype of *FabAi* software, after which the survey was carried out. The users were asked various questions regarding the efficiency of the software, its relevance, how helpful it was to the users and their views on it. The responses were noted to implement the feedback procured. A visual representation of the data is depicted in Fig. 8 (a), (b), and (c), respectively. The user's requirements were identified, and it was found that the proposed solution met most of these requirements. When asked whether they would utilise the software for optimising DfM, 70% of the users answered, 'Yes' while 30% said 'Maybe'. None of the users chose 'No', proving that the proposed software was relevant and necessary in the product design field. Individual components of the system were also tested. Stakeholders were asked to rate the usefulness of a digital twin in their design process on a scale of 1-5, 1 being not useful and five being very useful. 70% of the users rated 5, and 20% rated 4. The ratings for 2 and 3 were 5%, and 0% of the users rated them as 1. The confidence of users in this component was prominently stated. A similar linear scale was provided to test the usefulness of the generative AI model. In this component, 30% of the users rated 5, 25% rated 4, and 40% chose 3. A scepticism was observed in users when it came to AI-aiding designs. Although the responses were positive, future iterations of this system will investigate how to improve confidence in the AI model. The evaluation of the data gained from the surveys validated the solution system due to the positive response from the users.

4. Discussions

The successful amalgamation of disruptive technologies, such as generative artificial intelligence and digital twins, for the digitalisation of the product design and development industry is showcased in this paper. Thus, by proposing a 'smart manufacturing' via the proposed framework (*FabAi*), the design and development process is optimised. Moreover, production costs and manufacturing time are improved. Although the separate use of both technologies is evident in the manufacturing industry, the combination is a novel and unique approach that has proven beneficial in various ways. It was found that even though the importance of DfM was prominent amongst users, various other parameters have been shown to hinder and prevent the implementation of design for manufacturability. The system proposed in this paper has proven to ease designing for manufacturability and consider the different parameters and requirements that users may have. Thus, the software addresses all the identified problems and provides a thorough design solution. Furthermore, market trends are also accounted for. Customisation of the software enables a unique solution for all different problems and requirements that users may have. The iterative process between the system's two components has allowed for quick generation, simulation, and evaluation of numerous design alternatives. The system's adaptability to manufacturing constraints and the ability to dynamically adjust design parameters based on simulation results have been critical in enhancing the manufacturability of the final product. This adaptive feedback loop ensures that design decisions align with practical manufacturing considerations.

However, it must be noted that scepticism among users regarding the use of artificial intelligence was observed. Such issues must be addressed by improving the generative AI algorithm to provide state-of-the-art designs and flawless solutions. Further enhancement and testing of the digital twin model to improve accuracy is also required. The successful synergy of these technologies holds significant potential for

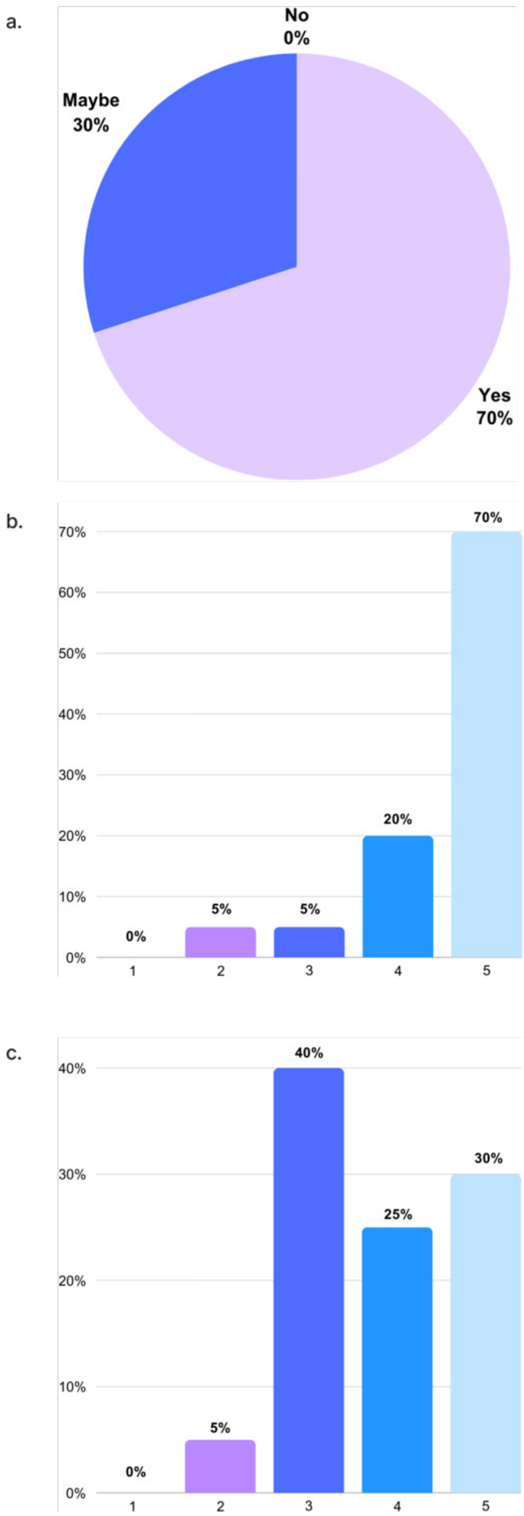

Fig. 8. (a) Will a software be useful for DFM?; (b) How useful is DT in DFM?; (c) How helpful is generative AI in DFM?

streamlining the design process, optimising iterations, and ensuring the practical feasibility of designs in real-world manufacturing scenarios. The combination has facilitated the exploration of diverse design alternatives while considering real-world manufacturing constraints and processes.

5. Conclusion

To conclude, this paper focuses on optimising design for manufacturability by incorporating different technologies. The unique amalgamation of generative AI and digital twin proposed in this paper can become a powerful tool to help the growth of the manufacturing industry. It can also generate solutions and test them in other fields, such as healthcare, construction, and space exploration, to bring about significant change and solve real-world problems. Implementing this system benefits the industry and the environment since data can be collected on manufacturing processes that are the most sustainable for the planet. If sought, *FabAi* can be used in unlimited ways that will be the most beneficial, from manufacturing a product to disposing of it. Furthermore, this unique combination of separately disruptive technologies is a step forward in the growth of digitalisation, and further studies and implementation of the same is possible.

References

[1] McCarthy, John. “What is artificial intelligence?” 2007.
[2] IBM Data and AI Team. “AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What’s the Difference?” IBM Article; 2023.
[3] Zhihan, Lv. “Generative artificial intelligence in the metaverse era.” Cognitive Robotics. 2023.
[4] Kerner, Sean. “Large language models” TechTarget; 2023.
[5] Eric VanDerHorn, Sankaran Mahadevan. “Digital Twin: Generalization, characterization and implementation.” Decision Support Systems. 2021.
[6] Marmolejo-Saucedo, Jose Antonio. "Design and development of digital twins: A case study in supply chains." Mobile Networks and Applications 25, no. 6.2020
[7] Boschert, S., Rosen, R. “Digital Twin—The Simulation Aspect. In: Hehenberger, P., Bradley, D.” Mechatronic Futures. Springer, Cham. 2016
[8] Amazon Web Services. “What is digital twin technology?” 2023.
[9] Waguih ElMaraghy, Hoda ElMaraghy, Tetsuo Tomiyama, Laszlo Monostori. “Complexity in engineering design and manufacturing.” CIRP Annals 2012.
[10] Vivian Liu and Lydia B Chilton. “Design Guidelines for Prompt Engineering Text-to-Image Generative Models” CHI Conference on Human Factors in Computing Systems. 2022.
[11] Mansar, Youness. “Training better deep learning models for structured data using semi-supervised learning. Towards Data Science” Medium; 2020.
[12] Ng, Andrew; Jordan, Michael. “On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes.” Advances in Neural Information Processing Systems; 2002.
[13] Angkush Kumar Ghosh, AMM Sharif Ullah, Roberto Teti, Akihiko Kubo. “Developing sensor signal-based digital twins for intelligent machine tools.” Journal of Industrial Information Integration; 2021.
[14] The Usability People. “Hick’s and Fitt’s Law: Two important psychological principles to consider when designing navigational menu structures” 2015.