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Opportunities and challenges of AI in design: a practical study from the manufacturing industry

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ABSTRACT: Artificial Intelligence (AI) techniques are increasingly explored to support design activities within the manufacturing context mainly driven by the development of AI technologies. However, few studies were conducted in practice from industrial perspectives. This research aims to understand the opportunities and challenges of AI in design in the real world. A workshop involving twenty-five participants from more than ten manufacturing firms is organised to collect relevant information. The opportunities and challenges identified are categorised by adopting a readily available data-driven design framework. Seven research directions are proposed accordingly to address the industry challenges and opportunities. This research serves as a guide for ensuring future AI in design research and applications are grounded in practice to bridge the gap between academic research and industry practice.

KEYWORDS: artificial intelligence, design practice, design engineering, AI in design, manufacturing

1. Introduction

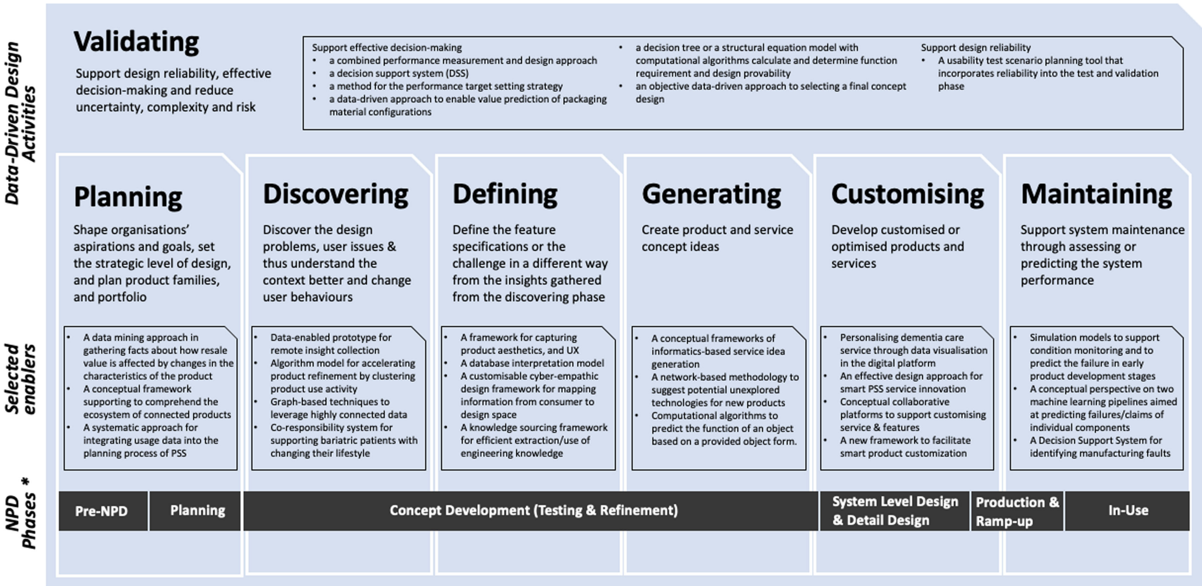
Artificial Intelligence (AI) techniques have been used to support various design activities within the engineering and manufacturing sector for decades to improve design efficiency and enhance design outcomes (J. Han et al., 2024a). Conventionally, AI techniques are often utilised for design simulation, modelling and optimization, while studies over the past few years have expanded to focus on early design stage activities, such as task planning and knowledge retrieval. Recently, AI has advanced remarkably with the development of computing power and techniques such as machine learning (ML) and natural language processing (NLP). These advancements in AI have led to new applications, particularly generative ones related to design innovation (Song et al., 2024). For example, generative adversarial network (GAN) for generating synthetic images (Goodfellow et al., 2020), DALL·E (Ramesh et al., 2021) and Stable Diffusion (Rombach et al., 2022) for generating images from textual descriptions, and ChatGPT (OpenAI, 2022) for generating responses based on prompts or questions. Such advancement in AI technologies is leading to a significant increase in the digitalisation of design activities in the manufacturing sector.

In recent years, a number of research studies have explored the use of AI for supporting design activities. For example, Chen et al. (2019) and Wang and Han (2023) employed GAN to generate stimuli fusing different product images for supporting design creativity; L. Chen et al. (2023) used DALL·E to generate ideas in pictorial formats based on textual descriptions; Chen, Zhang, et al. (2024), Chen, Zuo, et al. (2024) and Zhu et al. (2023), utilised Large Language Models (LLMs), such as Generative Pre-trained Transformer (GPT), to generate design concepts; and J. Han et al. (2024b) employed a Unet3D structure-based diffusion model to produce short videos as creative design stimuli. However, most of these AI in design studies are driven by the development of AI technologies, such as the reasoning and image generation capabilities of the AI models. It is unclear whether these studies are in line with the needs of the industry and could be applied in practice. In

addition, very few studies have explored the opportunities and challenges of AI in design in practice from the perspectives of the industry.
To address the issues, this research aims to explore the current state of the opportunities and challenges of AI in design within the manufacturing context in the real world, and to illuminate potential directions for future research to embrace the opportunities and tackle the challenges. State-of-the-art studies in AI in design are reviewed. The reviewed papers are thematically analysed and categorised into relevant design activities using a readily available framework. An industry-facing workshop is organised to collect data from design and manufacturing firms regarding their AI in design opportunities and challenges. The opportunities identified are categorised using the same framework, while the challenges are categorised using a newly developed scheme. The results of the review and the workshop are then discussed and synthesized for eliciting future research directions. This research bridges the gap between theoretical research and practical needs in the area of AI in design, and provides useful insights into how AI could be better adopted and transform the current and future design and manufacturing industry.

2. AI in design - state-of-the-art research

AI-relevant search phrases, such as "*artificial intelligence*", "*AI*", "*machine learning*", and "*natural language processing*", are used to run a comprehensive search in top engineering design journals, including "*Artificial Intelligence in Engineering Design, Analysis and Manufacturing*", "*Journal of Engineering Design*", "*Research in Engineering Design*", "*Journal of Mechanical Design*", "*Journal of Computing and Information Science in Engineering*", and "*Design Science*". As AI has been advancing rapidly in recent years, the search was limited to papers published in the past two years (2023-24) to capture the latest state-of-the-art research of AI in Design. The titles and abstracts (and full texts if necessary) of the retrieved papers are scanned through for deciding papers to review, which are related to AI in design and manufacturing, for yielding the state-of-the-art review result. Please note that due to the different scopes of the journals selected, some journals returned fewer results than others.



* NPD process are modified based on Ulrich and Eppinger (2015)'s NPD process by adding Pre-NPD and In-use stages. 'Testing & Refinement' is integrated into the 'concept development' phase.

Figure 1. The data-driven design framework (Lee and Ahmed-Kristensen, 2023, 2024, 2025)

To present a more structured review, the papers reviewed are thematically analysed and then categorised according to the seven design activities as indicated in the Data-driven Design Framework proposed by Lee and Ahmed-Kristensen (2023, 2024, 2025), as shown in Figure 1. The Data-driven Design Framework reviewed research using big data and AI for designing products and services over a decade until 2022. Thus, the focus of this study is on the last two years, enabling more recent research to be captured and focusing specifically upon the use of AI. The categorisation scheme of AI in design activities, alternatively the coding scheme, involves two levels. As shown in Figure 1, the scheme involves seven level 1 codes of activities: "Planning", "Discovering", "Defining", "Generating", "Customising", "Maintaining", and "Validating". Each of the level 1 design activities involves sub-level (level 2) activities, for example, "Planning" consists of "Shape business strategy" and "Plan product families, and portfolio". See (Lee and Ahmed-Kristensen, 2023, 2024, 2025) for more information. Please note that not every code indicated has been used in this study due to the limited data collected.

To shape business strategy in "Planning" activities, Zhang et al. (2023) proposed a Grey-Markov model to predict user demands using online reviews, which helps enterprises optimise product design.

In "Discovering" activities, Chen, Xiao, et al. (2024) developed a heuristic-based algorithm, employing NLP and computer vision techniques, to interpret the components that constitute a combinational design, which helps designers understand the underpinning design processes. Zhou et al. (2024) developed a persona tool, using ChatGPT and SadTalker models, to enhance persona perception. Y.-h. Chen et al. (2023) proposed an AI-driven method, using a graph neural network (GNN), to discover brand-related features to help designers better understand a brand. Jiang et al. (2023) explored the use of natural language processing (NLP) to discover the "*Motivation*", "*Specification*" and "*Structure*" from patent descriptions to help designers gain design intent. Obieke et al. (2023) used NLP and Markov chain for discovering new engineering design problems.

Regarding "Defining" activities, the papers retrieved mainly focus on managing knowledge. Rahman et al. (2024) developed a design agent, employing reinforcement learning (RL) and the Markov Chain model, to transfer design knowledge from source to target tasks. R. Wang et al. (2024), X. Han et al. (2024) and Hu et al. (2023) proposed automated methods, employing machine learning techniques, for creating knowledge graphs using existing data, which can then be used as the infrastructure for supporting varying design tasks.

In "Generating" activities, a few studies have focused on using AI for concept generation. Chen, Zhang, et al. (2024) presented an AI foundation model, adopting LLM and Text-to-Image (T2I) Models, to generate textual and visual combinational ideas for facilitating designers in creative conceptual design. Chen, Zuo, et al. (2024) proposed an approach leveraging LLM to generate Function-Behavior-Structure (FBS) ontology to prompt creative design concepts. Zhu et al. (2023) used LLM to retrieve and map biological analogies for generating biologically inspired design concepts. Yuan et al. (2023) proposed a GAN-based model incorporating user sentiments for generating desirable design concepts. In addition to concept generation, Liu et al. (2024) used Cycle-GAN for generating synthetic sketches For "Customising" activities, Kumar and Chhabra (2024) employed a hybrid machine learning approach for scanning human wrists, which reduces scanning time and improves scanning accuracy, to support rapid prototyping of customised products.

To assess/predict/improve system performance in "Maintaining" activities, Zhang et al. (2024) proposed a dynamic gesture recognition system employing deep learning algorithms, which is linked to the digital twin model and then the physical manufacturing cells to enable complex operations involving human-robot interactions. X. Wang et al. (2024) introduced an integrated approach employing deep learning (Deep Neural Network (DNN) and Recurrent Neural Network (RNN) models) to minimise patch panel assembly completion time by analysing production capacity. Hou et al. (2024) proposed a performance evaluation method employing GNN to facilitate frame structure designs. Chiu et al. (2023) explored the use of NLP to assess design progress by visualising design processes. H. Chen et al. (2023) proposed a modular framework, using radial basis function neural networks (RBNN), for topology optimisation in additive manufacturing to reduce support structures.

In "Validating" activities, studies have explored the use of AI to aid decision-making. Xu et al. (2024) united human designers with AI to collaboratively solve complex and evolving problems in engineering systems design. Song et al. (2023) proposed an attention-enhanced multimodal learning model to evaluate design concepts based on sketches and textual descriptions.

The studies reviewed have provided state-of-the-art research in AI in design, and showed how AI techniques, such as LLM, NLP and deep learning, are used to enhance various design activities. A summary of the relevant studies on AI in design reviewed is presented in Table 1, with highlights of the AI in design activities coded to the scheme shown in Figure 1.

Table 1. AI in design in current studies

Codes - Activities (Level 1)	Codes - Activities (Level 2)	Role of AI in Design	Studies
Planning	Shape Business Strategy	User demands prediction	(Zhang et al., 2023)
Discovering	Understand User/Context Better	Design interpretation	(Chen, Xiao, et al., 2024)
		Persona perception	(Zhou et al., 2024)
		Brand recognition	(Y.-h. Chen et al., 2023)
		Design intend capture	(Jiang et al., 2023)
		Problem discovery	(Obieke et al., 2023)
Defining	Manage Knowledge	Knowledge transfer	(Rahman et al., 2024)
		Knowledge graph creation	(R. Wang et al., 2024), (X. Han et al., 2024), (Hu et al., 2023)
Generating	Generate Product/Service Design Idea	Sketch generation	(Liu et al., 2024)
		Concept generation	(Chen, Zhang, et al., 2024), (Chen, Zuo, et al., 2024), (Zhu et al., 2023), (Yuan et al., 2023)
Customising	Customise Products/ Services	3D scanning	(Kumar & Chhabra, 2024)
Maintaining	Assess/Predict/Improve System Performance	Gesture recognition	(Zhang et al., 2024)
		Production capacity analysis	(X. Wang et al., 2024)
		Performance evaluation	(Hou et al., 2024)
		Design progress assessment	(Chiu et al., 2023)
		Manufacturing optimisation	(H. Chen et al., 2023)
Validating	Aid Decision-making	Problem-solving	(Xu et al., 2024)
		Concept evaluation	(Song et al., 2023)

3. AI in design - workshop study

To explore the opportunities and challenges of using AI in design within the manufacturing context, an industry-facing workshop was organised. A total of twenty-five participants from over ten firms from the manufacturing sector, including aerospace, automotive, heavy machinery, and heavy industries, participated in the workshop. The participant and firm identities are fully anonymous with no personal information, such as age and gender, or firm name, collected. The study received ethical approval from the Faculty Ethics Committee at the authors' institution (approval number 759840).

In the workshop, a presentation on Research in AI in design was first provided to inspire and engage the participants. They were then briefed about the following interactive session, where the participants were asked to work in groups of four or five to discuss the opportunities and challenges of using AI in design activities for 20 minutes. This was to enable participants to share thoughts and experiences to motivate and learn from each other. A worksheet with the "*What are the opportunities of using AI*" and "*What are the challenges of employing AI*", was provided to each participant. The participants were then asked to fill in the worksheet individually to identify opportunities and challenges of using AI in design in their own firms for 10 minutes. A member from each group was then invited to present their discussion outcomes. The worksheets were collected for further analysis. Overall, sixteen participants (P1 - P16) provided valid results. The data collected was thematically analysed. The codes from the Data-Driven Design Framework (Lee and Ahmed-Kristensen, 2023, 2024, 2025), as shown in Figure 1, were used. These are presented in Table 2. A new categorisation scheme was developed to summarise the challenges of AI in design, as presented in Table 3.

As indicated in Table 2, "Validating" is the level 1 activity in which most participants indicated where the opportunities for using AI are, of which 8 participants mentioned that AI has the opportunity to "Aid Decision-making" (level 2 activity) such as "*Assist in decision making in complex situations*" (P5) and "*Augmented human activity*" (P7). "Generating", "Maintaining", "Planning" and "Defining" are also primary design activities where opportunities exist. In “Generating”, 7 participants indicated examples such as “*Idea exploration*” (P11) and “*Generative design*” (P16) for “Generate Product/Service Design Idea”. For “Maintaining”, 7 participants showed examples such as “*Isolation of faults through clustering of data*” (P4) and “*Quality improvements*” (P16) for “Assess/Predict/Improve System Performance”. In “Planning”, 7 participants indicated AI could be used to “Shape Business Strategy”, such as “*More opportunities in manufacturing (trends etc.)*” (P6) and “*Accurate quoting*” (P13). For “Defining”, 5 participants indicated examples such as “*Knowledge retention in company*” (P6) and “*Democratisation of information*” (P10) to “Manage Knowledge” and 1 participant indicated “*Bring better access to expertise*” (P9) to “Support Sense-making”.

Table 2. AI in design - opportunities

Codes – Opportunities (Level 1)	Codes – Opportunities (Level 2)	Examples	Frequencies (by participants)
Planning	Shape Business Strategy	“*More opportunities in manufacturing (trends etc.)*” (P6); “*Connectivity*” (P8); “*Accurate quoting*” (P13)	7
Discovering	Understand User/Context Better	“*Unlock company knowledge*” (P9); “*Find answers to already solved problems*” (P16)	2
Defining	Manage Knowledge	“*Knowledge retention in company*” (P6); “*Knowledge retention*” (P9); “*Democratisation of information*” (P10)	5
	Support Sense-making	“*Bring better access to expertise*” (P9)	1
Generating	Generate Product/Service Design Idea	“*Idea exploration*” (P11); “*Design ‘task’ automation*” (P14); “*Generative design*” (P16)	7
Customising	Customise Products/ Services	“*Personalisation/Bespoke development of products*” (P4); “*Opportunity for bespoke design in a short time frame + validation (simulated)*” (P5)	4
Maintaining	Assess/Predict/Improve System Performance	“*Isolation of faults through clustering of data*” (P4); “*Improve product + processes*” (P15); “*Quality improvements*” (P16)	7
Validating	Aid Decision-making	“*Assist in decision making in complex situations*” (P5); “*Augmented human activity*” (P7)	8

As indicated in Table 3, three level 1 and eleven level 2 codes for AI in design challenges are newly developed. Among the eleven level 2 codes of challenges, three codes are relevant to “Data” (level 1 code) including “Data Analysing” such as “*Data Interpretation*” (P1) and “*Quality of data + assessment*” (P4), “Data Capture” such as “*Appropriate data capture*” (P12) and “*Source of data*” (P16), and “Data Wrangling” such as “*Data Cleansing*” (P1). Two codes are relevant to “Human” including “Human in the loop” such as “*There would have to be validation of the AI output-human intervention*” (P5) and “*Human in the loop production*” (P10), and “Human Knowledge and Skills” such as “*Team skills*” (P11) and “*Skills*” (P16). The remaining six challenges are related to “Governance” which are not directly related to design or AI, but are based on the broad coverage of challenges and frequencies mentioned by participants, including “Ethics”, “Legal”, “Regulation”, “Security, Privacy and IP”, “Transparency”, and “Trust and Verification”. 9 participants indicated “Security, Privacy and IP” challenges, such as “*Mainly security in protecting IP and systems*” (P4) and “*Public/cloud based AI with company data*” (P12), positioning it as one of the two biggest level 2 challenges identified. The other biggest level 2 challenge is “Trust and Verification”, where 9 participants identified challenges such as “*Misinformation*” (P8) and “*Trust in outcomes (too much trust?)*” (P14).

Table 3. AI in design - challenges

Codes - Challenges (Level 1)	Codes - Challenges (Level 2)	Examples	Frequencies (by participants)
Data	Data Analysing	"*Data Interpretation*" (P1); "*Quality of data + assessment*" (P4); "*Data input/ train AI systems*" (P13)	3
	Data Capture	"*Access to universally true data*" (P9); "*Appropriate data capture*" (P12); "*Source of data*" (P16)	3
	Data Wrangling	"*Data Cleansing*" (P1)	1
Human	Human in the loop	"*There would have to be validation of the AI output-human intervention*" (P5); "*Human in the loop production*" (P10)	4
	Human Knowledge and Skills	"*Team skills*" (P11); "*Skills*" (P16)	3
Governance	Ethics	"*Ethics and logic of decision making*" (P9); "*Perception of job changes/ losses*" (P10)	3
	Legal	"*Accountability*" (P11); "*Trust/ legislation/ regulation*" (P15)	2
	Regulation	"*Regulation*" (P6); "*Unlock company knowledge*" (P9); "*No regulations fully defined*" (P12)	7
	Security, Privacy and IP	"*Mainly security in protecting IP and systems*" (P4); "*Public/cloud based AI with company data*" (P12); "*IP Protection*" (P13)	9
	Transparency	"*Black box risk/ trust the answer is good*" (9); "*Adoption of a blackbox AI solution*" (P10)	2
	Trust and Verification	"*Trust" (P1); "Misinformation*" (P8); "*Trust in outcomes (too much trust?)*" (P14)	9

4. Discussion

The state-of-the-art AI in design papers reviewed in this study has shown that researchers have focused on exploring AI technologies in an extensive range of design activities, including "Planning", "Customising", "Defining", "Discovering", "Generating", "Maintaining", and "Validating", as shown in Table 1. Among these activities, "Generating" is the activity that has attracted significant attention, and studies have explored the use of AI in generating concepts and sketches by leveraging the recent advancements in generative AI technologies such as LLM, Text-to-Image Models, and GAN. These studies have demonstrated the significant potential of using AI technologies to enhance such creative processes in "Generating" activities. In addition, a few prior studies, such as (Han et al., 2018a; Han et al., 2018b), have also employed non-generative AI techniques, such as NLP, for developing tools for supporting generation tasks. The workshop conducted has also revealed that "Generating" is one of the primary opportunities for using AI in design for a range of creative generative tasks such as generating ideas and designs, as presented in Table 2. This alignment shows the relevance of the state-of-the-art research studies in addressing the current industry needs in generating product/service design ideas. This is also in line with the AI target areas in new product development (NPD) identified by Cooper (2024). "Maintaining" is another design activity that has attracted researchers' attention in exploring AI for improving system performance by analysing, evaluating and optimising design and manufacturing performances. This is also one of the priority AI in design opportunities identified by the workshop participants, showing an alignment between current academic research and industry needs in using AI to improve or assess the performance of systems.

“Discovering” is an opportunity identified in the workshop, which has been extensively studied in research. The studies reviewed in this paper have explored AI for supporting “Discovering” activities, focusing on understanding the user or context better, such as interpreting designs and recognising brands, as well as discovering new problems. Moreover, several prior studies have specifically explored the use of AI technologies in discovering new insights from data, particularly textual ones. For example, Cheong et al. (2017) used a natural language processing algorithm word2vec and also WordNet to discover functional knowledge from natural language text, and Yang et al. (2019) employed machine learning and text mining to discover user experience from online customer reviews for product design.

“Manage knowledge” in “Defining” is a popular AI in design opportunity identified by the workshop participants, which has also been explored by researchers. However, research studies are mainly aimed at employing AI for using or reusing knowledge, while industry participants indicated the main opportunity is to retain knowledge. Therefore, in addition to exploring the use/reuse of knowledge, research studies should also investigate methods or approaches to support the retention of knowledge.

“Planning” focuses on shaping business strategies which is another opportunity identified by the participants and is also considered an AI target area in NPD (Cooper, 2024), while only one study reviewed has explored AI to predict user demands and optimise product design. This has suggested more studies on shaping business strategies are needed to meet the industry demands. “Validating” is also one of the AI in design opportunities identified, and the participants indicated there are opportunities to use AI in aiding decision-making. However, from the studies reviewed, only two studies explored the use of AI for supporting decision-making, which indicates the need for more relevant studies. Similarly, “Customising” is considered a good opportunity for applying AI in design, while only one study reviewed has explored the use of machine learning for enhancing 3D scanning to customise products. This suggested the need for more studies on AI in design for “Customising”.

According to the discussions on the current research and industry opportunities in AI in design, four future research directions of AI in design within the manufacturing context are recommended to meet the industry demands:

- **Research Direction 1:** To explore AI methods and approaches to support industry firms in retaining knowledge to preserve and access information or expertise accumulated over time.
- **Research Direction 2:** To use AI technologies to help industry firms shape business strategies, such as to better address consumer needs, ultimately leading to success.
- **Research Direction 3:** To develop AI tools and systems for supporting human design engineers in making decisions throughout the design process.
- **Research Direction 4:** To investigate AI methods for achieving and enhancing product and service customization, enabling tailored design solutions meeting individual needs.

Although current studies in AI in design have delivered substantial theoretical contributions, these studies may not be applicable in the industrial context due to practical challenges. In the manufacturing sector, some of the key barriers to adopting digital technologies that are well recognised include: leadership, skills of teams, understanding the value, and the infrastructure that is around the adoption of digital technology (Maier, 2017). The workshop conducted has enabled a more nuanced understanding of the needs around data, governance, privacy and ethics of AI and expanded the challenges to also consider the trust and the need for a human-in-the-loop, as indicated in Table 3. Three groups of challenges were identified: “Data”, “Human”, and “Governance”. The data-related challenges include data analysing, capture and wrangling. Many existing and prior research studies, including the ones reviewed, have explored and addressed relevant data challenges to a certain extent. For example, in the studies reviewed, R. Wang et al. (2024) captured data from patents and papers and then categorised the data into concept, decision and knowledge spaces; Jiang et al. (2023) captured and linked patent information relevant to discovering design intent; and Obieke et al. (2023) extracted engineering design project titles from various databases and cleaned the data using ML and NLP, serving as the knowledge corpus for problem discovery. In prior studies, Shi et al. (2017) retrieved design knowledge data from an academic journal database and structured the data using machine learning to form a knowledge network for analysing the relationships between knowledge; and Luo et al. (2018) constructed a technology network map from a patent database using a knowledge proximity metric to identify design opportunities. This has shown the research initiatives in tackling data-related challenges, improving data analysing, capture and wrangling to better support the application of AI in design in industrial contexts.

To improve machine accuracy and reliability, as well as enhance human efficiency and effectiveness, interactions between humans and AI are often needed (Mosqueira-Rey et al., 2023). This is generally known as human-in-the-loop, which is a challenge identified in the workshop. Recent studies, such as (Zhu & Luo, 2023), (J. Han et al., 2024a) and (Song et al., 2024), have explored human-in-the-loop AI in design. However, these studies only explored theoretical models, and more practical studies are needed to better deploy human-in-the-loop AI in design. In addition, participants also indicated that lacking staff members with the knowledge and skills in AI has caused barriers to adopt and apply AI in design. This is challenging to solve within a short period of time, and it may need to be tackled in a long-term plan, such as through education.

The governance-related challenges identified, such as security, privacy and IP issues, trust and verifications issues, and regulation issues, are the major challenges identified for AI in design by the workshop participants from the industry. Prior studies have explored ethical issues (Chan, 2018; van Gorp, 2007) and trust issues (Pink et al., 2020) in design. However, due to the nature of AI technologies, such governance challenges are becoming more complicated and require collaborative efforts to resolve. Therefore, three future research directions of AI in design are proposed to help the design and manufacturing industry address the challenges faced, which involve:

- **Research Direction 5:** To investigate practical interactive methods and approaches to enhance human and AI collaboration in design activities.
- **Research Direction 6:** To develop a pedagogical framework to equip future design and engineering students with AI knowledge and skills, meeting the industry demand.
- **Research Direction 7:** To produce governance policies and guidelines for AI in design by collaborating with governance experts.

5. Conclusions

This study contributes to the rapidly growing research on AI in design, and identifies the opportunities and challenges of AI in design in practice within the manufacturing context by conducting a workshop involving industry practitioners from several well-known design and manufacturing firms. A readily available Data-driven Design Framework was used to categorise the AI in design activities identified in the studies reviewed and the opportunities identified in the workshop conducted, with a new categorisation scheme developed to summarise the challenges. This showcased how the Data-driven Design Framework could be used to categorise AI design activities and support the development of AI in design. Through analysing the state-of-the-art AI in design research and practical AI in design opportunities identified by industry participants, as well as the practical barriers to applying AI in design, seven future research directions are proposed to address the challenges and opportunities. Some of the research directions proposed might not be “new” for academic research but are “new” and essential for industry practice. This study serves as a guide to ensure future research and applications of AI in design are grounded in practice to help the design and manufacturing industry better adopt AI technologies, bridging the gap between academic research and industry practice.

Moving forward, more literature from a broader range of design and manufacturing journals, covering a longer period of time, will be retrieved to produce a more comprehensive review to enhance the findings. The participant number in the workshop is limited in this study, and more participants will be recruited in a future workshop to better reflect the needs of the industry. In addition, extra tasks will be provided to future workshop participants to explore how the current design and manufacturing industry is using AI and their learnings. Further analysis will be performed to better implement the seven research directions, by identifying appropriate methodologies and potential impacts and transformations. This allows researchers to co-develop approaches with industry practitioners to jointly address the challenges to better support industry development.

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References

Chan, J. K. H. (2018). Design ethics: Reflecting on the ethical dimensions of technology, sustainability, and responsibility in the Anthropocene. *Design Studies*, 54, 184-200. https://doi.org/10.1016/j.destud.2017.09.005

Chen, H., Joglekar, A., Whitefoot, K. S., & Burak Kara, L. (2023). Concurrent Build Direction, Part Segmentation, and Topology Optimization for Additive Manufacturing Using Neural Networks. *Journal of Mechanical Design*, 145(9). https://doi.org/10.1115/1.4062663

Chen, L., Sun, L., & Han, J. (2023). A Comparison Study of Human and Machine-Generated Creativity. *Journal of Computing and Information Science in Engineering*, 23(5). https://doi.org/10.1115/1.4062232

Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., Childs, P. R. N., Xiao, J., & Wu, C. (2019). An artificial intelligence based data-driven approach for design ideation. *Journal of Visual Communication and Image Representation*, 61, 10-22. https://doi.org/10.1016/j.jvcir.2019.02.009

Chen, L., Xiao, S., Chen, Y., Sun, L., Childs, P. R. N., & Han, J. (2024). An artificial intelligence approach for interpreting creative combinational designs. *Journal of Engineering Design*, 1-28. https://doi.org/10.1080/09544828.2024.2377068

Chen, L., Zhang, Y., Han, J., Sun, L., Childs, P., & Wang, B. (2024). A foundation model enhanced approach for generative design in combinational creativity. *Journal of Engineering Design*, 1-27. https://doi.org/10.1080/09544828.2024.2356707

Chen, L., Zuo, H., Cai, Z., Yin, Y., Zhang, Y., Sun, L., Childs, P., & Wang, B. (2024). Toward Controllable Generative Design: A Conceptual Design Generation Approach Leveraging the Function–Behavior–Structure Ontology and Large Language Models. *Journal of Mechanical Design*, 146(12). https://doi.org/10.1115/1.4065562

Chen, Y.-h., Kara, L. B., & Cagan, J. (2023). BIGNet: A Deep Learning Architecture for Brand Recognition with Geometry-Based Explainability. *Journal of Mechanical Design*, 146(5). https://doi.org/10.1115/1.4063760

Cheong, H., Li, W., Cheung, A., Nogueira, A., & Iorio, F. (2017). Automated Extraction of Function Knowledge From Text. *Journal of Mechanical Design*, 139(11). https://doi.org/10.1115/1.4037817

Chiu, M., Lim, S., & Silva, A. (2023). Visualizing design project team and individual progress using NLP: a comparison between latent semantic analysis and Word2Vector algorithms. *AI EDAM*, 37, e18, Article e18. https://doi.org/10.1017/S0890060423000094

Cooper, R.G. (2024). The AI transformation of product innovation. *Industrial Marketing Management*, 119, 62-74. https://doi.org/10.1016/j.indmarman.2024.03.008

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. *Commun. ACM*, 63(11), 139–144. https://doi.org/10.1145/3422622

Han, J., Childs, P. R. N., & Luo, J. (2024a). Applications of artificial intelligence and cognitive science in design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 38, e6, Article e6. https://doi.org/10.1017/S0890060424000052

Han, J., Obieke, C. C., Zhao, H., & Jiang, P. (2024b). Using AI to generate short videos as stimuli for supporting design creativity. *DS 136: Proceedings of the Asia Design and Innovation Conference (ADIC) 2024*. 11-18.

Han, J., Shi, F., Chen, L., & Childs, P. R. N. (2018a). The Combinator – a computer-based tool for creative idea generation based on a simulation approach. *Design Science*, 4, e11, Article e11. https://doi.org/10.1017/dsj.2018.7

Han, J., Shi, F., Chen, L., & Childs, P. R. N. (2018b). A computational tool for creative idea generation based on analogical reasoning and ontology. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 32(4), 462-477. https://doi.org/10.1017/S0890060418000082

Han, X., Liu, X., Wang, H., & Liu, G. (2024). An automatic completion method for design domain knowledge graph using surrogate model, for rapid performance evaluation. *Journal of Engineering Design*, 1-23. https://doi.org/10.1080/09544828.2024.2332121

Hou, W., Li, Y., & Wang, C. (2024). FrameGraph: A Scalable Performance Evaluation Method for Frame Structure Designs Using Graph Neural Network. *Journal of Mechanical Design*, 146(12). https://doi.org/10.1115/1.4065612

Hu, Z., Li, X., Pan, X., Wen, S., & Bao, J. (2023). A question answering system for assembly process of wind turbines based on multi-modal knowledge graph and large language model. *Journal of Engineering Design*, 1-25. https://doi.org/10.1080/09544828.2023.2272555

Jiang, P., Atherton, M., & Sorce, S. (2023). Extraction and linking of motivation, specification and structure of inventions for early design use. *Journal of Engineering Design*, 34(5-6), 411-436. https://doi.org/10.1080/09544828.2023.2227934

Kumar, A., & Chhabra, D. (2024). Hybrid machine learning approach for accurate and expeditious 3D scanning to enhance rapid prototyping reliability in orthotics using RSM-RSMOGA-MOGANN. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 38, e7, Article e7.

Lee, B., & Ahmed-Kristensen, S. (2023). Four Patterns of Data-Driven Design Activities in New Product Development. *Proceedings of the Design Society*, 3, 1925-1934. https://doi.org/10.1017/pds.2023.193

Lee, B., & Ahmed-Kristensen, S. (2024). D^{3}IKIT: data-driven design innovation kit. *Proceedings of the Design Society*, 4, 2109-2118. https://doi.org/10.1017/pds.2024.213
Lee, B., & Ahmed-Kristensen, S. (2025). D3 framework: An evidence-based data-driven design framework for new product service development. *Computers in Industry*, 164, 104206. https://doi.org/10.1016/j.compind.2024.104206
Liu, X., Fan, H., Hansen, P., Zou, N., & Chai, C. (2024). Exploring the efficacy of hybrid-sketch: an investigation into conceptual support in the early design stage. *Journal of Engineering Design*, 1-23.
Luo, J., Song, B., Blessing, L., & Wood, K. (2018). Design opportunity conception using the total technology space map. *AI EDAM*, 32(4), 449-461. https://doi.org/10.1017/S0890060418000094
Maier, J. (2017). *Made Smarter Review*. Available from: https://assets.publishing.service.gov.uk/media/5a74fceced915d502d6cc9dd/20171027_MadeSmarter_FINAL_DIGITAL.pdf
Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: a state of the art. *Artificial Intelligence Review*, 56(4), 3005-3054.
Obieke, C. C., Milisavljevic-Syed, J., Silva, A., & Han, J. (2023). A Computational Approach to Identifying Engineering Design Problems. *Journal of Mechanical Design*, 145(4). https://doi.org/10.1115/1.4056496
OpenAI. (2022). *Introducing ChatGPT*. https://openai.com/index/chatgpt/
Pink, S., Osz, K., Raats, K., Lindgren, T., & Fors, V. (2020). Design anthropology for emerging technologies: Trust and sharing in autonomous driving futures. *Design Studies*, 69, 100942.
Rahman, M. H., Bayrak, A. E., & Sha, Z. (2024). Empirical evidence and computational assessment on design knowledge transferability. *Design Science*, 10, e10, Article e10. https://doi.org/10.1017/dsj.2024.7
Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., Chen, M., & Sutskever, I. (2021). Zero-Shot Text-to-Image Generation. *Proceedings of the 38th International Conference on Machine Learning, Proceedings of Machine Learning Research*. https://proceedings.mlr.press/v139/ramesh21a.html
Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*,
Shi, F., Chen, L., Han, J., & Childs, P. (2017). A Data-Driven Text Mining and Semantic Network Analysis for Design Information Retrieval. *Journal of Mechanical Design*, 139(11). https://doi.org/10.1115/1.4037649
Song, B., Miller, S., & Ahmed, F. (2023). Attention-Enhanced Multimodal Learning for Conceptual Design Evaluations. *Journal of Mechanical Design*, 145(4). https://doi.org/10.1115/1.4056669
Song, B., Zhu, Q., & Luo, J. (2024). Human-AI collaboration by design. *Proceedings of the Design Society*, 4, 2247-2256. https://doi.org/10.1017/pds.2024.227
van Gorp, A. (2007). Ethical issues in engineering design processes; regulative frameworks for safety and sustainability. *Design Studies*, 28(2), 117-131. https://doi.org/10.1016/j.destud.2006.11.002
Wang, D., & Han, J. (2023). Exploring The Impact of Generative Stimuli on The Creativity of Designers in Combinational Design. *Proceedings of the Design Society*, 3, 1805-1814. https://doi.org/10.1017/pds.2023.181
Wang, R., Sun, Y., Peng, T., Hua, Y., Wang, G., & Yan, Y. (2024). A knowledge graph-aided decision guidance method for product conceptual design. *Journal of Engineering Design*, 1-40. https://doi.org/10.1080/09544828.2024.2368405
Wang, X., Lin, C., Yang, S., Chen, J., Liu, B., & Chipusu, K. (2024). A deep learning approach for balance optimisation of patch panel assembly line. *Journal of Engineering Design*, 1-19. https://doi.org/10.1080/09544828.2024.2309861
Xu, Z., Hong, C. S., Soria Zurita, N. F., Gyory, J. T., Stump, G., Nolte, H., Cagan, J., & McComb, C. (2024). Adaptation Through Communication: Assessing Human-Artificial Intelligence Partnership for the Design of Complex Engineering Systems. *Journal of Mechanical Design*, 146(8). https://doi.org/10.1115/1.4064490
Yang, B., Liu, Y., Liang, Y., & Tang, M. (2019). Exploiting user experience from online customer reviews for product design. *International Journal of Information Management*, 46, 173-186.
Yuan, C., Marion, T., & Moghaddam, M. (2023). DDE-GAN: Integrating a Data-Driven Design Evaluator Into Generative Adversarial Networks for Desirable and Diverse Concept Generation. *Journal of Mechanical Design*, 145(4). https://doi.org/10.1115/1.4056500
Zhang, F., Xu, B., Zeng, X., & Ding, K. (2024). Gesture-driven interaction service system for complex operations in digital twin manufacturing cells. *Journal of Engineering Design*, 1-27. https://doi.org/10.1080/09544828.2024.2360852
Zhang, N., Qin, L., Yu, P., Gao, W., & Li, Y. (2023). Grey-Markov model of user demands prediction based on online reviews. *Journal of Engineering Design*, 34(7), 487-521. https://doi.org/10.1080/09544828.2023.2233058
Zhou, L., Fang, Y., Ding, S., Cheng, Y., Yan, B., Zhu, W., Bao, S., Wang, J., & Song, S. (2024). Vivid-persona: customizable persona tool with interactive and immersive experiences. *Journal of Engineering Design*, 1-22.
Zhu, Q., & Luo, J. (2023). Toward Artificial Empathy for Human-Centered Design. *Journal of Mechanical Design*, 146(6). https://doi.org/10.1115/1.4064161
Zhu, Q., Zhang, X., & Luo, J. (2023). Biologically Inspired Design Concept Generation Using Generative Pre-Trained Transformers. *Journal of Mechanical Design*, 145(4). https://doi.org/10.1115/1.4056598