PROCEEDINGS OF ASIA DESIGN AND INNOVATION CONFERENCE
20–21 NOVEMBER, 2025, SHANGHAI, CHINA

CREATIVITY-RAG: A FRAMEWORK FOR CREATIVE DESIGN IDEA GENERATION

Ji HAN[1], Boheng WANG[2], Yuan YIN[1] and Pingfei JIANG[1]
[1]University of Exeter, United Kingdom
[2]Imperial College London, United Kingdom

ABSTRACT
In recent years, there has been a growing interest in developing Large Language Models (LLMs)-driven tools for supporting varying design activities, including idea generation. However, current LLMs frequently generate ideas that exhibit limited creativity, demonstrate contextual misalignment, and lack practical feasibility. Therefore, this paper proposes the Creativity-RAG framework for creative design idea generation by adopting the Retrieve Augmented Generation (RAG) technique using LLMs. The framework involves two RAG processes supported by two knowledge bases: (1) a domain-specific product design knowledge base for retrieving relevant design attributes of the target design, and (2) a creative product design knowledge base for retrieving corresponding design precedents that contain or are related to the design attributes. The framework combines design features from the retrieved creative design precedents to inform new design ideas that are creative, contextually relevant, and feasible. A case study was conducted to demonstrate the applicability of the framework by realising it through a customised ChatGPT using Wikipedia and Red Dot Design award winners as the two RAG knowledge bases. The paper advances research in design and creativity, demonstrating how LLMs can reuse existing knowledge and precedents to enhance creative design idea generation.

Keywords: Design Creativity, Idea Generation, Large Language Models, Retrieve Augmented Generation, Creativity Tools

1 INTRODUCTION

Creativity is "the process by which something so judged (to be creative) is produced" [1], which is considered a significant part of new product development. It underpins the generation of novel and useful ideas that lead to breakthrough products in both tangible and non-tangible forms [2, 3]. Studies have shown that a product with higher creativity is more likely to succeed than others, for example, in crowdfunding campaigns [4] and design competitions [5]. In the current increasingly competitive market, designers are often required to possess the ability to generate creative design ideas to develop innovative products [6]. However, it is challenging for designers to come up with ideas, especially creative ones. Such attempts are often constrained by the limited knowledge possessed and the difficulties in conceptualising unique product features and parts. These barriers may have suppressed the potential of generating ground-breaking innovative products that lead to business success, but have only resulted in incremental advancements.

To tackle these barriers and challenges, designers often employ tools, such as Mind Mapping [7], Brainstorming [8], and Six Thinking Hats [9], to support creative design idea generation. However, these tools are generic and were not developed specifically for use in the design context. To better support the generation of creative design ideas, design researchers developed several design-focused tools and methods, such as TRIZ (Theory of Inventive Problem Solving) [10], the CK theory [11], Bio-inspired design [12], the WordTree [13], the 77 design heuristics [14], the Creativity Diamond [15], and the three-driven combinational approaches [16]. Although these tools could help designers remove mental blocks and expand conceptual design space, they are considered cumbersome and not often deployed in practice. The requirements of sufficient design knowledge and experience have caused challenges and cumbersomeness for designers in applying these tools in the real world. A number of computational support tools are thereby developed to support designers in creative idea generation in a more effective and efficient manner. By leveraging the computational powers in reasoning, text and image generation capabilities, these tools often produce textual and/or pictorial stimuli to inspire designers' creative minds. A review of relevant computational design creativity support tools is provided in the following Section 2.

The recent developments in Artificial Intelligence (AI) have introduced transformative techniques, such as Large Language Models (LLMs), for augmenting human creativity. Well-known LLMs include OpenAI's GPT, Google's Gemini, Anthropic's Claude, and Meta's Llama. These LLMs have shown significant potential and capabilities in semantic understanding, natural language generation, reasoning and instruction following, which have been increasingly employed for supporting design activities [17]. Despite the advancements of LLMs, a lack of awareness of context, domain-specific understanding, and expertise has limited LLMs' performance in specialised scenarios [18]. This thereby constrains the capabilities of LLM tools in creative design idea generation, as it is challenging for LLMs to produce structured and feasible ideas tailored to solving a specific design task. For example, a design task requiring the generation of a sustainable portable food blender concept may lead to LLM outputs that are too generic, irrelevant to the context and not feasible to be realised in the real world. Retrieve Augmented Generation (RAG), introduced by Lewis *et al.* [19], has the potential to resolve these challenges by integrating external data sources in the generative process, leading to contextually relevant results. It is strongly beneficial for tasks that significantly require domain-specific knowledge, such as idea generation.

Therefore, this paper aims to propose a novel framework, named Creativity-RAG, that integrates LLMs with two domain-specific knowledge bases for producing creative ideas to solve specific design challenges by leveraging the RAG technique. The framework combines structured knowledge retrieval with generative AI capabilities, which deliver new insights into the development of LLM-driven design support tools. The following section reviews relevant computational idea generation support tools, including LLM-driven ones, to lay the foundation for the framework. Section 3 presents the details of the proposed Creativity-RAG framework. Section 4 presents a case study demonstrating a practical example of using the Creativity-RAG framework proposed for addressing a design challenge. The conclusions of the paper are provided in Section 5.

2 THEORETICAL FOUNDINGS

2.1 Computational design creativity support tools

Over the last decade, a growing number of computational tools and methods have been developed to support design creativity, which employs machine learning, data mining, information retrieval, natural language processing, image processing, and AI techniques. Several computational idea generation support tools have employed the concept of combination. Examples include the Combinator [20] that imitates human combinational creativity producing unfamiliar combinations of familiar ideas, such as "cup kettle", in both textual and pictorial forms. It uses a knowledge base containing keywords retrieved from product design descriptions as "familiar ideas" with the support of ConceptNet [21] for making an associated network of ideas. The Retriever [22] employed a specific alternative of combinational creativity (analogical reasoning) to produce new ontologies for supporting design idea generation employing ConceptNet as its knowledge base. The synthesising of scenes approach, proposed by Georgiev *et al.* [23], also adopted the means of combination. It combines existing scenes, which are stored in a pre-retrieved knowledge base, into a new scene through similar thematic relations. For instance, "microwave, bake, fish" and "fireside, roast, chestnut" could lead to a new scene "fireside, roast, fish" due to the similar thematic relations of "bake" and "roast". Chen *et al.* [24] used Generative Adversarial Network (GAN) to produce a synthesized image of two ideas retrieved from a technical knowledge base in a network format. Wang *et al.* [25] used GAN to combine design styles and design products producing pictorial outputs such as streamlining style chairs. Wang and Han [26] employed GAN to combine design features of two ideas to form new ideas, such as an image of a bike that has features of a horse. Chen *et al.* [27] explored the use of DALL·E to create images for combinational designs, such as "a swan chair", to prompt creative idea generation. Han *et al.* [6] leveraged a Unet3D structure-based diffusion model to produce short videos combining features of two objects, such as a car and a pterosaur, to stimulate creative idea generation.

There are also several computational tools that are underpinned by knowledge bases constructed using domain-specific knowledge to better support designers addressing design tasks in a more specific context. For example, IDeAL [28] utilises the function-behaviour-structure (FBS) model and a design knowledge repository for analogical design. The Concept Generator [29] uses the Functional Basis to produce feasible concept design variants. DANE (Design-by-Analogy to Nature Engine) [30] uses an FBS-based knowledge database containing biological and engineering knowledge to produce stimuli for idea generation. B-Link [31, 32] is underpinned by a large knowledge base in a network structure constructed using knowledge from academic publications and design blogs. It helps users discover relevant technical design knowledge in need and make further knowledge associations. InnoGPS [33, 34] has employed a technology space knowledge base constructed using the US patent database. It allows users to identify new design directions and opportunities through exploring an interactive knowledge map. TechNet [35] is also underpinned by a knowledge base created using the US patent database. It can be used to support users in idea generation [36], and also represent a design as a semantic network [37]. Pro-Exlpora [38] has employed a knowledge base created using retrieved research and design problems. It utilises the Markovian model and machine learning to produce new design problems based on the problem knowledge base to inspire users.

2.2 LLMs for design creativity

In recent years, new initiatives have emerged in developing LLM-driven computational tools to support diverse design activities [39]. LLMs have shown particular potential in enhancing design reasoning, generating design inspirations, and proposing design concepts [40]. Several studies have explored the use of LLMs for bio-inspired design, for example, Zhu *et al.* [41] utilised LLMs to retrieve and map biological analogies to produce bio-inspired design ideas in textual formats, such as a pterosaur-inspired flying car, while Chen *et al.* [42] used LLMs to retrieve textual knowledge from a bio-inspired knowledge base and map the knowledge for divergent thinking. Similarly, in analogical design, Wang *et al.* [43] integrated LLMs with an analogy-based structured retrieval mechanism for knowledge reuse, concept combination and analogy reasoning. Beyond bio-inspired design and analogical design, Obieke *et al.* [44] introduced a framework of AI collaboration in engineering design by employing multi-agent LLM technology to augment designers' abilities in conceptual design and problem definition. Furthermore, LLMs have demonstrated the ability to evaluate creative design ideas at a level comparable to human experts when guided by structured evaluation procedures [45]. However, these LLM-driven approaches often lead to results that may be overly generic, contextually misaligned, or lacking in feasibility.

As indicated in the preceding, RAG has the potential to tackle such limitations by grounding LLM generative processes in task-relevant knowledge. Several studies have explored the use of RAG techniques to advance the performance of LLMs in supporting design. Jiang *et al.* [46] proposed a two-stage RAG framework to generate sustainable product design guidelines by employing a systems design principles knowledge base and a sustainable design strategies knowledge base. Zhang *et al.* [47] introduced a multilingual design knowledge graph-guided RAG framework for product design knowledge recommendation, leveraging a multilingual design knowledge base. In addition, Siddharth and Luo [48] presented a method using triplet representation to identify explicit design facts from patents for supporting RAG in the design process. Although RAG could enhance LLMs' capabilities through employing external knowledge bases, its potential application in creative idea generation could be further explored.

3 THE CREATIVITY-RAG FRAMEWORK

As discussed in the preceding section, many computational idea generation support tools adopted the concepts of combination, demonstrating that combining ideas to inform new ones can effectively stimulate designers' creativity during the idea generation process. To support addressing specific design tasks, such as generating ideas for technical designs and exploring new design problems, domain-specific knowledge bases were also used in several design computational tools. This is in line with the RAG approach, which leverages external data sources in the generative process for more contextually relevant results, to a certain extent. Recently, there has been a growing interest in applying LLMs to support creative design idea generation. However, due to the limitations of current LLMs, the outputs of such LLM-driven tools may lack creativity, be contextually irrelevant and unfeasible. The RAG technique has the potential to address such issues by grounding LLMs' outputs in task-relevant knowledge. Based on the studies reviewed, we therefore propose the Creativity-RAG framework, which integrates two RAG processes with the principle of combination to enhance LLMs in producing contextually relevant, feasible, and creatively valuable design ideas tailored to specific design tasks.

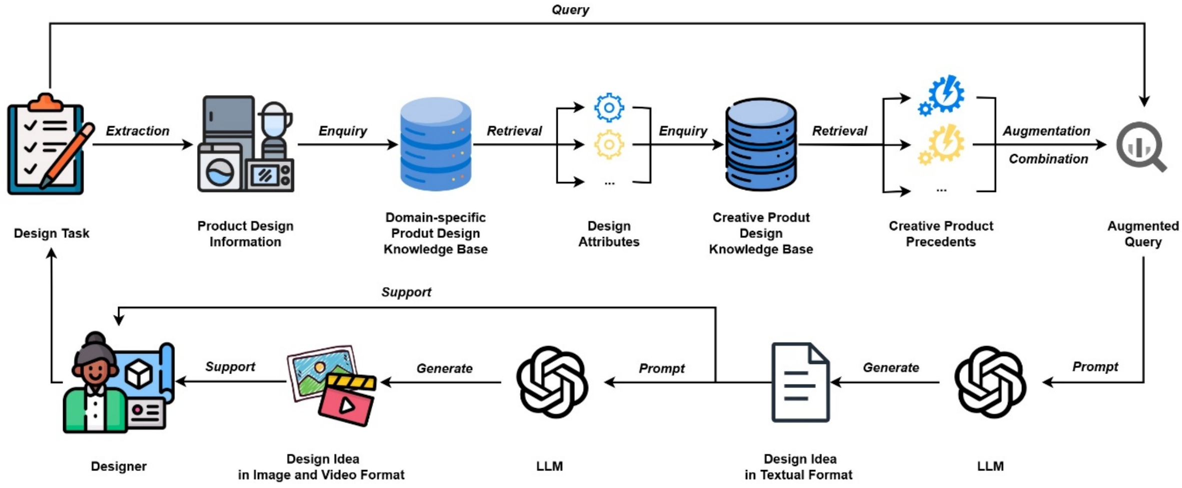

Figure 1. The Creativity-RAG framework

As shown in Figure 1, the Creativity-RAG framework starts with design task initialisation, where a design task is provided by a designer. The key product design information of the design task, including the target product to be designed and specific design requirements, is extracted by using LLMs to structure the enquiry process. The information then drives the first RAG process on domain knowledge retrieval, in which the design task is transformed into an enquiry to search for a domain-specific product design knowledge base. Example domain-specific product design knowledge bases include private ones, such as a company's own product catalogue, or public ones, such as Wikipedia and patent abstracts [46]. This process retrieves design attributes, including relevant product parts and technical components, core functionalities, and key features, to establish a foundation for the following RAG process. For example, if the task is to design a reusable water bottle, the retrieval might return knowledge on a container body to hold water and a cap.

The second RAG process, which focuses on creative product design knowledge retrieval, uses the design attributes retrieved to form new enquiries to a creative knowledge base containing relevant design examples and precedents. The creative product design knowledge base could be a product-focused database, such as a repository of design competition winners, or an inspiration database, such as AskNature. Creative product precedents, corresponding to the design attributes, are then retrieved. For example, the cap might lead to the retrieval of a child-resistant medicine bottle using push-and-turn caps or squeeze-and-turn caps, while the container body could connect to bamboo or a lotus leaf.

The retrieved creative product precedents are then used to augment the initial design task query, forming a full prompt that guides the LLM to generate a creative design idea by combining design features or attributes drawn from each of the precedents. In this way, the produced ideas are grounded in the design precedents while remaining contextually relevant and feasible. For example, the LLM might come up with a design idea of a water bottle using bamboo as the body and a push-and-turn cap.

The textual design idea is then provided back to the designer for evaluation and further refinement, or as the basis for a new design task query. To better support comprehension and communication, the textual idea can also be converted into image or video formats. By integrating two RAG processes with LLM-driven generation, the framework enhances contextual relevance, feasibility, and creativity in supporting human designers in creative design idea generation.

4 CASE STUDY

To demonstrate the applicability of the proposed Creativity-RAG framework, a customised ChatGPT was created. Rather than using conventional vector embedding for capturing semantic meanings and supporting information retrieval in RAG systems, this case study has leveraged the advanced natural language processing and reasoning capabilities of GPT 5.0. This enables the RAG system to move beyond purely similarity-based retrieval, enabling richer contextual understanding, more flexible interpretation of design knowledge, and the generation of creative associations that would be difficult to achieve with embedding-based methods alone. The core prompts used, mapping to the framework proposed as shown in Figure 1, are summarised in Table 1. Please note that the retrieval, generate and support stages do not require LLM prompts. The domain-specific product design knowledge base employed in this case study for the first RAG process is Wikipedia. Wikipedia has been widely adopted as a domain-specific knowledge base for supporting design, such as for constructing a semantic network for data-driven design [49] and identifying appropriate design stimuli [50]. For the creative product design knowledge base, a dataset from the Red Dot Design Award was compiled by the authors. Specifically, textual descriptions of 300 "Product Design 2025" award winners, including furniture design, kitchen appliances, lighting, and robotics, were randomly scraped and stored in a JSON file to serve as creative design precedents. Design competition awards are frequently adopted as data sources in design creativity studies, such as for uncovering the creative patterns underlying award-winning products [16]. The customised Creativity-RAG ChatGPT could be accessed via: https://chatgpt.com/g/g-68c1bf007c8081919a1d0f077529d39b-creativity-rag.

Table 1. Prompts corresponding to the Creativity-RAG framework stages

Framework Stage	**Function**	**Prompt**
Extraction → Product Design Information	Extract key design information from the design task	*You are a design expert. Please extract the following product design information from the free-text description of the design task provided: (1) Target product; (2) Specific design requirements (e.g. sustainability, safety, cost, …)*
Enquiry → Domain-specific Product Design Knowledge Base → Design Attributes	Retrieve design attributes from the domain-specific product design knowledge base	*Using the extracted design information, please retrieve a list of design attributes, including (1) product parts and technical components; (2) core functionalities; (3) key features from Wikipedia (https://www.wikipedia.org/).*
Enquiry → Creative Product Design Knowledge Base → Creative Product Precedents	Generate queries for retrieving creative precedents from the creative product design knowledge base	*Based on the list of retrieved design attributes, please retrieve 1 design precedent per design attribute, which contains or is related to the design attribute, from the "Creative Products" knowledge base provided.*
Augmentation & Combination → Augmented Query → LLM → Design Idea in Textual Format	Generate an idea based on the retrieved creative precedents through combinations	*Only based on the list of the retrieved creative precedents, generate a design idea to solve the initial design task provided. The idea should combine the design features only drawn from each of the precedents.*
Prompt → LLM → Design Idea in Image/Video Formats (*Optional*)	Translate the textual design idea into visual formats	*Please convert the generated textual design idea into a visual format, either an image or a video.*

A design task, "design a portable blender", was provided to the Creativity-RAG ChatGPT, and the resulting textual outputs are provided in Table 2. Several instances are included showing how the Creativity-RAG utilised the design attributes, such as self-cleaning blend cup and USB-C charging, retrieved from the domain-specific knowledge base to inform the retrieval of corresponding creative product precedents, such as *Hiblendr Juice Cup Ultra* and *Solis Vac Stick*, from the creative product design knowledge base. Please note that the IDs of the precedents in the table correspond to their entries in the knowledge base. These existing creative product precedents were then combined into a coherent design idea for a portable blender, with features that reference specific design precedents. For comparison, a zero-shot method was also applied by prompting ChatGPT 5.0 with the same design task directly. The idea produced by the zero-shot method relies entirely on the model's pre-trained knowledge. As shown in Table 2, the portable blend idea produced by using the Creativity-RAG has design features, such as a swappable blade module, magnetic interlock and extra power bank functionality, which demonstrate a higher level of creativity, both novelty and usefulness, in comparison with the idea generated by the zero-shot method. The zero-shot idea remains closer to a refined iteration of existing portable blender designs, such as adding LED indicators or making it fit in cupholders, rather than introducing functions or features that are highly novel or useful. The Creativity-RAG idea is also more feasible, as the design is grounded in existing design precedents by combining proven features rather than inventing untested ones. In contrast, the zero-shot idea may face engineering challenges, such as housing a high-torque motor in a slim form and employing waterproof magnetic charging. In addition, the Creativity-RAG idea is more contextually relevant to the design task that focuses on portability, safety and maintainability (which are key product design information extracted from the design task), while the zero-shot idea is more oriented toward general consumer usability.

Table 2. Example idea generated by the Creativity-RAG and using zero-shot

<table>
<tr><th>Creativity RAG</th><th>Zero-shot</th></tr>
<tr><td>Design Attributes → Creative Product Precedents:
• Self-cleaning blend cup → Hiblendr Juice Cup Ultra (ID 265): portable blender with self-cleaning operation.
• USB-C charging → Solis Vac Stick (ID 261): cordless device charged via USB-C.
• Rechargeable Li-ion pack & runtime mindset → Rota-Master Precision Screwdriver (ID 152): cordless tool with lithium-ion battery and multi-hour use.
• Magnetic cap/attachment ease → Col. magnetic cap product (ID 113): cap with magnetic function for quick attach/remove.
• …</td><td rowspan="2">Idea: A next-gen portable blender could be a sleek, bottle-shaped device made from lightweight, durable Tritan plastic with a stainless-steel base housing a rechargeable battery and high-torque motor. The blending chamber doubles as a drinking bottle, with a leak-proof lid and detachable blade assembly for safe cleaning. A magnetic charging port enables quick, waterproof recharging via USB-C, while an LED ring indicates battery level and blending progress. Safety features include auto shut-off if the lid isn’t secured, and a lock mechanism to prevent accidental activation in bags. Compact enough to fit in a cupholder, it would allow users to blend smoothies, protein shakes, or even baby food on the go, with enough battery capacity for 10–12 blends per charge.</td></tr>
<tr><td>Idea: PulseGo Modular Portable Blender is a bottle-format, travel-ready blender that pairs a self-cleaning Tritan jar (ID 265) and carry-strap, easy-wash ergonomics (ID 216) with a USB-C–charged Li-ion power base (IDs 261, 152); a magnetic cap provides rapid closure and doubles as a run-enable interlock (ID 113), while leak-resistant sealing and a stable anti-tip base prevent messes on the move (ID 210). The modular architecture lets users swap the blade module or battery puck for maintenance or upgrades (ID 1), and—between blends—the base can serve as a compact power bank for small devices (ID 269). This yields a compact, safe, and easy-to-maintain companion for smoothies and shakes on the go.</td></tr>
</table>

5 CONCLUSIONS

This paper has introduced the Creativity-RAG framework, which leverages the RAG technique by integrating LLMs with two domain-specific knowledge bases, a domain-specific product design knowledge base and a creative product design knowledge base, to support designers in generating creativity but also feasible and contextually relevant design ideas. A case study conducted has demonstrated the applicability of the proposed framework, showing how it can overcome key limitations of current LLM-driven design support tools. The paper has contributed to the knowledge in research on design, creativity, innovation, computational design, and product design, demonstrating how existing design knowledge and precedents can be reused to augment design creativity by adopting LLMs.

REFERENCES

[1] Amabile, T. M. *The Social Psychology of Creativity*, 1983 (Springer, New York).

[2] Han, J., Forbes, H. and Schaefer, D. An exploration of how creativity, functionality, and aesthetics are related in design. *Research in Engineering Design*, 2021, 32(3), 289–307.

[3] Taura, T. and Nagai, Y. Creativity in innovation design: the roles of intuition, synthesis, and hypothesis. *International Journal of Design Creativity and Innovation*, 2017, 5(3–4), 131–148.

[4] Han, J., Jiang, P., Hua, M. and Childs, P. R. N. An exploration of the role of creativity in crowdfunding product design projects. *Proceedings of the Design Society*, 2023, 3, 535–544.

[5] Wang, H.-H. Winning formulas for metaphor design: a case study of design competitions. In *DS 84: Proceedings of the DESIGN 2016 14th International Design Conference*, 2016.

[6] Han, J., Obieke, C. C., Zhao, H. and Jiang, P. Using AI to generate short videos as stimuli for supporting design creativity. In *DS 136: Proceedings of the Asia Design and Innovation*

Conference (ADIC) 2024, 2024.
[7] Buzan, T. and Buzan, B. *The Mind Map Book*, 2006 (Pearson Education).
[8] Osborn, A. F. *Applied Imagination: Principles and Procedures of Creative Thinking* (3rd ed.), 1963 (Charles Scribner's Sons, New York).
[9] De Bono, E. *Six Thinking Hats: The Multi-Million Bestselling Guide to Running Better Meetings and Making Faster Decisions*, 2017 (Penguin UK).
[10] Altshuller, G. S. *Creativity as an Exact Science: The Theory of the Solution of Inventive Problems*, 1984 (Gordon and Breach Science Publishers).
[11] Hatchuel, A. and Weil, B. A new approach of innovative design: an introduction to C–K theory. In *DS 31: Proceedings of ICED 03, the 14th International Conference on Engineering Design, Stockholm*, 2003.
[12] Fu, K., Moreno, D., Yang, M. and Wood, K. L. Bio-inspired design: an overview investigating open questions from the broader field of design-by-analogy. *Journal of Mechanical Design*, 2014, 136(11).
[13] Linsey, J. S., Markman, A. B. and Wood, K. L. Design by analogy: a study of the WordTree method for problem re-representation. *Journal of Mechanical Design*, 2012, 134(4).
[14] Yilmaz, S., Daly, S. R., Seifert, C. M. and Gonzalez, R. Evidence-based design heuristics for idea generation. *Design Studies*, 2016, 46, 95–124.
[15] Childs, P., Han, J., Chen, L., Jiang, P., Wang, P., Park, D., Yin, Y., Dieckmann, E. and Vilanova, I. The Creativity Diamond: a framework to aid creativity. *Journal of Intelligence*, 2022, 10(4), 73.
[16] Han, J., Park, D., Shi, F., Chen, L., Hua, M. and Childs, P. R. N. Three driven approaches to combinational creativity: problem-, similarity- and inspiration-driven. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2017, 233(2), 373–384.
[17] Jiang, S., Xie, M. and Luo, J. Large language models for combinatorial optimization of design structure matrix. *arXiv preprint*, 2024, arXiv:2411.12571.
[18] Yang, F., Zhao, P., Wang, Z., Wang, L., Zhang, J., Garg, M., Lin, Q., Rajmohan, S. and Zhang, D. Empower large language model to perform better on industrial domain-specific question answering. *arXiv preprint*, 2023, arXiv:2305.11541.
[19] Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W.-t. and Rocktäschel, T. Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems*, 2020, 33, 9459–9474.
[20] Han, J., Shi, F., Chen, L. and Childs, P. R. N. The Combinator: a computer-based tool for creative idea generation based on a simulation approach. *Design Science*, 2018, 4, e11.
[21] Speer, R., Chin, J. and Havasi, C. ConceptNet 5.5: an open multilingual graph of general knowledge. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2017.
[22] Han, J., Shi, F., Chen, L. and Childs, P. R. N. A computational tool for creative idea generation based on analogical reasoning and ontology. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 2018, 32(4), 462–477.
[23] Georgiev, G. V., Sumitani, N. and Taura, T. Methodology for creating new scenes through the use of thematic relations for innovative designs. *International Journal of Design Creativity and Innovation*, 2017, 5(1–2), 78–94.
[24] Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., Childs, P. R. N., Xiao, J. and Wu, C. An artificial intelligence based data-driven approach for design ideation. *Journal of Visual Communication and Image Representation*, 2019, 61, 10–22.
[25] Wang, D., Li, J., Ge, Z. and Han, J. A computational approach to generate design with specific style. *Proceedings of the Design Society*, 2021, 1, 21–30.
[26] Wang, D. and Han, J. Exploring the impact of generative stimuli on the creativity of designers in combinational design. *Proceedings of the Design Society*, 2023, 3, 1805–1814.
[27] Chen, L., Sun, L. and Han, J. A comparison study of human and machine-generated creativity. *Journal of Computing and Information Science in Engineering*, 2023, 23(5), 051012.
[28] Bhatta, S. R. and Goel, A. K. Model-based design indexing and index learning in engineering design. *Engineering Applications of Artificial Intelligence*, 1996, 9(6), 601–609.
[29] Bryant, C. R., Stone, R. B., McAdams, D. A., Kurtoglu, T. and Campbell, M. I. Concept generation from the functional basis of design. In *DS 35: Proceedings of ICED 05, the 15th*

International Conference on Engineering Design, Melbourne, Australia, 15–18 Aug. 2005, 2005.
[30] Goel, A. K., Vattam, S., Wiltgen, B. and Helms, M. Cognitive, collaborative, conceptual and creative—four characteristics of the next generation of knowledge-based CAD systems: a study in biologically inspired design. *Computer-Aided Design*, 2012, 44(10), 879–900.
[31] Shi, F., Chen, L., Han, J. and Childs, P. A data-driven text mining and semantic network analysis for design information retrieval. *Journal of Mechanical Design*, 2017, 139(11).
[32] Chen, L., Shi, F., Han, J. and Childs, P. R. N. A network-based computational model for creative knowledge discovery bridging human–computer interaction and data mining. In *ASME 2017 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2017.
[33] Luo, J., Song, B., Blessing, L. and Wood, K. Design opportunity conception using the total technology space map. *AI EDAM*, 2018, 32(4), 449–461.
[34] Luo, J., Yan, B. and Wood, K. InnoGPS for data-driven exploration of design opportunities and directions: the case of Google driverless car project. *Journal of Mechanical Design*, 2017, 139(11).
[35] Sarica, S., Luo, J. and Wood, K. L. TechNet: technology semantic network based on patent data. *Expert Systems with Applications*, 2020, 142, 112995.
[36] Luo, J., Sarica, S. and Wood, K. L. Guiding data-driven design ideation by knowledge distance. *Knowledge-Based Systems*, 2021, 218, 106873.
[37] Sarica, S., Han, J. and Luo, J. Design representation as semantic networks. *Computers in Industry*, 2023, 144, 103791.
[38] Obieke, C. C., Milisavljevic-Syed, J., Silva, A. and Han, J. A computational approach to identifying engineering design problems. *Journal of Mechanical Design*, 2023, 145(4).
[39] Han, J., Childs, P. R. N. and Luo, J. Applications of artificial intelligence and cognitive science in design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 2024, 38, e6.
[40] Wang, B., Han, J., Zhao, X., Yin, Y., Chen, L. and Childs, P. Creative combinational design through generative AI in different dimensional representations: an exploration. *Design and Artificial Intelligence*, 2025, 1(1), 100006.
[41] Zhu, Q., Zhang, X. and Luo, J. Biologically inspired design concept generation using generative pre-trained transformers. *Journal of Mechanical Design*, 2023, 145(4), 041409.
[42] Chen, L., Cai, Z., Jiang, Z., Luo, J., Sun, L., Childs, P., and Zuo, H. AskNatureNet: a divergent thinking tool based on bio-inspired design knowledge. *Advanced Engineering Informatics*, 2024, 62, 102593.
[43] Wang, B., Zhao, X., Zuo, H., Song, Y., Han, J., Childs, P. and Chen, L. From analogy to innovation: a creative conceptual design approach leveraging large language models. *Advanced Engineering Informatics*, 2025, 67, 103427.
[44] Obieke, C. C., Bridgeman, J. and Han, J. A framework of AI collaboration in engineering design (AICED). *Proceedings of the Design Society*, 2025, 5, 91–100.
[45] Zhang, J., Han, J. and Ahmed-Kristensen, S. Exploring the use of LLMs to evaluate design creativity. *Proceedings of the Design Society*, 2025, 5, 1773–1782.
[46] Jiang, P., Han, J. and Ahmed-Kristensen, S. A two-stage retrieval-augmented generation framework for producing sustainable product design guidelines. *Sustainable Futures*, 2025, 10, 101094.
[47] Zhang, H., Wang, T., Liang, Z., Huang, Z., Chen, C. and Cheng, L. Multilingual graph retrieval-augmented generation for product design using design knowledge. *Journal of Engineering Design*, n.d., 1–32.
[48] Siddharth, L. and Luo, J. Retrieval augmented generation using engineering design knowledge. *Knowledge-Based Systems*, 2024, 303, 112410.
[49] Zuo, H., Jing, Q., Song, T., Sun, L., Childs, P. and Chen, L. WikiLink: an encyclopedia-based semantic network for design creativity. *Journal of Intelligence*, 2022, 10(4), 103.
[50] Wang, K. and Nickerson, J. V. A Wikipedia-based method to support creative idea generation: the role of stimulus relatedness. *Journal of Management Information Systems*, 2019, 36(4), 1284–1312.