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Artificial Intelligence in engineering design: an industry perspective

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ABSTRACT: This research is a first of its kind, building an understanding of the opinions of industry professionals on the imminent AI revolution. Semi-structured interviews with eight experienced engineers from a range of industries were conducted. Transcripts of interviews were coded revealing engineering practitioner's understanding of, experience with, and vision for the use of AI technologies. The significance of the outcomes reveals the challenges industry face in realising an AI-driven design future and the actionable support that researchers and educators can provide to achieve this future.

KEYWORDS: design engineering, design practice, multi- / cross- / trans-disciplinary processes

1. Introduction

Artificial intelligence (AI) promises to revolutionise engineering practice, yet successful integration of the technology into the design process remains challenging. The McKinsey Global Survey on AI of 1,684 participants in April 2023 revealed 79% of businesses have experimented with Generative AI technology and 22% use it regularly (Chui, 2023). The extent to which engineers working in design have used and tested AI technologies is relatively unknown despite the acceleration of research into the potential uses of the technologies.

AI is often afforded the ability to save humans time by performing laborious and repetitive tasks and managing complexity (Burggräf, 2024). While this benefit remains significant in today's discussions, the potential for AI extends far beyond efficiency. Current research explores how AI tools can transform design processes (Hamilton et al., 2024), enhance creativity (Zhao et al., 2024), and foster collaboration (Zhang et al., 2021). On the contrary, studies highlight challenges in the use of AI in engineering design that may limit the efficacy and suitability of the application (Bender et al., 2021; Adeleye, 2024) or the acceptance of AI outputs by engineering designers with low self-confidence (Chong et al., 2022), and difficulties in ensuring the transparency of AI decisions (Vasiliu, 2024), hindering the ability of engineers to realise and trust AI-driven solutions (Lipton, 2017).

Whilst there is an abundance of research in educational settings such as the publications of the Engineering and Product Design Education Conference 2024 on the theme of AI in engineering education, the potential of AI to deliver measurable changes in engineering design practice remains to be determined. Alongside the long-standing debate of the overreliance of students within design research (Maier et al., 2018), this paper reveals a first-of-its-kind insight into the perspectives of experienced engineering industry professionals. Using a semi-structured interview methodology, engineers across industry reveal their understanding of AI as it relates to their practice. The outcomes of this research are an identification of the barriers to AI technology implementation and reflections on future research directions to support the adoption of novel AI technologies in engineering practice. Gaining a broader overview of the use of AI in professional settings is crucial to understanding how AI could be more effectively implemented into engineering design.

2. Literature review

Early efforts in AI development focused on logic and recognised problem-solving techniques such as 'the logic theorist', a programme aimed at automating reasoning (Gugerty, 2006). Further advancements from 1960's onwards saw the development of expert systems, which sought to tackle domain specific challenges, following a rule-based system which became highly popular in design research. These systems had significant challenges such as the generalisations and their ability to effectively handle dynamic information (Partridge, 1987).

In the 1990s and 2000s, AI research advanced with the rise of machine learning and neural networks, allowing for systems that can adapt to new and changing situations and effectively recognise patterns (Toosi et al., 2021). This development enabled AI to tackle real-world scenarios, though early iterations were limited by data availability and computational power (Thompson et al., 2023). By the 2010s, deep learning and advancements in big data processing further advanced AI, leading to breakthroughs in image recognition and the generation of detailed visual content (Shao et al., 2022), and the AI functionality supporting engineering designers today.

2.1. The role of artificial intelligence in engineering design

State-of-the-art research on AI in engineering design focuses overwhelmingly on the application of AI tools and how this changes the engineering design process (Liao et al., 2020; Williams et al., 2022). Brisco et al. (2023) and Dhami and Brisco (2024) explored the effectiveness of generative AI as a 'concept' generation tool. These studies concluded that generative AI is not yet suitable for this purpose where it may be in the future. Currently, AI generated images can be used as inspiration for designers. Similarly, Ranscombe et al. (2024) explored the use of generative AI to create inspiration boards for concept generation, where they found that generative AI could produce a wide variety of derivative ideas suggesting it is not yet best placed for novel ideation.

Song et al. (2022) reflects on homogeny, highlighting that reliance on AI's proposed design outcomes could lead to design fixation, negatively affecting the creation of novel conceptual ideas (Jannson & Smith, 1991). However, there is evidence that AI agents used during the design process can overcome fixation (Wang et al., 2024) as designers tended to avoid selecting their own ideas or others in the group, which sounds initially desirable. This suggests that there is a need to understand how to use AI best and to provide these recommendations to practitioners.

In addition, the use of AI has been proven to lead to an undesirable increase in 'free-riding' and a decrease in productivity (Andersson et al., 2012) in an educational context. This aligns with Hamilton et al. (2024), who observed that novice designers who used AI to assist them over-relied on the AI-generated material, with a perception that it was of better quality, despite 75% believing that sketching was more accurate to designers' intentions than AI (Holiman & Brisco, 2024). Zhang et al., (2021) agrees and succinctly presents this observation as "Human designers in high-performing teams aided by AI have an illusion of success". This is to say that the implementation of AI is complex.

Research exploration is beginning to build upon understanding of use (case studies) and reflect on ontological aspects such as 'characterising' generation (Bordas, 2024) 'frameworking' dependencies (Guertler, 2024) and 'modelling' AI creativity (Chen et al., 2024) which will overcome this complexity with theoretical assumptions.

2.2. The role of artificial intelligence in the industry

Research on AI use in real-world industry settings, particularly in engineering design, remains sparse until recently with a focus on research into public and industry engagement with UKRI Responsible AI in the UK, and the Human+AI Design Initiative in the USA, and other examples globally. This is likely due to the sensitive nature of the company's intellectual property. There are examples of successful implementation of AI technologies across various industries: In aerospace engineering, AI enhances remote sensing and quality control in component manufacturing (Li, 2024); In the automotive industry, AI enhances the efficient collection of data related to vehicle systems (Raj, 2023); In manufacturing, AI plays a critical role in human-robot collaboration and material design (Bin Akhtar, 2024). Case studies focus on large enterprises with significant resources to experiment with and implement AI, whereas small to medium-sized enterprises (SMEs), which dominate the design economy, lag in exploring and integrating AI in their processes due to cost, expertise, and infrastructure limitations (Design Council, 2022). Gero (2007) in AI EDAM at 20: Artificial intelligence in designing, reflected "Surprisingly little of the AI-based research into designing has overtly found its way into industry compared to, say, the optimisation-based research into designing" and which has, was done "without sourcing it to AI". However, this has changed with increased access to AI powered tools. Given the rapid pace of AI development and the interest of industry in the technology, it becomes imperative to understand the perspectives of experienced engineering designers, the experts in engineering design practice. This will reveal research challenges in the short term and societal challenges in the long term. This research will contribute to the research agenda by addressing the gap between theoretical research and practical applications of AI.

3. Methodology

The aim of this interpretivist study was to better understand experienced engineering design practitioners' perceptions of AI within industrial applications. Using a qualitative approach, this study explores perceptions of AI at the time of the study (August and September 2024) and the potential of AI in the future.

Semi-structured interviews were conducted with eight experienced engineering designers of 10+ years across a range of industries to collect diverse viewpoints. This method of enquiry was suitable for building knowledge and understanding in a semi-formal way and collecting motivations and attitudes. Participant metadata can be found in Table 1 with alias used for anonymity. There was no aim to recruit practitioners with or without AI experience; however, this aspect is of interest enabling enabled a more representative participant selection as reflects industry. The primary consideration of the recruitment was to invite a diverse range of perspectives in engineering, at different levels of career and company sizes from Small and Medium size Enterprise (SME) and Large Multinationals.

Table 1. Participant alias and professional profile

Alias	Industry	Company size	Job title	Years in practice	Experience with AI
Tars	Automotive	SME	Special Projects Lead Engineer	10	No
Sonny	Industrial Machinery	Large Multinational	Senior Design Engineer	10	No
Cal	Product Design and Manufacturing	Large Multinational	User Centred Design Manager	18	Yes
David	Software and Technology Development	SME	Director & Chief Product Officer	20	Yes
Brian	Product Design and Manufacturing	SME	Director	22	No
Ilia	Metrology	Large Multinational	Application engineer	10	No
Hal	Biotech	SME	Products Engineer	11	Yes
Marvin	Design Consultancy	SME	Product Design Lead	15	Yes

Fifteen open-ended questions were created to build an understanding of the role of AI in engineering design, the affordances of AI in engineering design, the value of AI for engineering design in the future, and the decision to use AI within industry. These questions were:

1. Tell me about your professional and educational background.
2. Can you describe your understanding of current AI technologies.
3. Do you have experience with AI technologies in your current job role?
4. Do you have experience with AI technologies beyond your job role (personal use)?
5. Do you consider current AI technologies as having an influence on your current work?
6. Do you consider current AI tools to have a benefit for you in your current work?
7. Do you consider AI technologies to have a benefit to your company currently?
8. Are there any barriers to implementing AI into your current work?
9. Do you think AI technology will have value for your current job role in the future?
10. Which barriers to you perceive in implementing future AI technologies in your current job practice as it currently is?

11 Do you think AI technology will have value for your company in the future?
12 Which barriers to you perceive in implementing future AI technologies in your company?
13 Which AI technologies do you think have the most potential to impact current practices?
14 What do you consider will drive a transition to AI technologies within engineering design practice in industry?
15 If we are to prepare the next generation of engineering designers to use AI technologies within their design practice, what attributes and skills do they need to have?

Interviews with each participant lasted between 15 and 40 minutes. Interviews were transcribed and inductive coding was completed by the interviewer and checked by a second researcher. Where differences occurred, a third or fourth researcher was consulted. Thematic analysis of the coding was conducted by all researchers.

4. Results

Seven of the eight participants referred to specific AI tools and their current uses during the interviews (Figure 1). One participant did not mention any AI tools or use cases during their interview due to their lack of awareness of AI and its abilities. Three participants mentioned they had no direct experience using AI technologies, whilst five mentioned they had experience using AI technologies.
Of the reported technologies, three of the overall use cases were of a personal nature, for music generation, summarising large sets of information and learning computer programming skills. They reflected that this was exploratory in nature, to understand what AI could do rather than achieving a specific purpose. Those who used AI for summarising content outside of professional settings did so as an aid to their personal education, e.g. David, who was using AI to summarise audio recordings of podcasts. The remaining 4 use cases were in a professional context. These were typically small and mundane tasks associated with an individual's job as a time-saving measure. These use cases include chatbot and transcription, refactoring of text, digital twins (digital avatars) and image manipulation. The most frequently mentioned task in a professional setting was summarising content. Table 2 expands on the awareness of AIs and the mentions of specific tools.

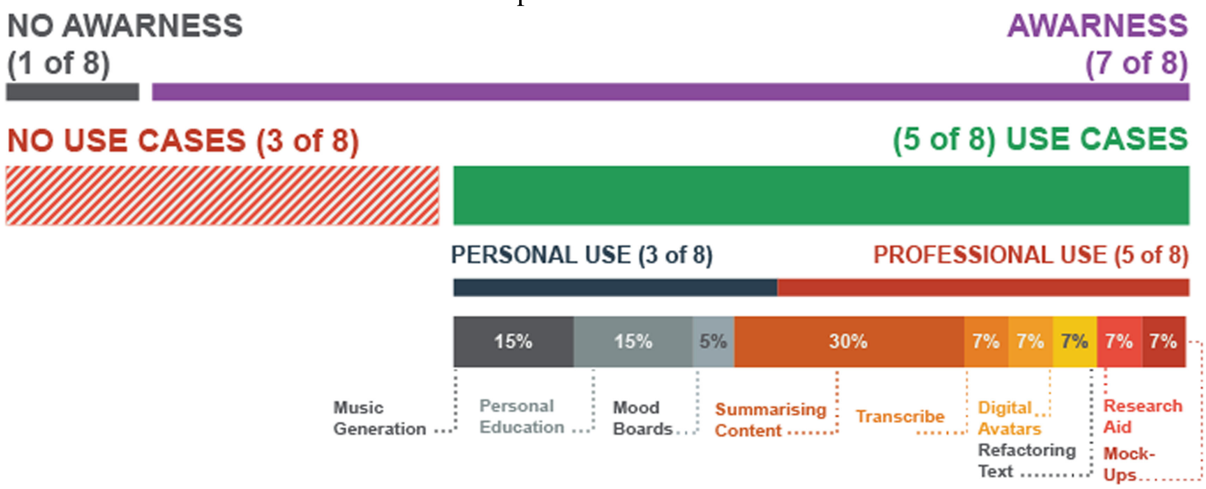

Figure 1. Awareness and use cases of AI

Participants reported knowledge of AI-associated functionalities for engineers, including text-to-image, computational analysis, topography optimisation, rendering, and code creation. Although, many of these functionalities are not currently implemented in engineering design practice as discussed in Section 5. Six of the eight participants mentioned ChatGPT, associating the AI with text-based activities such as refactoring text or asking for quick summaries. The same applies to Copilot and Google Gemini. Those who mentioned generative AIs, such as Midjourney, reflected that the AIs were not useful and did not produce desired outcomes. One participant, Hal, mentioned the use of a software called TensorFlow, which has AI integration; they commented that they knew about the hardware of the program but failed to reflect on the application. Only one participant mentioned the use of AI in terms of engineering analysis, Tars, who reflected on the use of AI for gearbox calculations and ratios. However, this was in response to future applications of AI rather than current uses. 62.5% of participants mentioned the concern of

Intellectual Property (IP) related issues, with the largest concern revolving around open access data and AI's learning. This is further discussed within Section 5.

Table 2. Awareness of AI's

	ChatGPT	Copilot	Gemini	Midjourney	Adobe	Krea	Tensor Flow	% Time Discussed
Tars	X		X		X			**43%**
Sonny	X		X		X			**43%**
Cal		X		X				**29%**
David	X			X				**29%**
Brian								**0%**
Ilia	X			X	X			**43%**
Hal	X						X	**29%**
Marvin	X	X		X		X		**57%**
Mentioned	**75%**	**25%**	**25%**	**50%**	**38%**	**13%**	**13%**	

5. Discussion

This research has revealed the awareness and perceptions practising engineering designers hold on AI use within their industry. Practitioners have shared the recent applications of widely available AI technologies or those they soon envisage as relevant to their practice. Their personal insights reveal potential future engineering applications for the industry. The outcomes have been coded and key themes emerged into the following:

a) Industry practitioners are aware of the functions that AI can perform. There are examples of AI affordances across engineering.
b) Industry practitioners can envisage new applications of AI based on their knowledge of current functions but lack vision of new functions and therefore new affordances.
c) There is a shared sentiment that industry will overcome barriers to implementation.
d) There is a desire to enhance the design process (automate less desirable tasks) with new AI-powered tools and processes.

This section will discuss the various perceptions held by practising engineer designers on AI technology use. These have been collated into appropriate categories within which findings will be identified.

5.1. Anticipated near-future AI use cases

Participants expressed a general awareness of AI tools but acknowledged a need to learn more about the functionality and tools available and how AI could support their practice. A major barrier to this is a lack of time in their working day to learn about these new technologies, even if potential improvements in process and efficiency might lead to greater time savings in the future.

> *"speak to us, it can be stuff like that that's a bit so like generate responses as well . . . "- Brian in response to Q11*

Study participants had sufficient understanding to know that AI can contribute to the streamlining of processes. There was a clear positive attitude towards AI technology's ability to automate mundane tasks that many consider less desirable, such as managing client relationships, allowing engineering designers to focus on creative tasks where a human can add value, which are considered more enjoyable. Alternatively, it might be used to complete time-consuming tasks such as, administrative tasks or design activities of rendering a 3D model, which can be used to inspire a client and secure buy-in for an idea. Half of those interviewed reflected on AI's uses for administrative and non-design-specific tasks within an engineering designer's role. Cal and David emphasised their views that future AI can help free up the workload for designers and allow them to tackle 'more creative' tasks. Participants were optimistic about AI's ability to collect, screen, and summarise information, allowing the designer to be a curator of knowledge and to go to the extent of drafting reports and proposals.

There was an optimistic reflection from participants that AI will one day have 'beyond human' capabilities. Which could solve systemic problems (Joksimovic et al., 2023) or may lead to trust in AI outputs without justification due to humans' inability to understand the complex connections that AI can make. However, the experienced engineers interviewed, such as David, reflected that they "... wouldn't trust it to do any insight generation", and Hal reflected that "it's hilarious how wrong it is", commenting on the abilities of current tools, demonstrating current AI tools must demonstrate and justify their reliability to be adopted by industry. The participants reflected that AI was suitable for providing inspiration, referring to the outputs of systems as 'Pinterest-like'. This is common in individual and team ideation through associative thinking, enabling the activation of one concept for others. Therefore, we might think of AI as part of a design team, providing inspiration beyond what the team possesses either because of effort or considering ethical, cultural, disability representation or a range of other identified factors. Unsolicited, those interviewed provided an estimate for AI technology adoption by practitioners. Tars and Sonny estimated 5-10 years, whereas Cal and David reflected that they "were not there yet", commenting more on societal acceptance than technology ability.

5.2. AI scepticism

Despite these future-thinking expressions of optimism, it is perceived by Cal that software developers and vendors are relabelling standard software as AI, which is simply a marketing tactic. This was reflected in a perception that the AI boom is overhyped, similar to the use of VR for engineering, a technology without widespread adoption.

5.3. Concerns of AI use

In contrast to the potential efficiency improvements that AI technology may provide, there is an expressed fear that AI may replace jobs either because of these very efficiency improvements or because of its ability to replace the workforce. Tars was confident in his reflection: "I hope it doesn't replace us completely. Nor do I think it could", which is an optimistic view considering the history of automation in the workplace (Antón et al., 2022). However, in contrast to these improvements in the engineering process, there was a sense that AI use could lead to a lack of creativity and homogeneity of products either through designers becoming lazy and over-relying on the solutions presented by AI (which itself only knows what it has been trained on), or a lack of skills in creative thinking as a result of a lack of need when AI tools are used. This could be useful, for example, to create simple products, e.g., jigs for manufacturing, but perhaps not those that embody user requirements.

5.4. Future AI vision

Within a design activity use case, engineering designers were interested in using future AI tools for specific design activities, including augmentation of form, such as topography optimisation. Significant future AI use case examples were reflected on an ability to "keep the designer right", relating to safety regulations and compliance with legislation, and as David put it, a "catalyst for inspiration" by using AI tools to prompt further ideation. These are all functions that AI can currently perform, and as such, there is no need to develop new functions of AI, but to make industry aware of the current tools and package them in a way that industry can utilise them effectively.

This lack of working knowledge of AI functionality is illustrated by the case of David, using Autodesk Revit[1] in an architecture role:

> *"You could upload all your Revit files, which is the architectural files, and then share that link out. And then anyone could look at it and garner their thoughts. And that's where we're going to be using AI, we want to use AI to do context aware sentiment analysis" - David in response to Q11*

David expressed a desire for an AI tool that can take 3D models and produce quick renders and images of proposed ideas but believes this is not yet possible. Tools, such as ArkoAI, have rendering capabilities and are open source. David further reflected on other AI's abilities, including summarising locally stored large datasets such as feedback and surveys and making real-time changes and additions to survey questions based on received responses. If someone responded to a survey, "It'd be nice if there were more trees, [it could respond] Where would you put the trees?". This highlights to us that whilst research and

[1] Autodesk Revit: BIM software https://www.autodesk.com/uk/products/revit/

creation of new AI tools is being conducted at a rapid pace, there is a lack of awareness of these new technologies.

5.5. Barriers to the use of AI in industry

Data security and intellectual property issues are major concerns for each participant's organisation, reflecting the general sentiment held across most industries and representing a significant barrier to adoption. For data security concerns, a lack of understanding and transparency around AI tool data usage prevents businesses from adopting the technology. A widely held concern is that free-to-use AI tools such as OpenAI's ChatGPT use input data as further training data, in effect "learning from the data it is provided". Tars reflected that data security and intellectual property is a "rational fear" for companies with a competitive advantage by securing their data. This indicates that current commercial AI software does not yet have appropriate security features. This will come in time as other software, e.g. file storage tools, demonstrate this ability, as confirmed by Sonny.

In the short term, this leads to a ban on AI tools being used in many industries and a stagnant adoption of AI tools. Locally managed AI tools on an individual's PC or a company server can alleviate this risk. Yet there is an associated cost implication, which most businesses are not prepared to pay, as illustrated in Tars's example:

> *"Good optics [and] good simulation of thermal and vibration. Those are things that AI could do. And the barriers are simply it will be expensive [to develop] and we [the company] won't want to pay for it" - Cal in response to Q12*

For AI technology-associated intellectual property concerns, there is a perceived legal "grey area", as demonstrated by a question posed by Cal's "Who holds the liability?". As there has not been a high-profile legal case to settle the matter, guidance from interest groups leads the narrative with work largely belonging to the public domain (Kop, 2019). Locally managed AI solutions require training data provided by the company to build the intelligence of the AI. Participants reflected that there was a barrier in the training of AI in new applications within their field amongst Sonny, David, Ilia and Hal, with concerns about the ownership of the training data (linking back to data security concerns) and having enough training data to make a viable tool. This led to the concern of cost to create an AI and, therefore, the initial investment (monetary and time) that a company would have to make with no guarantees of its usefulness. Of UK companies already implementing AI technology, 40% of are using in house developed technology, 40% purchased off-the-shelf solutions and 20% outsourced the development (Jarvis, 2024).

5.6. Reflections on this research

It was identified that there is a lack of conversational proficiency to discuss AI technologies and their affordances. 'Chat GPT' was often used to describe any AI tool capable of text-to-text or text-to-image conversion. Beyond this, 'Chat GPT' was used to describe functionalities of different technologies which had no relation to the capabilities of a GPT. Perhaps 'Chat GPT' is to AI as 'Google' is to search.

This misunderstanding extends further to the classifications of intelligence of different AI systems. Rule-Based Systems and Expert Systems were popular areas of research from the 1970s through to the early 2000s (Toosi et al., 2021). They represent a type of reactive AI based on the knowledge (rules) it possesses for a specific topic area. As mentioned in Section 2, early expert systems were flawed in their ability to learn and adapt to changing problems by following this rule-based system (Tan, 2017). As modern AI develops and deviates from its predecessors, the level of transparency from generated information may be seen as lower than what was gained from past expert systems (Longpre et al., 2023; Worth et al., 2024).

As educators, we reflect that there is a need to ensure that users of AI technologies are versed in critical thinking. Practitioners reflected their concerns about AI providing false outputs and that the outputs need to be justified to be used in any engineering project of value. Cal reflected that "just because you've got an answer from an AI doesn't mean it's accurate", and Ilia reflected that "Depending on the engineer and their expertise … you need a guideline … [to] defeat the AI machine in order to give you good information". Practitioners are responsible for ensuring that this newly generated knowledge is not accepted without evidence overcoming research findings of homogeneity and laziness.

In engineering design research, we are beginning to piece together an understanding of how these newly developed AI tools are being used, as industry also explores the possibilities. Workflows are being developed (Edwards et al., 2024) leading to design methodologies (Williams et al., 2022). The sentiment of the participants of this research reflected a welcome to AI technology, but they were cautious about its abilities. Our analysis demonstrates that there are signs of an understanding of the role AI can play for engineering design practitioners.

There is extensive research on the value of front-loading critical decisions, leading to significant overall cost savings for engineering project (Thomke & Fujimoto, 2000). What if AI could act as a supervisor, highlighting when design decisions conflict with a later known requirement of standards, legislation, or compliance documents? This is only the beginning; consider materials, force analysis, and legislation, which are all typically left to the end of the process but have a huge impact on cost.

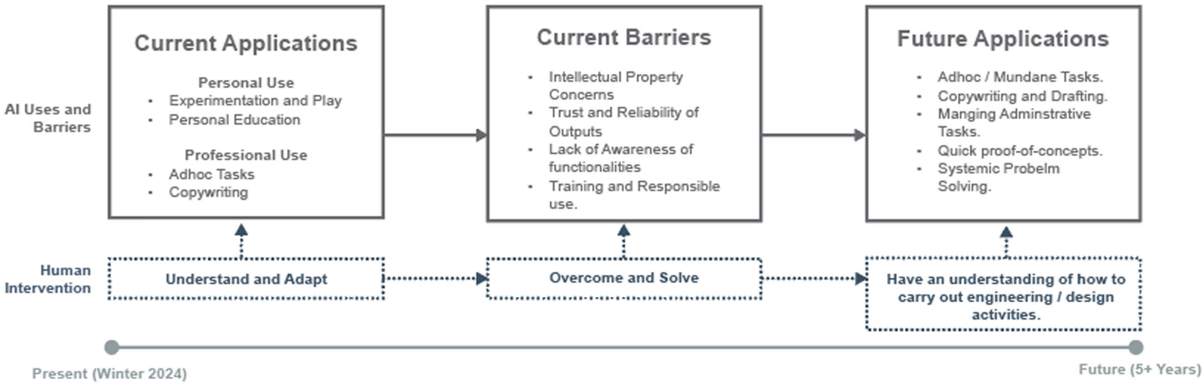

Figure 2. Present and future of AI within engineering design

6. Conclusion

This research has revealed the perspectives of professionals on the use of AI in engineering. Using semi-structured interviews with eight experienced engineers from a range of industries. As displayed in Figure 2, this study reveals that practitioners have an understanding of pervasive AI tools but lack vision for future innovations. There is a desire for more advanced AI tools that can automate undesirable tasks and enhance design processes, but there are barriers to its development and use. AI has cost savings potential, yet companies do not have the resources (financial and human power) to invest. The technology is expected to become cheaper over time because of economies of scale. Participants envision new applications of AI in areas such as form optimisation, safety regulations, and creativity inspiration. However, concerns around security, intellectual property, and availability of training data hinder the widespread adoption of AI technologies.

As publicly available AI tools are becoming more prevalent, there is a need for extensive training on AI potential and responsible use. Developing comprehensive education programs on AI use and critical thinking can help address the skills gap and ensure seamless integration into industry workflows. For design research, there is a need to better understand how design methodologies can adapt to incorporate AI tools, leading to new possibilities for collaboration and innovation. Encouraging collaboration between industry, academia, and research institutions can facilitate the development of standardised training programs, design methodologies, and standards for AI use.

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