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AI-led design innovation: understanding design-centric AI methods and assistance types

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ABSTRACT: With recent advancements in data-driven methods, there has been a growing interest in implementing AI in design. Despite this, a comprehensive understanding of the critical AI methods in design and how they support design practices remains lacking. To deepen our understanding, we conduct a comprehensive literature review and propose a novel, design-centric AI typology, associated with six AI assistance types for product service development. Our typology differs from traditional ones by shifting the focus from an algorithmic perspective to how models support design practice. Key findings highlight how these six design-centric AI methods support design practices in different ways, each with its own application challenges. Establishing a shared design-centric AI typology and assistance framework will enhance the understanding of how AI works differently and supports practitioners.

KEYWORDS: artificial intelligence, design practice, machine learning, AI-led design innovation, data-driven design

1. Introduction

Industry 4.0 is driving the development of increasingly interconnected products and services, requiring new business processes and opening up opportunities to derive value from data (Lee, 2022; Porter and Heppelmann, 2014). In this context, there is a growing interest in the design field, where AI-powered techniques, methods, and tools are rapidly reshaping the design landscape, fostering innovation in products and services (Lee et al., 2022; Lee and Ahmed-Kristensen, 2023; Verganti *et al.*, 2020). Due to the remarkable success of large generative AI systems, such as ChatGPT and large language models (LLMs), design practitioners are increasingly integrating these technologies into their everyday work—extending beyond intelligence-based document processing or numerical reasoning to include AI-assisted sketch (Qi and Song, 2020), design reviews (Gallega and Sumi, 2023), persona creation (Goel *et al.*, 2023), and developing new value proposition (Lee et al., 2019; York, 2023). Lee and Ahmed-Kristensen (2025) identify seven design activities that data and AI can support for product, service and system development, such as planning, discovering, defining, generating, customising, maintaining and validating.

While the benefits of AI in driving design innovation are widely recognised (Jyoti and Riley, 2022), comprehending which and how AI supports design and innovation practice remains a significant challenge (Lee, 2023). In academia, between 2020 and 2024, seven papers were published in leading journals for new product development, including the Journal of Product Innovation Management and R&D Management (Cooper, 2024). Some comprehensive literature review papers explore the use of AI to support designers; however, these reviews often focus on specific design disciplines, such as UI/UX design (Lu *et al.*, 2024), engineering design (Tsang and Lee, 2022) or architectural design (Castro Pena *et al.*, 2021). Moreover, these studies often focus on specific AI technologies rather than encompassing a broader range of AI methods applied to design practices, such as machine learning (Shi *et al.*, 2023) or generative AI (Furtado *et al.*, 2024). Despite their valuable contributions, previous review papers have been conducted within a limited and narrow scope, leaving a research gap in comprehensive reviews that integrate various design fields and AI methods.

In practice, although design practitioners are willing to employ data-driven methods (Gorkovenko *et al.*, 2020) and they have been good at value creation (Speed *et al.*, 2019), they often lack a comprehensive understanding of and training in data related skills (Lu *et al.*, 2024; Lee et al., 2022). We argue that a profound understanding of the types and underlying principles of AI for design and innovation is essential for design practitioners to independently apply design thinking when adopting data and AI techniques for value creation, ultimately driving design innovation in the development of product, services and systems. Therefore, in this work, we aim to provide a profound understanding of how data-driven methods are utilised across different design practices, and phases. A comprehensive literature review conducted from the lens of design innovation allows us to identify the typology of computational techniques employed for design innovation in product, service, and systems development, and in what way AI can assist design practice. Our overarching goal is to provide deeper insights into data-driven computational methods for design practices, fostering common ground and advancing AI-focused design innovation research. Accordingly, we identify our research questions as follows:

RQ 1. What AI methods are primarily used in design innovation?
RQ 2. How do AI methods support design practices?

This paper makes following contributions. First, we identify a novel typology of AI techniques in the context of design innovation, thus enabling practitioners and scholars to comprehend how different types of AI can support their daily practice in different design phases. Our novel design-centric AI typology differs from traditional AI categorizations by reorienting AI classification toward how models support design practice, treating data as a design material rather than focusing on the algorithmic perspective. The six types of design-centric AI include traditional machine learning (ML), reinforcement learning (RL), deep models in natural language processing (NLP), deep models in computer vision (CV), large generative AI and generative AI. Second, as a methodological contribution, we define a novel coding scheme for AI assistance types across design process. From the thematic analysis, AI methods can support design in seven different ways, including knowledge augmentation, knowledge generation, design generation, classification, prediction (using either symbolic reasoning or numerical reasoning), decision-making, and coordination. This differentiates our research from existing review studies.

This article structured as follows: in Section 2, we describe the methodology of comprehensive literature review. Section 3 provides the findings and discussions on the trajectory of AI-focused design innovation research for the last five years, typologies of AI techniques and AI assistance type for design innovation, and differences and commonalities of AI use in different design disciplines. Finally, conclusions are drawn in Section 4.

2. Methodology

To address our research questions, we conducted a comprehensive literature review of papers across relevant research fields. The 'systematic' aspect of the review process emphasises identifying all research addressing a specific question to provide a balanced and unbiased summary (Nightingale, 2009). The comprehensive review process began with a database search. We selected the established scientific databases, including Elsevier, IEEE Library, and ACM Library, to identify the relevant literature within the field of interest. These three databases are widely regarded as primary sources for literature searches. Relevant keywords were identified and combined into search strings to ensure a thorough and targeted search. Searched for papers including keywords "product design" OR "service design" OR "Product service system design" OR "user experience design" OR "human-computer interaction" OR "Industrial Design" AND "machine learning" OR "AI" OR "deep learning" OR "Gen-AI" OR "generative AI" OR "artificial intelligence" OR "Large Language Model" OR "GPT" in the title and author keywords. Figure 1 illustrates the research strategy employed in the comprehensive literature review.

We conducted our search in September 2024, indexing publications for the last five years between 2019 and 2024. Given the rapidly increasing interest in AI, we restricted the review period to this 5-year time frame. The initial keyword search yielded a total of 747 articles. After screening titles, and removing duplicates, non-English, and non-open access papers, the list was narrowed down to 104 articles.

Subsequently, a full-text review was conducted, resulting in a final selection of 65 papers. The selection was guided by the relevance of each study to the research question. Specifically, we included only those papers that clearly focused on the application or development of AI for design activities related to product and service development (e.g., industrial design, service design, UX/UI design, business design). We excluded papers investigating the design of AI systems. In addition to this, 17 studies were added through snowball sampling, a widely adopted literature search strategy that allows for the iterative inclusion of related papers either cited by or referencing the selected works (Wohlin, 2014). For the thematic analysis, we included only empirical studies conducted in real-world settings (n=46). This approach is crucial to ensure the findings are both academically grounded and relevant to industry.

Figure 1. Keyword combinations and the comprehensive literature review process

We developed coding schemes using two approaches: a top-down method based on existing categories, and a bottom-up method emerging from the initial data set. For example, we used a bottom-up, grounded approach and conducted a coding exercise from which to generate six AI techniques and seven AI assistance types inductively. We developed categories and codes from the data, and analytical memos were used between coding and writing. Conversely, the top-down approach was employed to categorise and define the stages of the design process where AI is utilised based on the Double Diamond framework (Design council, 2007). Two authors independently coded all the target articles, and then compared their results case by case, discussing any discrepancies to ensure consistency in coding (Lombard et al., 2002). The following section presents the findings from the thematic analysis and provides detailed discussions.

3. Findings and Discussions

3.1. What AI methods are primarily used in design innovation?

In this section, we present a design-centric AI typology identified through a comprehensive literature review. A total of 46 documents were reviewed and analysed to develop an AI typology for design and innovation. With the aim of supporting a deeper understanding of the various AI technologies applied in design practices, our novel AI classification framework is design-centric, distinguishing itself from existing technology-focused AI classifications, such as AI technologies across STEM fields (Berman *et al.*, 2023), AI methods in industry 4.0 (Alenizi *et al.*, 2023), and data-type-based generative AI classifications (Gozalo-Brizuela and Garrido-Merchan, 2023). Traditional AI categorizations, which focus on algorithmic perspective- such as how models learn data patterns and the types of training data used (e.g., supervised and unsupervised learning, deep learning, NLP, and CV) (Mukhamediev et al., 2022) fail to account for design practices. To address this gap, we reorient AI classification toward how models support design practice, treating data as a design material. The six types of design-centric AI methods are subcategories of three widely recognised computational methods- machine learning, deep learning, and generative AI (Rane *et al.*, 2024)- as follows: machine learning is divided into traditional machine learning (ML), and reinforcement learning (RL); deep learning is categorised into deep models in natural language processing, and deep models in computer vision; and generative AI is classified into large generative AI and generative AI (Figure 1). The detailed description of each AI method can be found in Table 1.

First two types of design-centric AI methods are the subcategories of machine learning technologies: traditional machine learning (ML) and reinforcement learning (RL). Traditional ML models heavily rely on statistical techniques to explicitly learn data distributions and patterns, thereby improving accuracy

Table 1. Six types of design-centric AI methods for design innovation

AI methods	Definition	Selected Model(s)	Design Applications	Limitations of AI applications in design	Selected studies
Traditional Machine Learning (ML)	Heavily rely on statistical techniques to explicitly learn data distributions and patterns, thereby improving accuracy (Sharifani and Amini, 2023).	Support Vector Machine (SVM), Random Forests, XGBoost	Feature engineering & recommendation; Data aggregation in design document management	Often requiring significant input from data engineers	Bodendorf and Franke, 2021; Golkarnarenji et al., 2019
Reinforced Learning (RL)	Based on the principled mathematical framework for reward-driven autonomous learning scheme (Arulkumaran *et al.*, 2017).	Particle Swarm Optimisation (PSO)	Predicting user activities, and engagement at a high abstract level	Computational complexity in certain scenarios; Poor reproducibility	Arulkumaran et al., 2017; Wang and Hu, 2024
Deep models in Natural Language Processing (NLP)	To derive effective feature representations for symbolic and sequential data from large corpora with billions of trainable parameters. They typically predict the next word based on a given sequence of previous words (Otter *et al.*, 2021).	Long Short-Term Memory (LSTM), Biodirectional Encoder Representations from Transformers (BERT)	Analysing user product reviews; Extracting design insights from design databases	Generating limited knowledge; Fine-tuning requires extensive datasets	Gammack et al., 2022; Wang et al., 2020
Deep models in Computer Vision (CV)	To extract latent and abstract features from collections of images using convolutional networks. They typically focus on identifying informative feature maps from sub-pixel data to predict image labels (Chai *et al.*, 2021).	Convolutional Neural Networks (CNN), ResNet	Design ideation; Visual aspect recommendations; Rapid prototyping	Restricted to specific design tasks, such as decision support with an emphasis on design feature understanding.	Zhou et al., 2022; Wu et al., 2020
Generative AI (GenAI)	Represents deep generative models to approximate complicated, high-dimensional probability distributions with high likelihood of a given sample (Ruthotto and Haber, 2021).	Variational Autoencoders (VAE), Generative Adversarial Networks (GANs)	Generating manufacturable design; characteristic-conditioned design	Issues with training bias and instability in optimisation	Zhang et al., 2019; Krahe et al., 2020
Large Generative AI (Large GenAI)	Primarily based on transformer models, particularly decoder-only architectures. They are trained on vast datasets with billions of parameters to generate symbols or images (Bandi *et al.*, 2023).	GPT3, Stable diffusion	Generating images or captions	High computational complexity; The need to train diverse datasets to achieve the performance	Goel et al., 2023; Jeon et al., 2024

(Sharifani and Amini, 2023). These models are particularly suited for predicting values based on extensive input training data and features in design practices (Bodendorf and Franke, 2021; Golkarnarenji *et al.*, 2019). In contrast, RL is based on a principled mathematical framework for reward-driven autonomous learning (Arulkumaran *et al.*, 2017) and is primarily adopted for decision-support tasks, such as predicting user activities, and engagement (Wang and Hu, 2024). Although some studies applied Traditional ML models for decision making tasks (Zhang, 2019), these applications were often constrained to specific, predefined, and selected features extracted from complex design resources, often requiring significant input from data engineers. The primary applications of machine learning (ML) include recommendation systems and classification, which are used to suggest design artifacts and tag them, enabling the implementation of image search engines. The use of traditional ML in design practice is limited due to their reliance on labelled and structured data for supervised learning. As a result, these models have been primarily used for simpler tasks, such as recommendations, data analytics, feature engineering, and data aggregation in design document management (Huo *et al.*, 2022). On the other hand, RL does not require a large, well-organised training dataset or extensive feature engineering performed by data engineers (Wang and Hu, 2024). However, its application remains limited to predicting user activities at a high abstract level due to computational complexity in certain scenarios and low generalisation performance.

Deep learning technologies are adopted differently in design practice depending on whether it is image-based symbolic reasoning or reasoning with language-model. Consequently, they are subcategorised into deep models in natural language processing (NLP) and deep models in computer vision (CV). Deep models in NLP aim to derive effective feature representations for symbolic and sequential data from large corpora to predict the next words (Otter *et al.*, 2021), often used for analysing user product reviews and extracting design insights from design databases (Gammack et al., 2022; Wang et al., 2020). These language model-based works rely on the symbolic reasoning capabilities of these models, limiting their assistance to generating knowledge, such as text summarisation or annotating tags and labels. Therefore, fine-tuning for design-specific tasks often requires extensive datasets. On the other hand, deep models in CV aim to extract latent and abstract features from image collections to identify informative feature maps from sub-pixel data (Chai *et al.*, 2021). Image-based symbolic reasoning is applied in design ideation, visual aspect recommendations, and rapid prototyping based on product specifications and requirements (Zhou *et al.*, 2022). While Convolutional Neural Networks (CNNs) have transformed the conventional design practices (Wu *et al.*, 2020), deep models in CV remain somewhat restricted to specific design tasks, such as decision support and design feature analysis. Numerous off-the shelf AI adopt deep learning technologies to support designers. Adobe's Neural Filters, for instance, leverage convolutional neural network (CNN)-based AI models to assist with photo editing tasks, including color correction, denoising, filter recommendations, and content-aware fill. Canva, on the other hand, has launched a CLIP-inspired deep learning model to recommend multilingual keywords for template labelling to assist creators.

The final two types of design-centric AI methods are subcategories of generative AI technologies: Generative AI (GenAI) and large generative AI. Distinguished by their underlying architectures, GenAI refers to early deep generative models, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) (Ruthotto and Haber, 2021), whereas large GenAI models are based on transformer models (Bandi *et al.*, 2023), including DALL-E, GPT-3, and Stable Diffusion. The two methods also differ in the scale of trainable parameters and training datasets, which directly impact generalisation and knowledge abstraction capabilities. Large GenAI can reproduce design artifacts from text prompts, whereas GenAI typically generates specific data samples closely tied to its training data patterns, with limited human-AI interaction. Unlike traditional models that predict class labels or dependent variables, GenAI creates plausible data points by mimicking data samples or distributions. For instance, GenAI has been employed to generate manufacturable components (Zhang et al., 2019), or characteristic-conditioned 3D objects (Krahe *et al.*, 2020). On the other hand, large GenAI is widely utilised for generating captions, images, and designs, ranging from rough sketches to replicas of masterpieces; (Jeon et al., 2024 (Gallega and Sumi, 2023).

This is attributed to the ability of large language models (LLMs), which can process and generate a wide range of text, from design brief, social media posts to technical reports (Goel et al., 2023). An interesting observation is that GenAI is predominantly applied within industrial design contexts, whereas large GenAI is mainly utilised in UI/UX design applications such as Figma. Despite the capability of both GenAI and large GenAI, their application in design practices remains limited. A well-known limitation of generative AI models is the instability of model training when limited datasets are used. Although large generative AI models can mitigate this issue through various knowledge transfer techniques, understanding new datasets remains a critical challenge, particularly in creative work. This limitation arises from insufficient training data, and it is unrealistic to assume that high-quality data will always be available for creative tasks.

In this section, six distinct design-centric AI methods are identified with specific design applications and challenges. The performance of traditional ML and RL heavily relies on specific features and statistical methods defined by data analysts. The design challenges are associated with adopting traditional ML and RL include labour-intensive data works and limited generalisation capabilities. Deep models in NLP and CV enhance the efficiency of design work by enabling the extraction of design insights, design classification, and recommendation. However, these methods bring design challenges, such as requiring extensive datasets, generating limited knowledge, and restricting the flexibility of deep models due to the integration of various types of multimodal design data. GenAI and large GenAI generate design outputs such as documents, and artifacts, thereby expanding their role beyond merely interpreting complex design data. The adoption of Gen AI is limited due to training bias and instability in optimisation whereas large GenAI has challenges, including high computational complexity.

While the six design-centric AI methods enable value creation, there are inevitable trade-offs, potential harms, and unintended consequences- such as destruction of other forms of value, such as social, moral, and environmental. It is because when data is selected, combined, contextualised and interpreted for AI methods, it represents particular versions of reality assembled for specific purposes- whether business plans, or political objectives (Jasanoff, 2018). Moreover, due to the lack of dataset controllability and outcome explainability, designers must be more mindful of potential ethical issues (e.g., copyright, discrimination) when adopting large GenAI models. The next section will describe where and how each design-centric AI method is adopted.

3.2. How do AI methods support design practices?

This section explains how AI supports design practices, ranging from knowledge augmentation, knowledge generation, design generation, prediction (symbolic reasoning and numerical reasoning), decision making, and coordination. The detailed descriptions of each type are as follows:

Knowledge augmentation: Large GenAI enhance designers' knowledge by providing quick access to extensive information, including design documents, user reviews, and market trends. Access to large datasets enables designers to make more informed decisions and stay updated with the latest developments in their field (Salminen et al., 2024).

Knowledge generation: Traditional ML, deep models in NLP, and large GenAI contribute to generating new knowledge by identifying patterns and correlations within complex datasets that may not be immediately apparent to designers. For instance, user interaction data can discover emerging behaviors, inspiring innovative design solutions that address unmet needs (Akay and Kim, 2021; Huang et al., 2023).

Design generation: GenAI and large GenAI assist in creating design outcomes by automatically generating a wide range of design alternatives (Solórzano Requejo et al., 2024). This accelerates the ideation process and facilitates the exploration of unconventional solutions that might otherwise remain unexplored.

Prediction (symbolic reasoning and numerical reasoning): Traditional ML and deep models in CV are employed to anticipate outcomes and simulate scenarios. Symbolic reasoning involves identifying design materials by predicting their labels. Image classification methods are adopted for symbolic reasoning in complex design datasets (Krahe et al., 2019). Numerical reasoning, on the other hand, predicts specific values or properties within design specifications (Golkarnarenji et al., 2019) or forecast production costs (Mandolini et al., 2024).

Decision making: RL, Traditional ML, and deep models in CV facilitate decision-making by evaluating design options based on criteria such as cost, feasibility, and user impact. These methods assist designers in making more objective and efficient decisions (Bodendorf and Franke, 2021; Wang, X. and Hu, 2024).

Coordination: Coordination focuses on enhancing communication and collaboration between team members. Deep models in CV and NLP, as well as large GenAI, support managing project timelines, assigning tasks, and monitoring progress to ensure alignment with project goals (Song et al., 2022). These methods also promote knowledge sharing within teams by organizing and retrieving relevant information when needed (Gammack et al., 2022).

These assistance types, linked to six AI methods, illustrate how AI supports various design practices across the four design stages of the Double Diamond design process (Table 2, Figure 2). During the Discovery phase, AI is used to provide well-defined information and predictions. Reinforcement learning (e.g., DRL) and traditional ML approaches help identify patterns and guide strategic choices. Deep learning models for NLP (e.g., BiLSTM, BERT) provide insights from large textual datasets, supporting

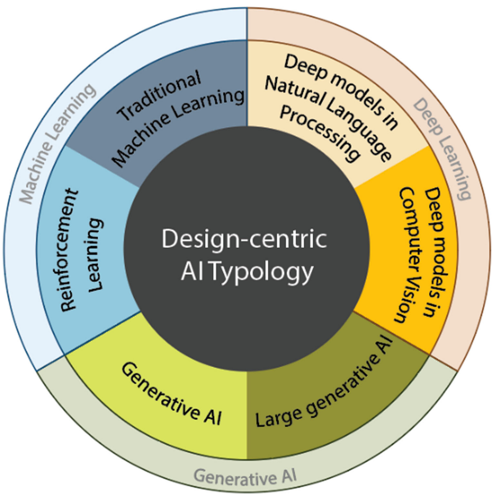

Figure 2. Design-centric AI Typology

teams in understanding user needs, market trends, and constraints. In the Define phase, AI methods focus on coordination and expanding the design knowledge for effective collaboration. Deep learning models in computer vision (CNNs) and NLP (BERT) facilitate clearer communication within teams and assist in identifying requirements from user feedback and reference materials. Large-scale generative models (e.g., ChatGPT, DALL·E, Midjourney) can aid in creating personas—both text and visual—helping teams refine their design concepts and establish a shared vision more efficiently.

Table 2. AI Methods and Assistance Types Across Design Phases

Design Phase	AI methods	Assistance types and selected studies
Discovery	Reinforcement learning	Decision making (Wang & Hu, 2024)
	Traditional ML	Prediction (Numerical reasoning) (Mandolini et al., 2024)
	Deep models in NLP	Knowledge generation (Huang et al., 2023; Liu et al., 2022)
Define	Deep models in CV and NLP	Coordination (Williams et al., 2019; Gammack et al., 2022; Chang et al., 2024)
	Large GenAI for text & image generation	Knowledge Augmentation (Goel et al., 2023; Salminen et al., 2024)
Develop	Deep models in CV	Coordination (Qi & Song, 2020; Wang et al., 2022; Li et al., 2024; Wu et al., 2023)
	Large GenAI for multimodal generation	Prediction (Symbolic reasoning) (Du et al., 2023; Requejo et al., 2024; Chong et al., 2024; Jeon et al., 2024)
	GenAI	Design generation (Kii et al., 2024; Krahe et al., 2020; Ye, 2024)
Deliver	Traditional ML	Decision making (Zhang, 2019; Liu et al., 2020; Wu et al., 2020; Zhou et al., 2022 Gallega et al., 2023)
	Deep models in CV	Knowledge Generation (Zhu et al., 2024)
	Large GenAI for multimodal generation	Prediction (Numerical & Symbolic reasoning)

During the Develop phase, AI methods support the generation of detailed concepts and the refinement of designs. Deep learning models for computer vision, Gen AI (e.g., GANs), and large GenAI (e.g., Stable Diffusion) enable the creation of multiple design alternatives through iterative processes. Techniques like RBF-ANN assist with symbolic reasoning, while multimodal models (StyleCLIP, DALL·E, LLMs) combine text and images to facilitate rapid design exploration. These tools allow designers to experiment with various aesthetics, functionalities, and colours before finalizing the design outcomes. Finally, in the Deliver phase, AI adoption focuses on decision-making and prediction as the product moves toward implementation. Traditional machine learning methods (SVM, KNN, Kalman filters) and deep learning vision models (e.g., CNNs, ResNet-50) help predict performance, verify quality, and ensure seamless integration. Generative models (Stable Diffusion) and large language models (e.g., GPT-3) assist with final documentation, adjustments, and minor refinements before launch.

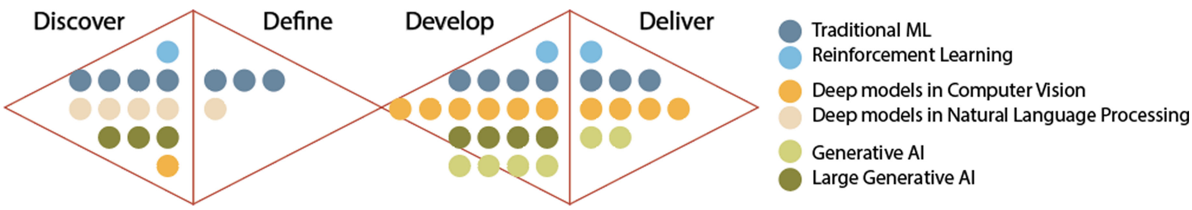

Figure 3. Mapping Design-centric AI Methods on Double-Diamond design process

AI methods are increasingly adopted to support designers' divergent thinking in discovering and managing design knowledge during the develop and discover phases, followed by supporting convergent thinking in the deliver and define phases. Traditional ML and RL are evenly used across four design phases, whereas other methods are applied to specific phases. Deep models in CV are used in the discover and define phases, while deep models in NLP and GenAI are utilised in the develop and deliver phases. Large genAI is primarily used for divergent thinking in the discover and develop phases. This section demonstrates how AI methods evolve to address the different needs of each design stage, beginning with data-driven exploration and progressing toward high-fidelity design generation and final optimisation. By employing six design-centric AI methods—traditional ML, RL, deep models in NLP and CV, and large-scale generative models—design teams can accelerate their process, enhance decision-making processes, deliver more refined solutions, ultimately driving innovation in design.

4. Conclusion

The paper has presented the results of a comprehensive literature review investigating how AI works and which AI is utilised for design innovation of products, services and systems. The comprehensive literature review identifies eighty-two scientific contributions to AI-focused design innovation research. The analysis focuses on the different AI technologies used for design practices, and the different assistance types of AI across design processes. The six design-centric AI methods include traditional ML, reinforcement learning, deep models in natural language processing, deep models in computer vision, generative AI and large generative AI. The six assistance types of AI for design include knowledge augmentation, knowledge generation, design generation, prediction, decision making, and coordination. Based on the design-centric AI methods and assistance types, this paper explores how AI methods differently support design practices, what challenges of each AI methods have when adopted for design. Given the profound impact of AI methods on design, it is timely to draw together this knowledge to identify design-centric AI methods and assistance types in design innovation. Establishing a shared design-centric AI typology and assistance framework would enhance understanding of how AI works differently and supports various design practices across design processes. This paper makes following contributions. First, we provide a design-centric AI typology that differs from existing classifications, providing practitioners and scholars with a deeper understanding of how six types of AI methods can support different design phases. While AI methods are conventionally categorised from an algorithmic perspective, our novel, design-centric AI typology shifts the focus toward how models support design practice, treating data as a design material. Additionally, we establish a new coding scheme for AI assistance types, which are linked with six AI methods throughout the design process. This aims to help scholars navigate the multidisciplinary research landscape, advancing current knowledge of AI in design and fostering increased cross-fertilisation across research fields. Like any review paper, this study has its limitations. First, the research period (2019-2024) is relatively narrow. Second, the review would benefit from a broader inclusion of key journals across various design fields, such as the Journal of Engineering Design, Journal of Service Research, and the International Journal of Human-Computer Interaction. This may limit a comprehensive and contextual understanding of the evolution of AI and Design methods, potentially overlooking long-term trends and the historical development of AI adoption in various design fields. Expanding the scope to incorporate these sources will provide a more comprehensive understanding of AI's role in engineering design, service design and UI/UX design. To address current limitations, our future research will compare AI applications across these fields and integrate insights from field data, contributing to a deeper understanding of AI-led design innovation.

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