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Enhancing Knowledge Capture and Reuse for Offsite Construction through A Container-based Knowledge Approach

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Abstract

Offsite construction (OSC) requires an integrated design and delivery system. Reusing prior OSC knowledge is paramount to the success of new OSC projects. However, a gap remains in managing and reusing this knowledge across the broader industry. The challenge lies in the fragmented nature of project-based organisations with isolated knowledge systems, which often lack integration and advanced capabilities for knowledge-based collaboration. This paper proposes a novel framework that leverages cutting-edge knowledge-based methods and artificial intelligence (AI) technologies to create a container-based knowledge system (CBKS) that can enhance knowledge capture and reuse towards collaborative OSC. Specifically, the semantic web stack is adopted to construct multimodal knowledge containers for both human users and AI agents. In addition, GPT-4o, a large language model (LLM), is embedded into the knowledge system for better knowledge querying, matching and retrieving. By using this framework, constructed modular knowledge units can integrate product, process and organisation factors to address specific OSC problems. To evaluate the technical feasibility of the proposed framework, a prototype is developed and illustrated through a modular connection design. This illustrative case study demonstrates how knowledge is captured for product representation under manufacturing and assembly constraints, enabling its reuse in different projects. Moreover, the usefulness of GPT-4o for enhancing this process is also tested.

Keywords: Offsite construction, Integrated knowledge base, Information container, Large language model

1 Introduction

Offsite Construction (OSC) refers to the manufacturing of building components away from the site, followed by their transportation to and assembly at the final location. In recent years, OSC has gained significant attention as a solution to address inefficiencies in productivity, affordability, and sustainability within the traditional construction industry (Wuni & Shen, 2019). OSC offers numerous benefits, including reduced construction time, improved quality control, and minimised on-site disruptions (Razkenari et al., 2020). The adoption of OSC relies on an integrated design and delivery system, where clients, designers, manufacturers and contractors need to collaboratively work together at the early stage of a project to reach the goals (Hosseini et al., 2018). Therefore, the reuse of prior knowledge is crucial for the success of new projects. However, there remains a gap in effectively managing and reusing OSC knowledge across the broader industry. The challenge lies in the fragmented nature of project-based organisations with isolated knowledge systems, which often lack integration and advanced capabilities for knowledge-based collaboration (Z. Zhang et al., 2024).

To address these challenges, effective Knowledge Management (KM) is essential for OSC. Managing OSC knowledge can facilitate the sharing of best practices, enhance process efficiency, and promote continuous improvement across projects. However, previous research on KM in OSC does not fully integrate technology, process, and people-related factors that are critical to successful knowledge capture and reuse (Z. Zhang et al., 2024). It is argued that this gap can be bridged by developing an integrated knowledge system for combining technological tools, process-oriented structures, and the necessary human factors so that OSC knowledge can be effectively captured, shared and reused. For this purpose, a novel approach leveraging the power of semantic web technology and artificial intelligence (AI) is proposed.

Firstly, involving the semantic web technology increases the level of integration and flexibility of KM in a wide range of OSC project lifecycles. The semantic web has increasingly attracted interest in the construction industry (Pauwels et al., 2017). It includes technologies such as Resource Description Framework (RDF), Web Ontology Language (OWL), and SPARQL. RDF provides a framework for representing information in a graph format, enabling data interoperability. OWL is used for defining complex relationships between concepts and facilitating reasoning over the knowledge base. SPARQL is a query language used to retrieve and manipulate data stored in RDF format, allowing efficient knowledge querying and integration. More importantly, knowledge in the real-world construction project is usually used in multimodal formats, such as texts, 2D drawings, 3D-models, etc., with highly dynamic requirements in different scenarios (Bilal et al., 2016), whereas current knowledge approaches for OSC mainly focus on specific data format (Z. Zhang et al., 2024). To flexibly integrate the multimodal knowledge for specific usage, a container-based approach can be adopted according to the international standard series ISO 21597 to link various data and documents together using ontologies and links datasets (ISO, 2020a; 2020b). Though semantic web technology offers significant advantages for representing and linking knowledge in a structured manner, the application it in KM for OSC has not been widely adopted in the OSC industry, leaving a gap in understanding its full potential in this domain. The reasons can include high cost of ontology development, the complexity of SPARQL queries, and the need to develop rule sets.

Additionally, large language model (LLM) is embedded in this framework to promote the management of OSC knowledge. The construction industry has witnessed the emergence of AI technologies, especially LLM, which show promising potential for enhancing KM in OSC. LLMs are AI models trained on vast amounts of text data, capable of understanding, generating, and translating human language. They leverage deep learning to comprehend complex patterns and semantics, making them powerful tools for a wide range of natural language tasks, such as automated construction reporting (Pu et al., 2024). However, challenges like ensuring accuracy, improving interpretability and maintaining context relevance in the construction domain persist (Abioye et al., 2021). This is where the synergy between LLMs and semantic web technology becomes crucial (Pan et al., 2024). For example, ontologies, which can formally represent domain-specific knowledge, offer a solution to enhance the performance of LLMs, ensuring accurate and context-sensitive knowledge retrieval. Furthermore, the semantic web can serve as a foundation for creating interconnected knowledge containers, enabling LLMs to deliver more accurate and informed responses. These knowledge containers enable LLMs to understand relationships between different OSC elements, such as components, processes, and stakeholders. By leveraging these interconnected datasets, LLMs can generate more precise and insightful responses to user queries, supporting decision-making processes in OSC (Wu et al., 2023). In this way, the knowledge hidden in previous OSC cases can be derived into knowledge containers for effective reuse in new projects enhanced by LLMs.

To explore the mechanism and feasibility of this approach, this study developed a theoretical framework of a container-based knowledge system and developed a system prototype that combines semantic web technology and LLM with effective human-computer interaction to facilitate knowledge capture, reuse, and management throughout the OSC lifecycle. The feasibility of this approach is illustrated through a case study, showcasing its potential to improve KM processes in OSC projects. In the next section, we introduce the method adopted in this study and outline the research questions. Next, this paper details the design and development of the proposed solution. After that, the system test is illustrated through a case study on modular building connections in Section 3. Finally, the discussion and conclusion sections evaluate and summarize the research findings.

2 Design and Development of CBKS

2.1 Research Method and Questions

A design science research methodology has been applied for developing and evaluating the prototype of proposed framework (Peffers et al., 2007). Firstly, the research problems and motivation were identified through literature review and our previous study (Z. Zhang et al., 2024). It was found that the study of a container-based knowledge system (CBKS) has been ignored. In addition, no research has explored the collaboration between CBKS and LLM, particularly how LLM can improve KM for OSC. To narrow down the scope, this study mainly focuses on knowledge capture and reuse enhanced by information containers and LLM. The following research questions (RQs) are investigated:

RQ1: How can a container-based knowledge system (CBKS) enhance knowledge capture and reuse for OSC?

RQ2: What are the potential ways of the proposed CBKS collaborating with LLM to facilitate OSC knowledge querying, manipulating and retrieving?

Therefore, the objectives were defined for developing the corresponding solution, namely, LLM-augmented CBKS. Then, this study conducted an iterative design and development process followed by a case study to illustrate and test the feasibility of the proposed CBKS. Finally, the test outcomes were discussed for directing future research.

2.2 The Theoretical Framework

The theoretical framework of CBKS uses a problem-solving-oriented method to make sure each container is a best practice guide for achieving its value (Barak & Goffer, 2002). The OSC knowledge in this framework is modelled at two layers, namely, the universal layer and the project-specific layer. The rationality of this method comes from the modular nature of OSC as the knowledge that can be modularised and standardised should be stored at a universal layer for maximum reusability on the top, whereas the knowledge that can only be used in the specific project should be treated case by case at the bottom. There are more opportunities for leveraging the value of universal knowledge in OSC projects. Moreover, knowledge modelling based on the semantic web requires high expertise (Davies et al., 2006). Therefore, KM professionals are necessary to maintain knowledge from the backend so that the CBKS can provide knowledge services to the frontend users. Meanwhile, embedded LLM is expected to promote this system by collaborating with the constructed knowledge container (Pan et al., 2024).

As shown in Figure 1, the knowledge container is configured by knowledge managers through a set of Terminology Box (T-Box), Assertion Box (A-box), and Rule Box (R-box). T-Box stands for the taxonomy of the concepts and their attributes and relations in the scope of the knowledge container. Based on the defined T-Box, instance facts can be asserted to form A-Box manually or through the execution of SPARQL code according to the specific cases and requirements. Then, classes and assertion facts can work with predefined rules in the R-Box to infer new facts, returning the expected outcomes to a knowledge user (L. Zhang & Lobov, 2024). The knowledge user can also interact with the CBKS through a user interface to assert case-specific facts that will be processed by the reasoning engines (R-Box) for knowledge reuse (Pérez et al., 2009). In addition, there is an opportunity to facilitate the transformation of required queries between natural language and SPARQL code by using GPT-4o as it is one of the most powerful LLMs developed by OpenAI (2024). This can potentially improve knowledge sharing and reuse because most of the industrial professionals (knowledge users) may not be familiar with semantic web technologies.

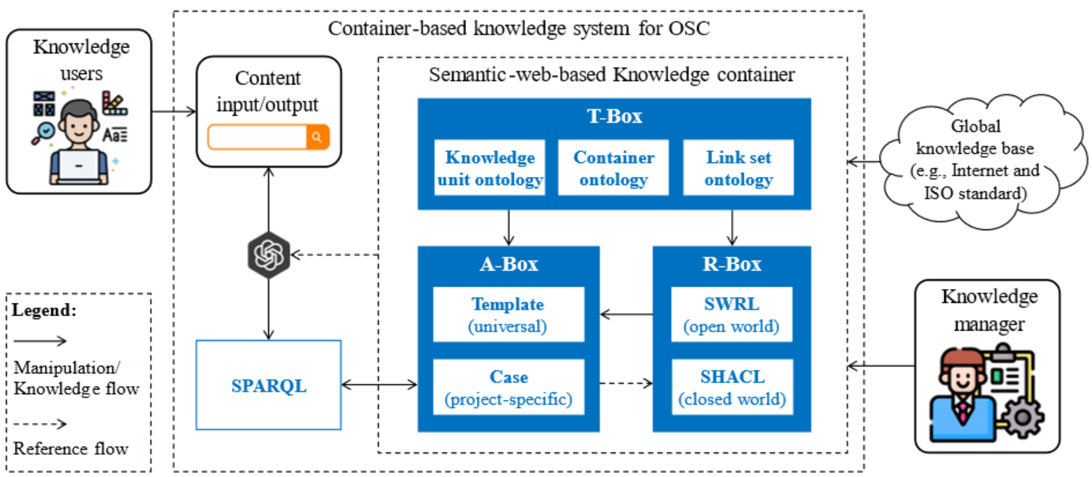

Figure 1: The theoretical framework of LLM-augmented CBKS

2.3 Semantic Modelling of Data and Rules

The core of the proposed CBKS is the semantic modelling of data and rules. The processes of building the knowledge base (KB) include the construction of the OSC knowledge model, container model, and rules in T-Box, A-Box, and R-Box.

There are three ontology resources in the T-Box: OSC knowledge ontology, container ontology and link set ontology. The OSC knowledge ontology aims to present domain knowledge for solving specific problems, such as OSC product design, quantity take-off, project scheduling, etc. The role of container ontology and link set ontology is to govern the actual data saved as document format and link these documents and their internal elements together (Hagedorn, Liu, et al., 2023). This is designed to present case-based experiential knowledge generated in previous OSC projects.

The A-Box contains instantiated data models presenting templates that can be used universally in different scenarios and the cases that have occurred in previous projects. After defining the classes, attributes and relations in T-Box, knowledge managers can start the construction of A-Box. At this stage, both the universal assertions in templates and case-specific facts can be input manually for debugging purposes. After the validation of semantic rules, some case-specific assertions can be derived by the reasoning engine embedding in the proposed CBKS. In addition, external documents can also be linked to the knowledge model through the link dataset asserted in the A-Box for providing case-specific references, which has been proved in many other studies (Hagedorn, Liu, et al., 2023; Höltgen et al., 2021; Liu et al., 2023).

In the R-Box, semantic rules are formed to provide a reasoning role that can conduct compliance checks and generate new facts according to assertions in the A-Box. Shap Constraint Language (SHACL) and Semantic Web Rule Language (SWRL) are two representative types of semantic rules. SHACL defines rules in the form of information availability requirements, while SWRL defines rules in the form of an implication between a set of antecedents and consequents (Nuyts et al., 2024). They stand for two different knowledge representation patterns, which will be described further in Section 2.4.

2.4 Mechanism of Knowledge Sharing and Reuse

For knowledge sharing and reuse in OSC projects, there are opportunities to utilise reusable ontologies defined globally, for example, the standardised product representation defined in the international or national standards (L. Zhang & Lobov, 2024). In this approach, the container ontology and link set ontology resources are directly reused from the international standard ISO 21597 about information container for linked document delivery (ISO, 2020a; 2020b). For a specific knowledge domain, knowledge managers can develop customised local ontologies and combine them with global ones to form the basis of T-Box. When facing a specific problem, knowledge users can assess the reusability of the components in global and local ontologies and directly create an instance of them to reuse predefined concepts, attributes and relations.

These reusable knowledge contents can be universally applied to different projects sharing the same scope. However, it is inevitable for projects to have their characters and unique environments, which means that project-specific data and rules must be taken into consideration. Hence, the proposed CBKS applies this kind of knowledge directly to the instances in A-Box rather than the classes in T-Box. In this way, universal knowledge and project-based knowledge can be modelled and stored in the template library and case library of the specially designed KB respectively.

Theoretically, this CBKS framework can be driven by various reasoning engines with corresponding rule languages. These rule languages generally fall into two categories of knowledge-representing mechanisms: Closed-World Assumption (CWA) and Open-World Assumption (OWA). Under a CWA, all entities and relationships in the KB cannot be changed but discovered (Reiter, 1981), whereas unseen entities, relationships and their attributes can be predicted and reasoned in an OWA (Shi & Weninger, 2018). As mentioned in Section 3.2, there are two representative rule languages in the semantic web world: SHACL and SWRL, in which SHACL naturally operates under a CWA while SWRL originally operates under an OWA. It is noticed that, however, the current research on SWRL in the construction field mainly applies it under the CWA patterns. In the present work, it is argued that utilising the OWA nature of SWRL can facilitate knowledge sharing and reuse in the OSC processes as universal knowledge and case-specific knowledge are used in hybrid in the real-world OSC projects.

2.5 User Interactions with CBKS Using LLM

There are two key roles: knowledge managers and knowledge users who are responsible for building and using this proposed CBKS. The overview of the general work processes and data flows for applying CBKS is shown in Figure 2 in the form of Business Process Model and Notation (BPMN) (Chinosi & Trombetta, 2012). The diagram contains three pools representing the key players responsible for knowledge use and management to interact with CBKS.

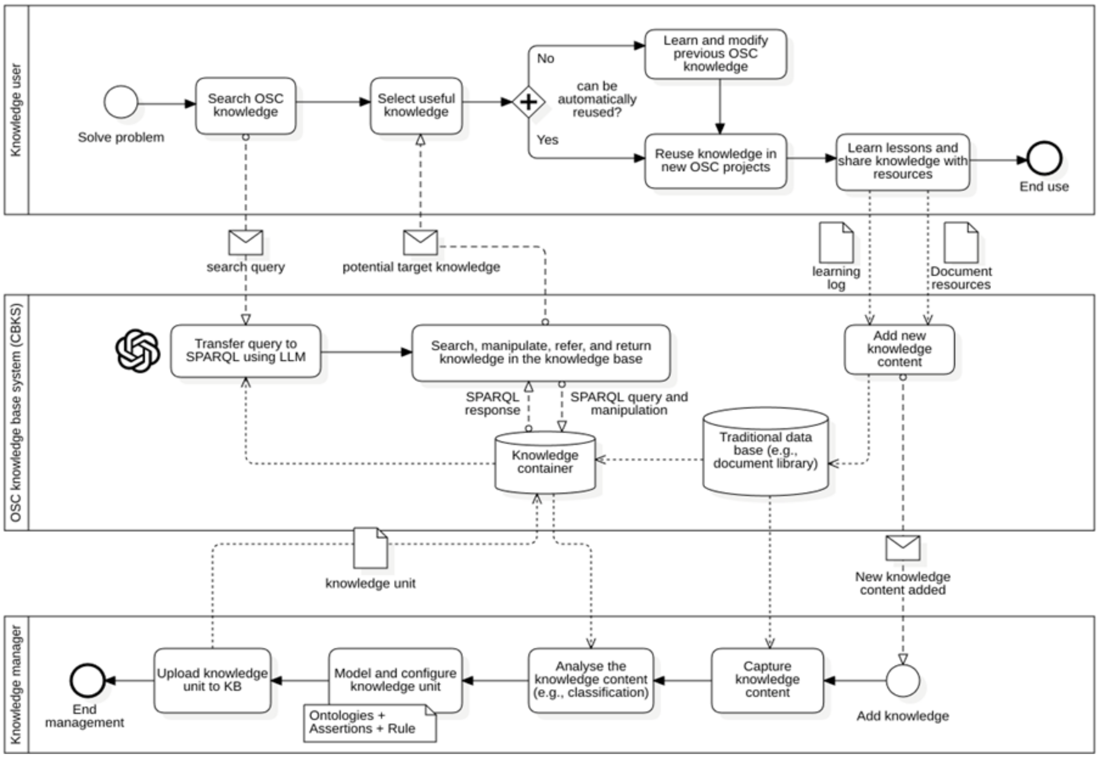

Figure 2: BPMN diagram of the application of CBKS

The CBKS enables knowledge users to search for knowledge and manipulate case-specific facts using SPARQL code. However, most professionals from the construction industry may not be familiar with writing the SPARQL query and update (Pérez et al., 2009). To decrease this barrier, the proposed CBKS leverages the power of LLM to conduct a mutual transformation of the professional content between natural language and SPARQL code. By providing proper prompts and the context of knowledge models, effective knowledge query and manipulation and high-quality responses can be expected from the LLM-augmented CBKS. Then, the knowledge users can select useful knowledge responses to directly use in their problem-solving process or make any necessary modifications. After that, new lessons may be learned and shared with partners and retained in the KB.

Universally applicable and case-based knowledge needs to be managed and integrated into the KB. In this process, knowledge managers first capture knowledge from a global knowledge base and a traditional database in CBKS. Then, the knowledge content will be analysed and formalised to construct knowledge units in the form of ontologies, assertions and rules. Subsequently, these knowledge units are uploaded to the CBKS for utilisation.

3 Illustration of the CBKS Framework

This section illustrates the development and test of the core functions provided by CBKS through a case study, including semantic-based knowledge inference and LLM-embedded knowledge manipulation and query. On the one hand, how OSC knowledge is modelled, stored, and inferred with restrictions of manufacturing and assembly to drive information delivery in project documents is described in detail (RQ1). On the other hand, a series of tests are conducted to explore the potential ways of, and prove the feasibility of, embedding LLM into the proposed CBKS (RQ2).

3.1 Semantic Web-based Knowledge Inference

A design case of modular building connection is adopted for study because the connection is more likely to be universally standardised but still affected by case-based factors in OSC projects. Figure 3 demonstrates the mechanism of CBKS performing knowledge representation and reasoning of the selected modular building connection design (Chen et al., 2017). This case consists of four main sections including a set of stay bolts, cover plates, intermediate plates, and a plug-in device, which are assembled with modular space modules.

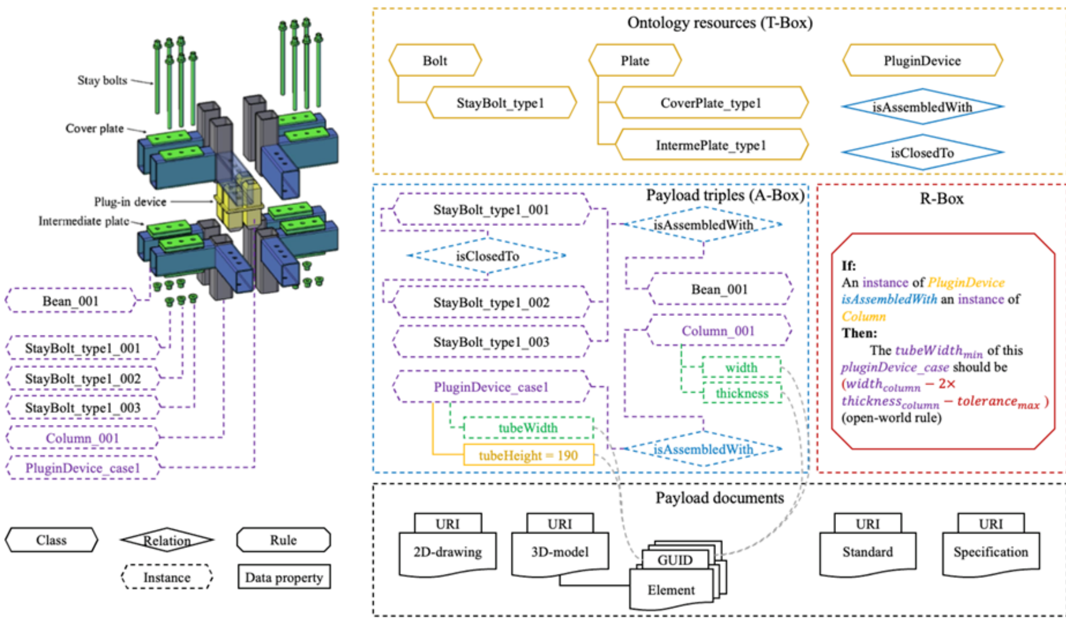

Figure 3: Case study for the CBKS

The semantic definition of the modular connection is achieved through classes and relations in T-Box, and its configuration is realised by asserting corresponding instances in A-Box. The first step, for example, is defining classes “Bolt”, “Plate”, “PluginDevice”, and relations “isAssembledWith” and “isClosedTo”. Then their instances are modelled in an object-oriented manner, presenting the actual solution of this modular connection. These instances can directly inherit the attributes defined in T-Box that are universally applicable for different projects, while the attributes depending on the actual project circumstances are derived from running of the predefined rules.

By way of illustration, the tube of the plug-in device needs to be inserted into the steel columns of related module frameworks for building assembly. The width and thickness of the modular steel columns are determined case by case as there are many uncontrollable effects from different projects. Consequently, external documents and their internal elements can be linked to the related instances in A-Box through identifiers, such as Universal Resource Identifier (URI) and Globally Unique Identifier (GUID), in which the inferred outcomes can drive the generation and adaptation of the business objects in external documents like a plug-in device in BIM model. It should be noticed that this deep link mechanism has been proved in (Hagedorn, Pauwels, et al., 2023), whereas the generation and adaptation process still need to be explored in the future.

This paper only focuses on the test of knowledge inferring part as it is the semantic foundation of up-layer applications such as generative OSC product design. For validating this scenario, Protégé, an open-source ontology editor, is adopted to implement the test. As shown in Figure 4, when the classes of the test connection case are defined and enough facts have been asserted, the predefined rule can derive implicit facts from these universal restrictions and case-based assertions.

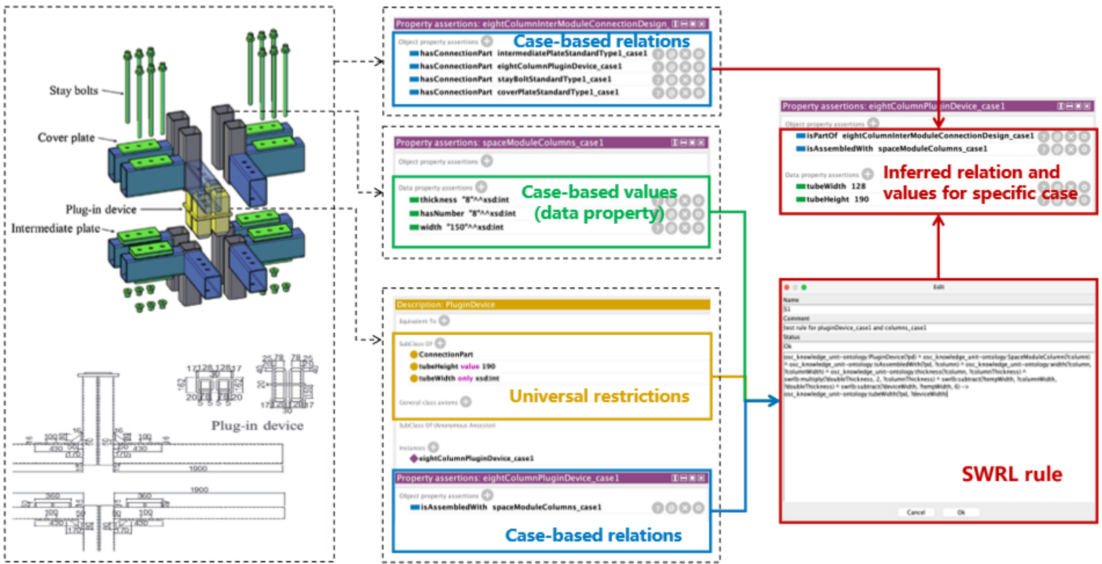

Figure 4: Knowledge reasoning of the CBKS

In this case, the tube width of the selected plug-in device is affected by the width and thickness of the modular columns directly assembled with it. The sizes of modular columns will inevitably change case by case in different projects. Under this CBKS framework with OWA, knowledge can be easily shared and reused by users asserting case-based facts from new conditions. However, for traditional industry professionals who are not familiar with semantic web technologies, it is hard to interact with this new knowledge base. Therefore, this study attempted to embed LLM to facilitate knowledge manipulation and query by transferring natural language to SPARQL code.

3.2 LLM-embedded Knowledge Manipulation and Query

This section demonstrates the potential opportunity to embed LLM for easier knowledge manipulation and query using GPT-4o. For knowledge manipulation, a prompt was formed as a template to insert a new instance for class "SpaceModuleColumn" named "spaceModduleColumn_case2" and adapt its "width" and "thickness" with two new values. Figure 5 shows one of the test results. It can be noticed that GPT-4o can provide acceptable responses followed by a set of interpretations as the contextual information of the given ontology is provided in the template prompts.

Figure 5: LLM for easier knowledge manipulation and query using GPT-4o

For knowledge query, the same method can also be used to generate the SPARQL code to retrieve target knowledge. However, for traditional industry users, it may still be inconvenient to use because the successful generation of SPARQL code needs a well-formed template, which leads to lower flexibility. Therefore, the LLM was tested further to directly parse and understand the knowledge content without using SPARQL. Firstly, the pre-developed knowledge model was fed into the conversation with GPT-4o. Then a task was assigned to GPT-4o to parse the given knowledge model stored in a .rdf-format file with RDF/XML syntax and let it list all classes, object properties, instances and restrictions in the file. As a result, the LLM successfully returned all ontology axioms, consistent with those in the original knowledge model. An example is shown in Figure 6. It was noticed that GPT-4o implemented these tasks through the path of generating visible Python code to treat and process the given document rather than only showing the results, which increased the AI interpretability in this process. Nevertheless, this does not mean that GPT-4o can directly understand the meaning of content in the uploaded knowledge model.

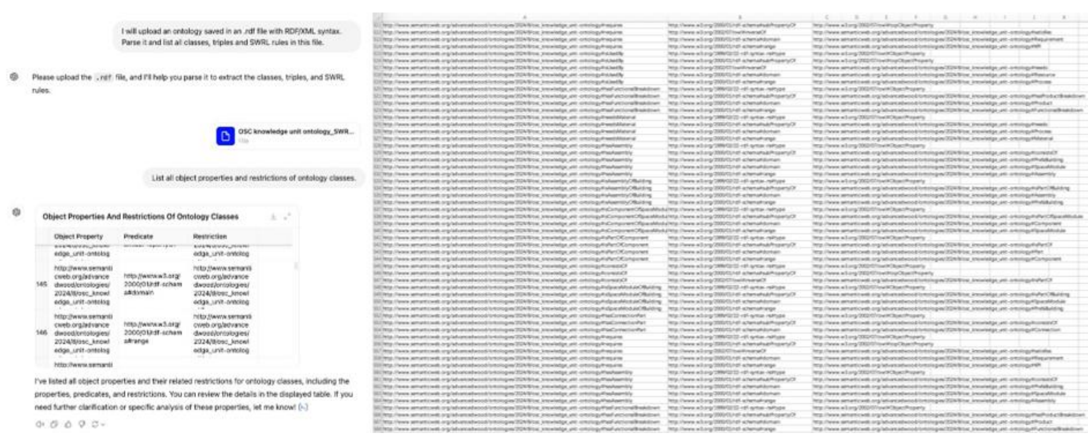

Figure 6: LLM for parsing of knowledge model

The preliminary test results of the embedded LLM for knowledge query are listed in Table 1, which indicate a good reliability of the embedded GPT-4o in these tasks. It was noticed that though the GPT-4o may fail in processing the provided data set, it can make self-checking automatically and finally return the correct answer. However, the tests were limited by using only one data set and specific prompts, which may lead to arbitrary problems. Hence, more data sets and interaction scenarios will be tested in the future research.

Measuring categories	Actual values in the data set	Retrieval/response results
Class retrieval count	53	53
Object property retrieval count	36	36
Data property retrieval count	9	9

Table 1: Reliability test results of the embedded LLM

Moreover, the augmentation of LLM in a specific knowledge problem was also tested by asking questions like "What are key components of a type of modular connection according to the existing cases?". In the given knowledge model, as mentioned in Section 4.1, an "EightColumnInterModuleConnection" was defined and has a configuration type assembled with four main components: "EightColumnPluginDevice", "CoverPlate", "IntermediatePlate" and "StayBolt". This was asked to assess the response accuracy of GPT-4o. The tests were run ten times. Though GPT-4o sometimes used different methods to parse the given knowledge at the backend, it could always return the same and accurate answer in each time (see Figure 7).

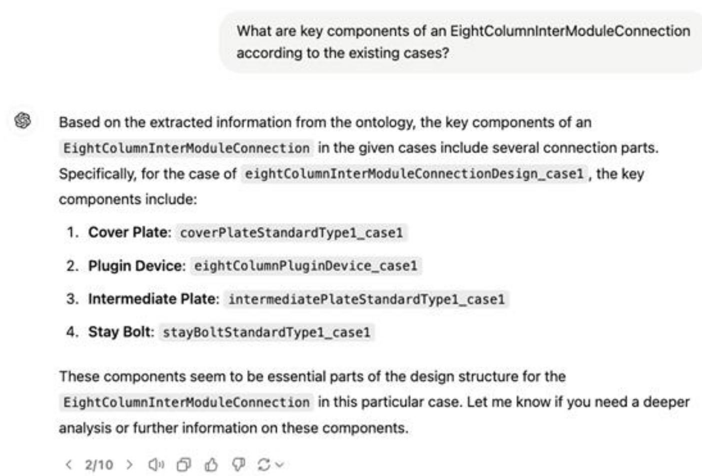

Figure 7: Augmentation of LLM in a specific knowledge problem

4 Discussion

The contribution of this study lies in proposing an innovative knowledge system, CBKS, and proving its feasibility of leveraging the capability of semantic web-based containers and LLMs for enhancing the management of OSC knowledge. Through the proposed CBKS, the universal and case-specific knowledge can be successfully captured and reused by modelling them into global and local ontologies and rules. The semantic web stack combining ontologies of OSC knowledge, information container and link set can provide linked multimodal data for satisfying dynamic knowledge demands ranging from documents such as a BIM model or a CAD drawing to their internal elements (e.g., beam, wall, connection, etc.). For the rule construction, the case study adopted SWRL to conduct the knowledge inferring under an OWA instead of adopting it under CWA, which can facilitate knowledge reuse in dynamic project conditions.

Additionally, LLM such as GPT-4o can facilitate the knowledge manipulation and query through transferring natural language to SPARQL code and parsing the ontology-based knowledge model to answer professional questions. In the test of understanding and answering questions, GPT-4o showed a stable performance for returning correct responses derived from the given knowledge model. However, more tests are needed for different scenarios and questions. It should also be noted that prompt templates are needed for better generation in the transformation from natural language to the SPARQL code, which leads to lower flexibility in the application.

Considering this paper serves as a proof-of-concept to propose a knowledge system framework for enhancing knowledge capture and reuse for OSC, the knowledge model in the case study was simplified and a limited number of scenarios were tested. Moreover, the effectiveness of deploying the proposed framework was not evaluated, and this will be addressed by our future research.

5 Conclusion

This paper introduces a knowledge base framework called CBKS that utilises semantic web and LLM technologies to enhance the knowledge capture and reuse for OSC. This framework is illustrated through a case study involving the representation of an OSC product (eight-column modular building connection). The findings are summarised as follows: 1) The semantic web stack as a core can link external documents and elements to the OSC objects driven by knowledge in CBKS; 2) Compared to SHACL, SWRL can support more flexible knowledge use by capturing open-world rules rather than asserting all constraints in a fixed pattern; 3) LLM, especially GPT-4o, has significant potential to augment the knowledge manipulation and query based on the given ontology model. In future research, it is essential to apply the proposed CBKS to a well-defined OSC problem and connect it to the application layer to evaluate the knowledge-driven automation processes, such as the generative design of an OSC product. Furthermore, the completed system will be deployed to an open server for more widely and systematic evaluation by industry experts.

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