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AI Large Models Bring Great Opportunities to Reusable Design of CAD Software

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Abstract. With the rapid development of artificial intelligence (AI), large models have achieved significant breakthroughs in general-purpose domains. However, their application in computer-aided design (CAD) software is still in its early stages. Reusable design is crucial for improving efficiency and innovation in CAD systems. This paper reviews progress in rule-based reasoning (RBR) and case-based reasoning (CBR), two prevailing techniques for reusable design. RBR represents expert knowledge as rules but lacks self-learning capabilities. CBR draws on prior cases to solve new problems but relies heavily on surface empirical knowledge. Recent advances in large AI models provide new opportunities to enhance reusable design, thanks to superior language and reasoning abilities.

However, adapting large models to effectively leverage CAD-specific design knowledge presents open challenges. To advance progress in this area, this paper analyzes the potential impacts of large models on improving knowledge acquisition, case retrieval, rule representation, and reasoning explain ability for hybrid CBR-RBR systems, and proposes a reusable design framework combing large language models, knowledge graphs, and databases to realize more intelligent and interpretable reuse. This review synthesizes key developments in RBR, CBR, and large AI models, highlighting promising directions for advancing reusable design in CAD software. The integration of reasoning techniques with large models, opening promising new directions for computer-aided engineering enhanced by artificial intelligence, as well as lays the foundation for more efficient, innovative, and sustainable engineering design.

Keywords: large model, CBR, RBR, reusable design.

1. Introduction

CAD technology since its inception through continuous updating and iteration [25], has been widely used in automotive, electronics, aviation, aerospace, chemical industry, construction, medical, civil engineering and other industries, to promote the traditional product design methods and production mode of continuous change and innovation, resulting in huge economic and social benefits. It has produced great economic and social benefits.

Every designer consults the relevant design drawings and data during the design process of new product development and tries to reuse the results of previous designs as much as possible. Practice has shown that despite the rapid changes in customer-oriented products, the components that make up a product are relatively stable. For simple parts in general, more than half of the parts can be found in the main types and basic types that can be selected or referred to, and more than 50 per cent of the parts do not need to be re-designed. As a result, the total number of drawings can be reduced by 10 per cent and the number of new working drawings can be reduced by 30 per cent. And a series of new products inherited from the old product more results, about 80 percent [10]. If each product development and design are from scratch, in the whole development and design process can not give full play to the role of the enterprise's existing technology and resources, and there is bound to be a lot of duplication of labour, these duplication of labour mainly from the product design (conceptual design, detailed design, process design) and a variety of design work around the repetition of the product. In the process of new product development, we should try to use the existing design resources of the enterprise to reduce the duplication of labour in the development work.

The so-called design reuse ideas, refers to the product function design, principle programme design, structural programme design, overall design, construction design, process design and other design activities around the product reuse, reference or reference to existing design results, new product development and design of various views and ideas [35], design reuse technology is to integrate the design reuse idea into the broad design process of the whole life cycle of the product [36]. Every designer has the idea of design reuse in his mind, but due to the early computer hardware and software technology can not meet the requirements of design reuse, design reuse has not been paid attention to and widely used. Each designer according to their own understanding of their own design reuse behaviour, there is no standard design reuse organisation and management.

From the development of mechanical design methods, people's exploration of CAD software design reuse is reviewed. There are similarities in the elements and layout of different equipment drawings, so it is feasible to effectively reuse the existing drawing results in the generation of new drawings. In the manual drawing period, engineers reuse existing design drawings in order to improve design efficiency. When drawing new products, they put existing drawings that can be used for reference on the table, cover the non-reusable parts, and re-copy the reusable parts to achieve the reuse of drawings. However, manual drawing is prone to errors and leads to more rework, resulting in low efficiency. With the advent of CAD software, with the help of computers, engineers can save reusable drawings as new design drawings, which can be modified on the basis of the original. However, neither of these two methods can use the existing results, and both need to be modified, and the reuse efficiency is low. With the deepening of research on reuse knowledge, engineers use the modular design idea to make simple reusable graphic parts in drawings into blocks for reuse, improving the reuse efficiency of parts. However, the block reuse method lacks the guidance of scientific ideas, and the management is difficult, so the design reuse idea cannot be truly implemented. How to apply computer aided design technology to reduce drawing reuse time, shorten drawing design cycle and improve drawing utilization is always a difficult problem in the field of mechanical drawing.

CAD software in the application of design reuse technology, its impact is mainly reflected in the following aspects.

1. New product development and design capabilities and innovation will be improved. As the saying goes, "learn from the past to understand the new", when engineers carry

out new product development and design, due to the support of the design reuse system, the designers' development and design ability and innovation ability will be greatly improved, so as to enhance the enterprise's new product development and design ability and innovation ability.

2. Shortening the time to market for new products. Since most new products are improvements on the basis of old products, there is a lot of information that can be reused, so by designing a reusable system, the workload of designers and the production preparation time are reduced, which of course shortens the time to market for new products.

3. Reducing product costs. Each new part will increase the manufacturing cost of the enterprise and increase the cost of the product. However, design reuse technology will avoid the emergence of new parts to the greatest extent possible, and at the same time reduce the design cost by making full use of the reusable information. Therefore, the total cost of the product will be reduced.

4. As the parts and components reused in new products are tested in production practice, so that the quality and function of many parts and components are guaranteed, relatively speaking, the quality of the product is guaranteed.

Design reuse technology can bring so much value to enterprises, but the design reuse rate in CAD software is still low. Due to the lack of scientific standardization and standardization of design resources and achievements, engineers have too many choices when reusing existing parts and lack of selection basis. Even if the existing design results are found, because the parts are not modeled with standardized and parametric methods, the time for engineers to modify the existing results exceeds the time for redesign, resulting in engineers not choosing reuse. In addition, the traditional performance appraisal of enterprises is based on the number of engineering drawings produced by engineers to evaluate the performance of engineers, which leads engineers to think that designing a new part and creating an additional engineering drawing is the embodiment of their labor costs. All these reasons are the challenges faced by CAD software reuse design.

In order to make full use of the existing design knowledge and the constructed knowledge base to shorten the development cycle of new product design, scholars have carried out a large number of researches on the techniques related to product design knowledge reuse, such as model similarity evaluation [18], model retrieval, and knowledge navigation, etc. A lot of research has been carried out on the evaluation of similarity and retrieval of CAD assembly models considering a variety of evaluation criteria [20, 21], free-form surface retrieval, efficient retrieval of assembly models based on improved Hausdorff distance, 3D CAD model retrieval based on image recognition [50, 14], and design knowledge reuse based on knowledge graphs or knowledge templates.

Knowledge-based reasoning is a thinking process in which new knowledge is inferred from one's own knowledge through a computer system according to a certain strategy, i.e., after inputting a problem to be solved, the existing design cases, expert experience, design formulas, specifications and other knowledge in the knowledge base are called upon to simulate human thinking, so as to complete the process of solving the problem [7, 17]. Common knowledge-based reasoning methods are rule-based reasoning (RBR), case-based reasoning (CBR) and Hybrid CBR-RBR. CBR and RBR are the key technologies in the field of AI, and they are widely used in many application fields such as natural language processing, image recognition and expert system. These technologies can improve our understanding and use of past experience and knowledge to better solve current problems, which is conducive to improving reusable design.

1. **RBR** is a method of making inferences based on a collection of pre-defined rules. These rules describe the causal relationships under specific conditions and the actions that should be taken when these conditions are met. For example, expert systems typically use rules to model the decision-making process of a human expert. The inference engine will infer new conclusions or recommendations based on known rules and input conditions. This approach is suitable for problem domains that can be expressed in terms of explicit rules [47, 26].

2. **CBR** is a method of learning and inferring from previously experienced cases. It uses an existing library of cases to solve new problems by comparing and matching similar problems that have been solved previously to find the best solution. This approach is similar to the process of human learning and experience building by using past cases to guide decision making. The CBR approach is suitable for situations where problems need to be solved based on prior experience with similar situations [15, 22].

3. **Hybrid CBR-RBR** Combining the characteristics of RBR and CBR, often using a combination of the two types of reasoning.

In summary, all three methods of reasoning have their applications in different contexts. RBR is suitable for domains that can be explicitly expressed as rules, while CBR is suitable for scenarios that draw on past experience to solve problems. In practice, the appropriate reasoning method is usually chosen based on the nature of the problem and the available data.

With the development of AI large model, the reuse design in CAD software has a new breakthrough point. This paper aims to propose a new framework combining AI large model to optimize the reuse design in CAD software.

The remaining papers are arranged as follows. Chapter 2 introduces the working process and characteristic analysis of artificial intelligence big model, RBR and CBR. Chapter 3 introduces the research and analysis methods. The Chapter 4 discusses the research results and propose a framework for reuse design based on AI large model.

2. Literature Review

This chapter introduces the working process and characteristic analysis of general and domain AI large models, RBR, and CBR.

2.1. Large Models of AI Opportunities of the Times

Artificial Intelligence (AI) [11] is an important driving force of the fourth industrial revolution and a core technology for digital transformation [48]. With the “explosive” growth of data volume and the rapid improvement of arithmetic power, AI technology is ushering in a new wave of innovation, of which the most striking is the large model technology.

Generalised Large Model of AI On November 30, 2022, OpenAI launched ChatGPT [9], a new conversational general AI tool. It was researched that within just a few days of its launch, the number of registered users exceeded 1 million, and the number of active users had reached 100 million in 2 months, attracting widespread attention from all walks of life, making it the fastest-growing consumer application in history, and setting off a technological tidal wave in the field of AI.

In recent years, many epoch-making large models have emerged, such as OpenAl's GPT-4, Huawei Cloud's Pangu NLP, Baidu's Wenshin, and meta's llama2 [40]. These large models have made landmark technological breakthroughs in the field of natural language processing [4, 6], and have achieved leapfrog development in terms of model accuracy, generality, and generalisation ability, and have achieved multi-scenario applications in the fields of finance, healthcare, media, and gaming, which have improved the efficiency, lowered the cost, and created value.

Large language models can be divided into pre-trained models and fine-tuned models. Pre-trained models refer to language models that are pre-trained on large-scale text corpora, such as Transformer and BERT. A fine-tuning model is a model that is fine-tuned to a pre-trained model for a specific task, such as ERNIE Bot, GPT-3, etc.

The release of GPT-3.5 and its great success has had a strong impact on the AI industry, in which many previously unsolved problems have been found to be solved (including fact-based quizzing, text-summary fact consistency [16], etc.). However, from another perspective, we can also think of large models as a tool to assist in the development, optimisation of models, and enrichment of application scenarios, e.g..

1. Code Development: Using ChatGPT to assist in code development and improve development efficiency, including code completion [37], natural language instructions to generate code, code translation, bug fixes, etc.

2. Combination of ChatGPT and specific tasks: ChatGPT generates results that are significantly better on many tasks compared to fine-tuned miniatures, and combines the strengths of ChatGPT on the basis of fine-tuned miniatures in order to improve the inference effect of miniatures.

3. Meanwhile, based on the ability of less sample learning inspired by ChatGPT instruction fine-tuning, for tasks with only a few annotations or no annotated data as well as tasks that require out-of-distribution generalisation [13], ChatGPT can be applied directly as well as used as a tool for cold-starting to collect relevant corpus [28], enriching the application scenarios.

Reviewing the underlying technology of the large model, the breakthroughs are mainly the following:

Vaswani A proposed a network architecture Transformer [41], which introduces the self-attention mechanism. Transformer outperforms other sequence transformation models in terms of machine translation quality and efficiency, and shows strong generalisation ability, which can be applied to other natural language processing tasks. The proposal of Transformer provides new ideas and references for sequence learning and neural network Machine translation research provides new ideas and references, and the architecture has become one of the mainstream frameworks for machine translation and other sequence learning tasks.

Reinforcement learning with human feedback (RLHF) techniques have made great strides in empowering intelligences to learn from external human suggestions, with RLHF acting as an important bridge to incorporate human feedback into the learning process by constructing a human feedback dataset and training an incentive model that mimics human preferences for scoring outcomes, allowing machines to learn by abstracting human values rather than simply mimicking human behaviour [19, 49, 32]. This is the core technology at the heart of the growing resemblance of human dialogue in large language models in the post-gpt-3 era. RLHF has recently come into the public eye through several high-profile AI large models, including OpenAI's ChatGPT, DeepMind's Sparrow, and Anthropic's Claude.

Bidirectional Encoder Representations from Transformers (BERT) [5] achieves breakthroughs in several natural language processing tasks. BERT achieves SOTA on 11 Natural Language Processing (NLP) tasks that demonstrating its powerful generalisation capabilities. BERT can be migrated to different tasks with simple fine-tuning without major changes to the model architecture, which greatly reduces the workload of developing the model. The proposal of the BERT model opens a new chapter in large-scale language understanding in NLP. Its powerful representation learning and task migration capabilities have led to its rapid application in various subfields of NLP, generating a wide range of impacts and greatly advancing the progress of NLP technology.

GPT is an approach based on generative pre-training and discriminative fine-tuning [29] to achieve transfer learning for NLP tasks, using task-oriented input transformations to achieve migration with only a few changes to the model architecture, empirically demonstrating the effectiveness of the approach on 12 tasks to achieve SOTA, and proposing a generalised framework to address the problem of data scarcity in NLP task learning. This paper is significant in the research of transfer learning and end-to-end learning in NLP. The authors' proposed approach provides an effective and practical framework for solving the data scarcity problem for different tasks.

The GPT-2 model [30] can automatically discover tasks from large-scale text data. pre-training the language model with the large-scale web dataset Web Text allows it to perform NLP tasks with zero-sample learning. proving that the capacity of the language model is crucial for migration learning and that a larger model achieves better performance. the model GPT-2 achieves SOTA on seven language modelling datasets. but still insufficient to fit the full Web Text. the authors demonstrate that pre-training of large-scale semantic models on suitable datasets can achieve zero-sample learning and adaptation for NLP tasks. This informs the solution to the problem of data scarcity and the construction of language models that can learn tasks from examples as humans do.

The T5 framework advances the development of transfer learning by systematically investigating different transfer learning methods and comparing them on multiple NLP downstream tasks, based on the Colossal Clean crawled corpus and model size, and reaching SOTA on many benchmark tests, T5 is important in the research and application of transfer learning in NLP [31].

The large-scale language model GPT-3 meets or exceeds the previous SOTA on many NLP tasks in a sample less setting, demonstrating the performance improvement that comes with scale, and GPT-3 performs at the human level on some tasks, but also faces methodological challenges. The robustness of GPT-3 foreshadows the significant advances that may be possible in deep learning in the field of NLP, but it also suggests that researchers need to confront and address the wide-ranging implications of AI [3].

Touvron [39] introduces Llama, a set of language models at different scales, where the authors use only publicly available datasets to train state-of-the-art language models that match or exceed proprietary models in terms of performance, opening up greater options for language modelling research and applications. Llama is important in the development and application of large-scale language models and neural network models, reducing the language modelling research barriers, allowing more researchers to access and develop large-scale neural network models, and helping to advance the technology in this area.

A large-scale multimodal language model, GPT-4, has been introduced, and GPT-4 meets or exceeds the human level in AI benchmark tests [34]. The model is developed using a scalable framework that can guarantee performance at different scales and provide experience for subsequent larger-scale models. The model provides a valuable reference for the study of multimodal intelligences and the development of artificial general intelligence .The powerful capability of GPT-4 indicates that the development of AI has entered a new stage in the development of AI, which points out the direction for the future development of AI.

In addition, popular language models include:

ERNIE Bot: ERNIE Bot is a knowledge-enhanced large language model developed by Baidu that can generate high-quality text content. It is based on the Transformer architecture, has 350 million parameters, and supports both Chinese and English.

PaLM-E: PaLM-E is a large language model from the Google Brain team with 540 billion parameters. Its unique feature is that it can combine language model and visual model to realize multi-modal understanding and generation.

XLNet: XLNet is a new pre-trained language model that combines the benefits of Transformer-XL and BERT. It is capable of handling longer text paragraphs and has greater generalization ability.

RoBERTa: RoBERTa is a pre-trained language model developed by Facebook AI, based on the BERT architecture. It has been trained by a large number of corpora and has a strong ability of natural language understanding and generation.

TechGPT: TechGPT has enhanced various information extraction tasks such as relational triplet extraction with "knowledge graph construction" as the core, which means that TechGPT has a stronger ability to handle information extraction tasks and can better understand and process various types of information.

Domain Large Models in AI Domain large models are large language models that have been trained and optimised in a specific domain or industry. Compared with general-purpose larde models, vertical domain large models concentrate more on the knowledge and skills within a particular domain, possessing increased domain expertise and practical applicability.

Through "zero sample" or small sample fine-tuning, the large model can achieve better results in a variety of tasks, with a strong generalisation ability, forming a large domain model. Large model training achieves upstream and downstream division of labour, assembly line collaboration, forming a new paradigm of "pre-training + fine-tuning", which brings a new standardized AI research and development logic, realizes the scale production of AI models in a more unified and simpler way, and enhances the performance of large models in different business scenarios.

Domain macromodels are more domain-specific than general-purpose macromodels, and industry macromodels are specifically trained to better understand and process domain-specific knowledge, terminology, and context. Due to the optimisation in a specific domain, the output quality of a vertical domain grand model in that domain is usually higher than that of a generic grand model. For domain-specific tasks, Vertical Domain Grand Models typically perform better than General Purpose Grand Models.

The classic domain large models for are enumerated in Table 1.

Table 1. Classic domain large models

Name	Domain	Characteristics
BloombergGPT	Financial Large Model	BloombergGPT builds a dataset of 363 billion labels to support various tasks within the financial industry.
FinBERT	Financial Large Model	FinBERT is pre-trained through multi-task learning on financial corpora to transfer knowledge from financial domain corpora.
LaWGPT	Chinese Legal Knowledge Model	LaWGPT constructing a dataset for dialogue and Q&A in the legal field and a dataset for China's judicial examination to conduct fine-tuning of instructions.
BenTsao	Chinese Medical Model	BenTsao integrates the medical knowledge of the Medical Knowledge Graph and fine-tuning it with knowledge-based instruction data.

The versatility and generalization of large models and new development paradigms such as "pre-training + fine-tuning" make the model customization process of AI scenario application more standardized, the effect optimization more simple, effectively reduce the ability requirements for data annotation and algorithm optimization, and make AI application research and development more convenient.

2.2. Research Progress in RBR

Definition of RBR RBR is a way to represent the empirical knowledge of experts in a certain domain in the form of rules, and the representation of these rules contains the problem and the solution to the problem, and the use of rule knowledge to simulate the reasoning process used by experts to solve a certain type of a certain type of problem [23]. RBR abstracts rule-based knowledge, encompassing expert experience, computational formulas, design specifications, etc., into symbolic, normative, and specific generative rules. These rules are then matched with the facts, ultimately leading to conclusions. Its reasoning process is shown in Fig. 1.

The advantages of RBR are: intuitive and natural, easy to understand, easy to computer reasoning; rules have the same format, easy to unify the processing; can effectively express the surface knowledge. But at the same time, RBR has certain disadvantages: the relationship between the rules is not obvious, resulting in low processing efficiency, management and maintenance is relatively difficult; cannot represent the structural knowledge; the rule base is large in size, the efficiency is not high, generally applicable to small-scale reasoning; at the same time, the rules of the acquisition of relative difficulties.

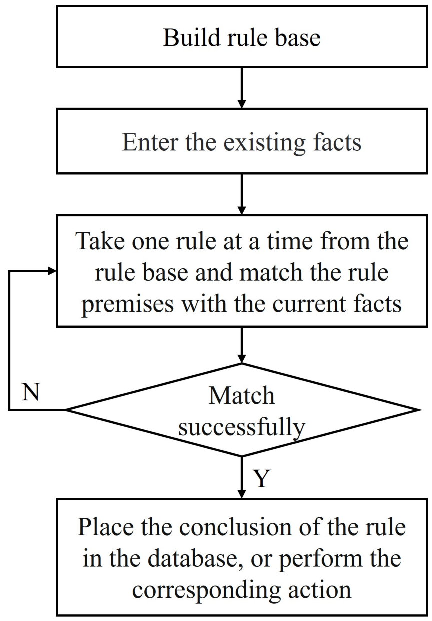

Fig. 1. RBR workflow

Different Technological Routes The implementation process of RBR has three main steps, firstly, the user input facts are matched with the antecedent part of the generative rule, if the match is successful, then this rule is selected. If more than one rule matches successfully at the same time, then it is processed by the conflict cancellation mechanism, and the appropriate rule is selected for inference; the matching operation is repeated in a cycle. The key technologies of RBR are mainly knowledge acquisition and its inference mechanism.

1. **Knowledge acquisition** is the process of delineating the scope of reasoning, the process of collecting and processing knowledge, and the basis for constructing a knowledge base, so this stage of the process is crucial. Knowledge acquisition mainly collects problem-related knowledge from industry experts or specific rules. The way of knowledge acquisition is usually manual, automatic and hybrid acquisition, the manual way is too labor-intensive although the integrity is high; on the contrary, the automatic way is the application of computer technology, compared to the former, it is more efficient and intelligent, so it is widely used in various industry sectors. Hybrid acquisition is a combination of the first two methods, with the ability to identify text, images, language, but also the ability to complete the analysis, understanding and induction, and self-learning from practice, which not only improves the completeness and accuracy of knowledge acquisition, but also ensures the efficiency of reasoning.

2. **Reasoning mechanisms** The commonly used reasoning algorithms are, forward reasoning, backward reasoning, and combined forward and backward reasoning.

Forward reasoning is the use of user-provided factual information as the basis for reasoning, and the positive use of rules for reasoning in a million ways, also known as data-driven reasoning or pre-necklace reasoning. Its basic process is based on known information as a starting point for the reasoning process. That is, the basic structure of the method is mainly divided into two parts: the premise and the conclusion. $P \Rightarrow Q$ or IF P THEN Q Forward reasoning takes the problem as a starting point, i.e., the process conditions are used as a starting point, and then the solution is reasoned out. However, forward reasoning generally has the disadvantages of low efficiency and lack of flexibility.

Reverse reasoning and forward reasoning are different, reverse reasoning and forward reasoning starting point is not the same, reverse reasoning is the conclusion of the problem as a starting point for reasoning, can also be called reverse chain reasoning or goal-oriented reasoning. The reasoning process is to take the hypothesis of the goal for the starting point of the reasoning process, according to the hypothesis of the goal to find information related to the hypothesis, if you find relevant information on the original hypothesis, the original hypothesis is established. If no information can be found to make the original hypothesis clear, then the original hypothesis is not valid, and the hypothesis target needs to be re-selected.

Forward and reverse reasoning is also known as mixed reasoning. This type of reasoning is a combination of forward and reverse reasoning, which make up for each other's deficiencies. Mixed reasoning is to use the conclusion of the result of the forward reasoning as the starting point of reasoning, and then reason out the result after the starting point has been determined. A reasoning goal is arrived at based on forward reasoning, and then the goal is confirmed based on reverse reasoning.

In the embryonic and developing stage of RBR technology, RBR related research mainly focuses on knowledge representation of rules and fast pattern matching algorithm of inference. During this period, many excellent fast pattern matching algorithms have emerged. Currently, the main pattern matching algorithms are Linear Algorithm, Treat Algorithm, Leaps Algorithm, and Rete Algorithm. Among them, Rete algorithm is the most widely accepted and used. The Rete algorithm was proposed by Charles Forgy in 1978. Although Rete algorithm improves the execution speed of RBR, its performance is still not enough to cope with massive data environment and high frequency inference applications.

In terms of the generalization of RBR technology, many open-source organizations, research institutions and manufacturers have launched their own products that integrate RBR technology into a complete system scheme or a separate system, such as Java rules engine standard JSR-94, based on Microsoft. NET platform BizTalk system business rules engine, JBoss Drools, open-source organization Apache Jena project, JESS and ILog JRules, etc. These rule engine products usually implement a variety of inference algorithms of RBR, but they still use rule-based knowledge representation, which is still limited in knowledge acquisition.

2.3. Research Progress in CBR

Definition of CBR CBR technique is a method of solving currently encountered problems based on the knowledge of past cases or experience gained from past cases, which is more suitable for solving problems that are difficult to establish theoretical models or complex problems. CBR is a kind of analogical reasoning method, which provides a new methodology to build an expert system that approximates the human thinking model, which is consistent with the solution of natural problems by human beings. When solving problems, human beings often recall the treatment of similar situations accumulated in the past and solve new problems by appropriate modification of the treatment of similar situations in the past. Past situations and their treatment are called cases. Cases can help form solutions to new problems and can be used to prevent possible errors. In 1994, A.P [1] proposed the 4R model of CBR (Retrieve-Reuse-Revise-Retain), and since then the 4R model of CBR has been widely disseminated. In the 4R model, historical cases that have been successfully solved in the past are stored in a case base; when a new problem arises, the decision is made by extracting the attributes of the current problem, using the pre-set retrieval algorithms of the CBR system, retrieving (Retrieve) in the case base, and obtaining one or a number of historical cases that are the most similar to the new problem, with the corresponding solution as the recommended The decision maker decides whether to reuse the recommended solution as the solution to the current new problem according to the actual situation; if the retrieved cases are far away from the target problem and the decision maker is not sure about adopting them, the revision (Revise) part of the model can be executed, and the retrieved solutions are revised using a certain method to make them meet the requirements of the current problem; finally, the current target Finally, after the new problem is solved by the revised solution, the target problem and the solution to the target problem are stored as a new case in the case base (Retain). The process of CBR is shown in Fig. 2.

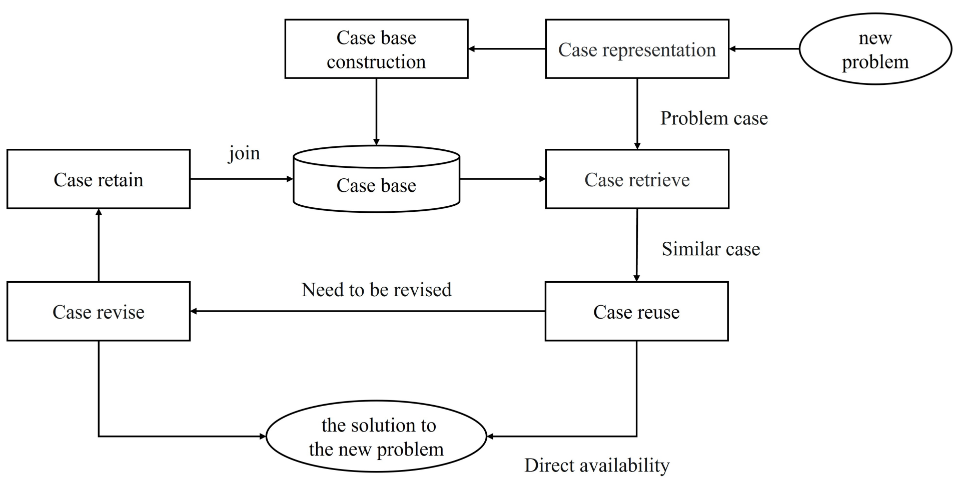

Fig. 2. CBR workflow

CBR does not require a detailed understanding of the principles of the new problem, and has the advantages of easy access to experience and knowledge, efficient problem-solving efficiency, and continuous updating of the case base to improve the accuracy of the solution. These related theories and techniques provide references and guidance for the study of case-based intelligent reasoning process in CAD software.

For example, in the field of static equipment, to apply CBR for drawing reuse, the process is as follows: A case base is constructed according to the existing static equipment design information and drawings, the upstream conditions are received, and similar static equipment is obtained through case retrieval. The platform automatically modifies the design parameters, and the applicable static equipment drawing cases are obtained. Users can modify other data according to additional requirements and deliver the modified drawing cases to the case library for subsequent use.

Different Technical Routes According to the CBR working process, it can be seen that the system mainly includes four key technologies [43]: case representation, retrieval, modification and learning. The more mature research is the retrieval of instances, including the nearest neighbour retrieval method, the retrieval method of frames, etc., and the modification of instances is currently the focus of CBR's research, which focuses on the following: the indexing of instances, the retrieval, the amendment, and the method of acquiring the amendment rules, the maintenance technology of the case base, and the evaluation about its performance.

1. **Case Representation** The case representation is to store the case in a way that the computer can identify and process, and the case representation has three main aspects: first, the background or reason for the event and the specific content of the problem; second, the characteristics of the case, the process of solving the problem; and third, the method and effect of solving the event. Through the case representation, it is possible to quickly retrieve cases that are similar to the target case. Commonly used case representation methods are framework representation, object-oriented representation, and semantic representation.

2. **Case Retrieve** The so-called case search, in essence, is to be given in the user after a case to be examined, the retrieval system can automatically from the case database (DB), looking for cases with the user case exactly the same or part of the same case; and the output results can be in accordance with the degree of compliance with the user's requirements for sorting, in line with the question of the high degree of priority output.

The current indexing algorithms for cases are nearest neighbour strategy, inductive reasoning strategy and knowledge guide strategy. The nearest neighbour strategy is a method that calculates the similarity between the problem representation and the case to find the most similar case. The nearest neighbour strategy is the most commonly used method.

3. **Case Revise** The examples retrieved in the example database through certain search methods are not necessarily fully applicable to the new problem, so the retrieved source examples have to be processed to adapt to the new problem, which involves the modification of the examples. Example modification is to use the source example as a reference for the target example and modify the part of the source example that is not applicable to the new problem [8] to solve the new problem. Case modification does not change the data of the source instance in the instance repository, but produces a new instance. Commonly used techniques for case modification are replacement, conversion, and derived analogy [33].

4. **Case Study** As new problems are continuously solved, the case base should have some learning capability [42] to facilitate the organisation and management of the case base and to improve the representativeness of the retrieved cases. Case learning mainly consists of adding new cases and deleting existing cases.

CBR technology has been widely studied and applied. Typical application cases include: Vilhena et al. applied CBR to predict the tendency of thrombosis; Erbacher et al. applied CBR to network early warning report; Horsman et al. applied CBR to evidence location in digital forensics.

2.4. Characteristic Analysis of RBR and CBR

RBR and CBR differ greatly in the following aspects:

1. A rule describes a function or pattern, while a case is a constant.
2. The rules of RBR need to match exactly, while the cases of CBR only need to match partially.
3. RBR adopts cyclic iteration of small events and deduces step by step; The CBR estimates the entire solution by analogy at one time and then adjusts the final solution.
4. Strict form of rules, difficult to obtain; Case form freedom, access to arbitrary.
5. RBR is based on deductive reasoning, while CBR is based on analogical reasoning.

As two concrete forms of knowledge reasoning, RBR and CBR have commonalities in the following aspects:

1. Rules and cases are different conceptual models of knowledge, but can be based on the same data structure or implementation technology in a concrete computer implementation.
2. The essence of the rules and cases is a relational mapping of the domain ontology and its attributes, and both reveal a division of the attributes and states of the domain ontology.
3. The rule base and case base in the same domain correspond to the state space of the same domain ontology.

It can be found that RBR and CBR are highly complementary, mainly reflected in:

1. RBR is good at expressing qualitative relations, while CBR is good at expressing quantitative relations.
2. RBR data maintenance is difficult, while CBR data maintenance is simple.
3. RBR reasoning speed is slow, CBR reasoning speed is faster.
4. RBR has strong interpretation ability, while CBR has weak interpretation ability.
5. The solving ability of RBR edge problem is weak, while the solving ability of CBR edge problem is strong.

It can be seen from the comparison that RBR and CBR have their own advantages, so we should consider combining RBR and CBR for reasoning, so as to bring better accuracy and efficiency of reasoning system.

3. Research Methodology

In this chapter, we outline our search methodology and inclusion criteria, which form the foundation for selecting relevant studies. Following that, we present a general analysis of the research content, offering an overview of the themes and patterns emerging from the studies we have selected.

3.1. Search Methodology and Inclusion Criteria

We searched the published literature on reasoning or large model distribution up to 2023 on Google Scholar, Web of Science and Scopus, using the following keywords:

- CBR, RBR, case-based reasoning, rule-based reasoning, mixed reasoning
- Artificial intelligence generated content (AIGC), large model, big model, domain large model
- CAD software, industry large model, reusable design, case intelligent recommendation

References to the retrieved articles are also within the scope of the search, determine which articles seem relevant, find those articles, read their references, and then repeat the process until there are no new relevant articles.

The following types of literature were excluded: research reviews or progress reports, non-inference or non-large model research, studies focusing on a single model only, and research on large models used for purposes other than those specified. Additionally, literature that solely relied on previous reasoning methods without introducing new analytical approaches was not considered.

3.2. General Analysis of the Research Content

The literature analysis process proposed in this paper starts from the preliminary reading and screening of the literature, and extracts the obvious or possibly relevant parts of the literature, so as to form a general understanding of the research content of reasoning and large models. Preliminary reading shows:

(1) There is a large literature with multiple research purposes, and in some literature different authors use different phrasing to express similar concepts. Examples include big models and large models.

(2) In recent years, researches on large models of artificial intelligence have emerged in many fields and brought different impacts to the fields.

(3) In the field of reusable design, there is almost no relevant research on domain large models.

Based on the above three findings, this paper analyzes the influence of artificial intelligence large model on reusable design CBR and RBR, and proposes a recommended framework combining artificial intelligence large model in view of the areas that can be improved in reusable design..

4. Results and Discussion

This chapter analyzes the influence of AI large models on reusable design, CBR, RBR, and proposes a framework for reusable design based on AI large model.

4.1. Impact of AI Large Models on Reusable Design

Industrial Internet is centred on the comprehensive linkage of the whole industrial chain, the whole value chain and the whole elements, building a new ecology of new-generation information technology empowering the manufacturing industry, emphasizing the interconnection and interoperability of the massive production elements, the value mining of operational data and the precipitation and reuse of industrial knowledge, which provides "natural soil" for the application of the large model.

In the era of large models, computing power, network and data constitute the "iron triangle" of the underlying infrastructure. Large models with large computing power, large algorithms and large data features can be used to further optimise the Industrial Internet and promote the reuse of design knowledge for solutions. Large models can assist in analysing large datasets through machine learning algorithms to identify patterns and correlations that may not be readily visible to researchers. Secondly, AI can analyse existing scientific literature and generate hypotheses that can be tested in further research, which can help identify new reusable design methods. In addition, the emergence of large models largely solves the problem that traditional models/services do not work well for cross-modal and cross-domain applications. The MaaS layer rooted on the industrial Internet platform can directly provide high-quality large model services for user terminals in a variety of scenarios. Enterprises can process and train the data by scheduling the relevant APIs and based on the business scenarios of a specific solution, thus reducing the development and application costs of enterprises and realising the deployment, optimisation, and upgrading of enterprises' personalised application businesses. The large model can improve language comprehension and image generation capabilities, invoke model microservices in the R&D design process, help R&D personnel to accurately mine and sort out effective basic knowledge, generate application-specific basic code or carry out three-dimensional visualisation design, as well as establish an intelligent industrial knowledge base and so on.

4.2. Impact of AI Large Models on RBR and Existing Work

The whole process of RBR includes: knowledge acquisition and reasoning mechanism. Now there are many ways to implement inference for various tasks based on large models, such as:

Richardson [32] provides a survey of recent research in conversational AI with a focus on commonsense reasoning. The paper lists relevant training datasets and describes the main approaches to incorporating common sense into conversational AI. The paper also discusses benchmarks used to evaluate common sense in conversational AI problems. Finally, the authors make initial observations about the limited common-sense capabilities of two state-of-the-art open dialogue models, BlenderBot3 and Lambda, and their negative impact on natural interactions. These observations further advance the study of common-sense reasoning in conversational AI.

Large pre-trained Transformer-based language models such as BERT, GPT and T5 have demonstrated a deep understanding of contextual semantics and language syntax. Their achievements have led to notable progress in conversational AI, fostering the creation of open dialogue systems proficient in maintaining coherent and relevant conversations. These systems can address queries, engage in casual chats, and accomplish various tasks.

In terms of knowledge acquisition, the use of large models for knowledge acquisition is much better than the original automatic acquisition. In order to express the structure of the knowledge base, knowledge graphs can be constructed, knowledge graphs using graph structure can present more complex relationships, the stored information is more full, and the recommended cases are definitely more relevant . Generic large models can use a model to combine multiple knowledge acquisition rules, the rules themselves need to be refined. For example: the height of the tower and the material of the tower construction, they themselves need two sets of rules to be obtained, but based on the large model, it is possible to solve these two tasks or even more with one model.

In terms of reasoning, when the information embedded in the knowledge base is sufficiently adequate, the large model can examine the results of rule reasoning and give inference results, or even automatically fine-tune the rules to meet the current usage scenarios and directly achieve reuse. Example: Code Inspection and Code Correction.

4.3. Impact of AI Large Models on CBR and Existing Work

The retrieval of cases belongs to an important part of CBR, and from the historical experience, traditional retrieval will face the following challenges:

1. Rely on the network. Because information retrieval models do not retain knowledge or information themselves, they rely on the Internet for external knowledge, which may limit their applicability in some scenarios.

2. Lack of reasoning skills. The existing IR model mainly provides the collected knowledge/information to meet the information needs of human beings, but lacks the ability to help users understand the information. Better reasoning will lead to friendlier and more valuable outcomes for humans.

Breakthroughs in Information Retrieval after Combining Large Techniques:

As the scale of large language models continues to grow (both in terms of model size and data volume), LLMs have demonstrated significant advances in their capabilities. On the one hand, LLMs have also made unprecedented breakthroughs in language comprehension and generation, resulting in more humane and human-intended responses. On the other hand, larger LLMs are more capable of generalising and reasoning when dealing with complex tasks [45]. Notably, LLMs can effectively apply their learned knowledge and reasoning abilities to solve new tasks with only some task-specific demonstrations or appropriate instructions [27, 44]. Furthermore, advanced techniques such as contextual learning significantly enhance the generalisation performance of LLMs without the need for fine-tuning for specific downstream tasks [3]. This breakthrough is particularly valuable as it reduces the need for extensive fine-tuning while achieving superior task performance. Supported by cueing strategies such as thought chaining, LLMs can generate output through step-by-step reasoning to guide complex decision-making processes [46]. By integrating these complex language models, IR systems can provide more accurate responses to users, ultimately reshaping the landscape of information access and retrieval.

The potential of LLMs for information retrieval has been initially explored, and in terms of practical applications, New Bing aims to improve the user's experience of using a search engine by extracting information from different web pages and compressing it into concise summaries in response to user-generated queries. In the research community, LLMs have been shown to be useful in specific modules of information retrieval (e.g., searchers), thus improving the overall performance of these systems.

Recently, dense retrieval has been extensively studied and approaches based on standard MIPS indexing and nearest neighbour search are common [12]. Given the success of Transformers as good associative memory stores or search indexes, Tay et al [38] proposed a novel architecture called micro-searchable indexing, where the indexes are stored in the model parameters.

The development of multimodal LLMs will facilitate indexing systems capable of indexing data in various modalities, including but not limited to text, images, and video, in a unified manner [2].

With the widespread use of LLMs in information retrieval, tailored evaluation strategies become essential to prove the effectiveness of LLMs. For this purpose, some properties such as robustness need to be emphasised. Many models are sensitive to distributional differences between training and test data [24]. It is eager to see the generalisation of LLM-enhanced IR models to out-of-distribution scenarios.

4.4. A Reusable Design Recommendation Framework Based on AI Large Model

Mixed CBR and RBR CBR for the requirements of the domain knowledge model is relatively broad, to facilitate the acquisition of domain knowledge, but there are certain drawbacks, stays on the surface of the empirical knowledge, the lack of deep knowledge, professional knowledge, the need for human participation, the lack of a rigorous theoretical foundation will be difficult to achieve the true meaning of AI. RBR relies too much on the experience of experts, so it does not have good self-learning ability, with the expansion of the knowledge base will easily be control saturation problem, not a good simulation of the judgmental thinking ability of the domain experts, the system will have a decline in reasoning and other problems.

Combining the characteristics of RBR and CBR, it can be seen that the advantages and disadvantages of CBR and RBR can be complementary. Previous studies have mostly used a single RBR or a single CBR for knowledge-based reasoning, but recent studies have often used a combination of the two types of reasoning, resulting in enhanced reasoning effects. Nowadays, there are four main types of reasoning fusion: RBR is mainly CBR, CBR is mainly RBR, CBR and RBR reasoning in parallel, and CBR and RBR are deeply fused.

1. RBR is dominated by CBR

This method is mostly applied in the case of small size of the case base, the first use of RBR reasoning, when the appropriate results can not be obtained, the choice of CBR to find the past cases for case retrieval.

2. CBR is the main RBR

This method is mostly applied in the case of a large case base, firstly, when using CBR case retrieval, the RBR rule is used to calculate the similarity in order to find similar cases, or for CBR retrieved cases using RBR for case modification and case evaluation. Most of the current fusion reasoning uses this approach

3. CBR and RBR Parallel Reasoning

Parallel reasoning is not considered to be a true fusion, where the two reasoning modalities operate in parallel to obtain separate results, and the two results are synthesised as the final result.

4. Deep integration of CBR and RBR

Deep fusion of CBR and RBR refers to the fusion of reasoning methods in all aspects of knowledge reasoning, which is more difficult to achieve, and thus less relevant research is conducted, generally using a combination of RBR and CBR for data analysis, RBR for generating recommendations or selecting solutions, and the same combination of RBR and CBR for case modification.

Recommended Framework After the study of two kinds of inference rules, CBR and RBR, it is found that the fusion of the two can improve the inference efficiency, so this paper proposes to apply the combined inference rules of CBR and RBR to the reuse design in CAD software. The function of RBR is to retrieve similar cases (i.e., CBR inference rules) according to a certain algorithm, and then the inference rules established by RBR are integrated into the CBR cases, and the combination of them This combination not only makes the system more efficient, but also helps to improve the use of knowledge.

The essence of large language model is a parameterised knowledge base, the main feature of parameterised knowledge base is to decompose the knowledge into a combination of parameters and rules, and generate specific knowledge instances by modifying the parameter values, which is a black-box and non-transparent process, which leads to some seemingly reasonable but absurd assertions that often appear in the natural language generation of large language model. Knowledge graph is a formal representation of knowledge, which inherently has the advantage of strong interpret ability. Therefore, the introduction of knowledge graph in case representation can help to improve the interpret ability of large language models.

Combined with the above technology we propose a set of case reuse design process, first of all, data for including text, pictures and other types of multimodal storage mode of data, and then combined with the powerful knowledge extraction capabilities of the large model to extract all kinds of services required by the value of the data; extracted to the data to build a knowledge base, which can rely on traditional relational databases, but also can be referred to the graph of the data in order to store more structure of the information, enhance the model reasoning ability in the process; knowledge retrieval intervenes in multimodal retrieval technology, aligning all kinds of data information to improve the retrieval efficiency; knowledge integration is the classification and summary of all the data in the knowledge base to organise the work, which helps to manage the knowledge base; at the same time, the knowledge base can't avoid modification, and the knowledge learning module realises the operations such as error identification, error correction, de-emphasis and updating; combining knowledge retrieval technology and grouping and aggregation Combined with knowledge retrieval technology and group aggregation tasks and recommendation algorithms, reusable programme recommendation can be carried out; the methods in knowledge learning can be empowered to the programme modification design module. The flow is shown in Fig. 3.

For further exploration, we propose a framework for collaborative LLMs, KGs and DBs, which consists of five layers, data, collaborative models, technologies, services and applications. In the data layer, textual and structural data can be stored with various types of DBs and KGs, and with the development of multimodal LLMs and KGs, the framework can be extended to handle multimodal data, such as images. In the collaborative modelling layer, LLMs, KGs and DBs can coordinate with each other to improve their respective

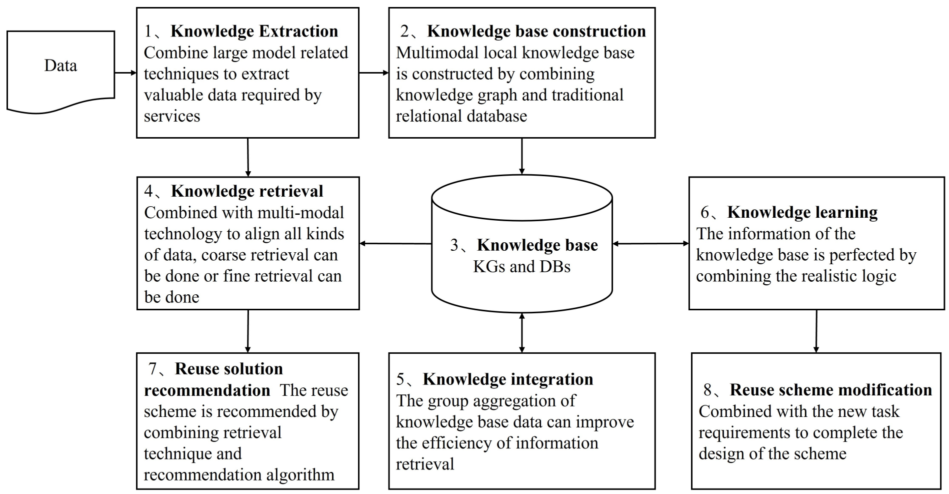

Fig. 3. Case reuse design flow

capabilities, and LLMs can fill in the missing data in KGs and DBs; in the pre-training phase, incorporating KGs and DBs into LLMs can help LLMs to learn the knowledge from the knowledge base. In the technique layer, relevant technologies used in LLMs and KGs can be incorporated into the framework, such as graph neural networks, few-shot learning and reinforcement learning, to further improve performance. At the service layer, related techniques can provide better solutions to the problems of case reuse, case modification, and rule representation in hybrid CBR-RBR. At the application layer, LLMs and KGs and DBs can be integrated to construct application products for large model-enabled reusable design. The framework is shown in Fig. 4.

The two most critical aspects of reuse design are information extraction and information alignment. We determine whether the current case is suitable for reuse through the results of alignment. There are already mature cases in information extraction. For example, TechGPT can extract domain terms, identify named entities, and extract relational triples, all of which are key technologies for knowledge graph construction. With the extracted information, we can get the case characteristics and lay the foundation for the subsequent work; GPT-4 has been able to perform multi-modal tasks, and it is also helpful for feature extraction of case images. In terms of information alignment, the large model has strong reasoning ability and generalization ability, and can clearly distinguish whether the extracted features are similar or not, and whether they are recommended cases. For example, in the reuse of drawings, the existing data include drawing design information, two-dimensional drawings and three-dimensional models. The key features of multi-modes can be extracted with the help of large models, and after obtaining similar drawings, the information can be aligned to determine whether the two equipment drawings are similar, which provides convenience for the reuse design of drawings.

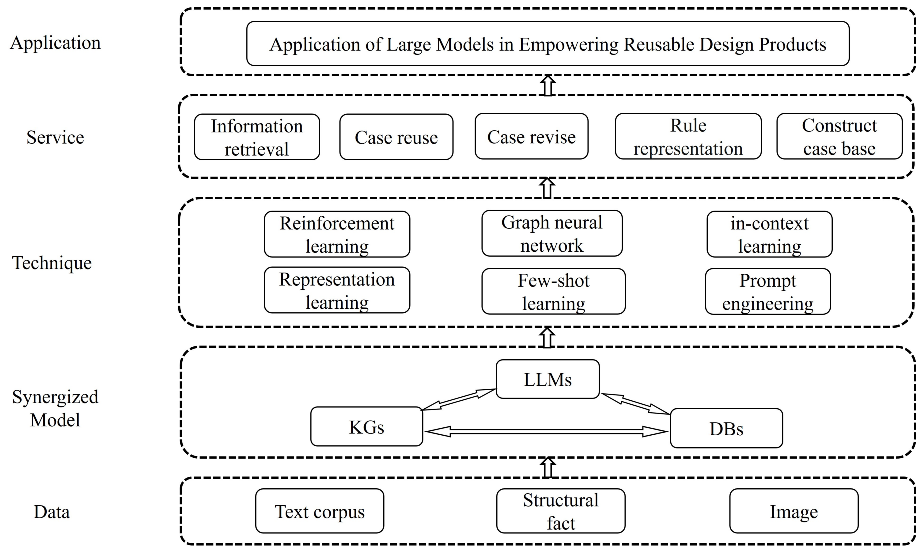

Fig. 4. Framework for co-operating with LLMs, KGs and DBs

4.5. Limitations and Future Work

This paper puts forward some new ideas and methods, but there are some limitations and need to be improved in the future. Future work needs to further explore how to apply these ideas and methods in practical scenarios to improve the efficiency and accuracy of the design.

1. Multimodal data processing. The knowledge base proposed in this paper can be extended to handle multimodal data, such as images. However, this paper does not give a specific scheme on how to deal with multimodal data. Future work could further explore how multimodal data can be processed and incorporated into existing knowledge bases.

2. The problem of large model enabling entity alignment tasks. In the future, we can make use of existing entity alignment methods and make appropriate improvements, give full play to the powerful generalization and reasoning ability of large language models, and effectively improve the accuracy and efficiency of entity alignment of commodity knowledge graph.

5. Conclusion

This review synthesizes recent progress in rule-based and case-based reasoning techniques for reusable design in CAD software systems and summarizes the advantages and disadvantages of CBR and RBR. The complementary strengths and weaknesses of RBR and CBR highlight the potential of hybrid CBR-RBR approaches. RBR effectively represents structured expert knowledge as rules but lacks learning capabilities and flexibility. CBR provides a framework for experience reuse from prior cases but relies heavily on surface similarities without deeper reasoning. The emergence of large language models and knowledge graphs in artificial intelligence research offers new opportunities to overcome these limitations. Advanced language comprehension and reasoning abilities enable large models to better acquire domain knowledge, retrieve contextual cases, explain connections, and adapt reasoning. Integrating them with structured knowledge graphs also improves interpret ability.

The proposed reusable design framework combines RBR, CBR, large models, and knowledge graphs into a hybrid approach. This allows leveraging the strengths of both reasoning techniques while mitigating their weaknesses through large model augmentations. Such a hybrid framework paves the path toward more efficient, innovative, and sustainable CAD reuse design. Intelligent case-based and rule-based reasoning empowered by AI advances could transform engineering design by fully utilizing prior knowledge. Further research is still needed to realize the potential benefits of reasoning-based CAD systems enhanced by large models. But this review highlights promising directions and a proposed framework to guide future efforts. Overall, the synergistic integration of reasoning techniques with modern AI can fundamentally reinvent reusable design, resulting in greater automation, creativity, and intelligence in computer-aided engineering.

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