Developments in the Built Environment 17 (2024) 100300

Contents lists available at ScienceDirect

Developments in the Built Environment

journal homepage: www.sciencedirect.com/journal/developments-in-the-built-environment

GPT models in construction industry: Opportunities, limitations, and a use case validation

Abdullahi Saka [a], Ridwan Taiwo [b], Nurudeen Saka [a], Babatunde Abiodun Salami [c], Saheed Ajayi [a,*], Kabiru Akande [d], Hadi Kazemi [a]

[a] School of Built Environment, Engineering and Computing, Leeds Beckett University, UK
[b] Department of Building and Real Estate, Hong Kong Polytechnic University, Hong Kong
[c] Cardiff School of Management, Cardiff Metropolitan University (Llandaff Campus), UK
[d] OVO Energy, UK

ARTICLE INFO

Keywords:
LLMs
ChatGPT
GPT
Artificial intelligence
Generative AI

ABSTRACT

Large Language Models (LLMs) trained on large data sets came into prominence in 2018 after Google introduced BERT. Subsequently, different LLMs such as GPT models from OpenAI have been released. These models perform well on diverse tasks and have been gaining widespread applications in fields such as business and education. However, little is known about the opportunities and challenges of using LLMs in the construction industry. Thus, this study aims to assess GPT models in the construction industry. A critical review, expert discussion and case study validation are employed to achieve the study's objectives. The findings revealed opportunities for GPT models throughout the project lifecycle. The challenges of leveraging GPT models are highlighted and a use case prototype is developed for materials selection and optimization. The findings of the study would be of benefit to researchers, practitioners and stakeholders, as it presents research vistas for LLMs in the construction industry.

1. Introduction

The architecture, engineering, and construction (AEC) industry is known for its slow adoption of innovation, when compared to other industries, due to the culture of the industry and the nature of its products (Gambatese and Hallowell, 2011). The industry is information-intensive and relies on myriad and diverse information from different stakeholders for successful project delivery (Chen and Kamara, 2005). However, there is a lack of information integration, reuse, and efficient management, all of which have a tremendous effect on stakeholders' collaboration and productivity of the industry. Past reports in the construction industry have emphasized the need for improvement in the modus Operandi of the industry to improve productivity and achieve value for money (Egan, 1998). Although the industry currently contributes about 13% to the global GDP, productivity growth has only been increasing at 1% per year over the last two decades (Ribeirinho et al., 2020). Also, the industry is facing a myriad of challenges such as delays, health & safety, cost overrun, shortage of skilled personnel, and stringent requirements by governments. With the advancement in information technologies and digital tools, the AEC industry has been embracing its usage to improve its performance in a bid towards the fourth industrial revolution (industry 4.0). Consequently, there has been an increase in the usage of building information modelling (BIM), application of big data analytics, offsite construction, automation, and artificial intelligence (AI).

AI deals with the ability of machines to perform tasks that typically require human intelligence, such as learning, reasoning, perception and decision-making. AI systems process and analyse large datasets with the view of identifying patterns, relationships, drawing inferences, recommendations and taking action. Abioye et al. (2021) listed the subfields of AI to include machine learning, knowledge-based systems, computer vision, robotics, natural language processing, automated planning and scheduling and optimization. These diverse fields have been employed in the AEC industry to improve productivity and efficiency. As such, AI has been leveraged in cost prediction, delay prediction, building design energy prediction, workers' activity recognition, construction site safety, cash flow prediction, structural health monitoring, resource allocation and optimization, predictive maintenance, and decision

* Corresponding author.
E-mail addresses: a.saka@leedsbeckett.ac.uk (A. Saka), ridwan-a.taiwo@connect.polyu.hk (R. Taiwo), n.o.saka@leedsbeckett.ac.uk (N. Saka), basalami@cardiffmet.ac.uk (B.A. Salami), s.ajayi@leedsbeckett.ac.uk (S. Ajayi), koakande@gmail.com (K. Akande), h.kazemi@leedsbeckett.ac.uk (H. Kazemi).

https://doi.org/10.1016/j.dibe.2023.100300
Received 30 May 2023; Received in revised form 26 October 2023; Accepted 4 December 2023
Available online 12 December 2023

support system, among others (Abioye et al., 2021). Studies have shown significant improvement in productivity and efficiency with the use of these tools; however, bottlenecks have been reported. Challenges such as lack of skilled workers, cultural resistance to change, cost of implementation, unavailability of structured data, trust and ethics have been highlighted as the major hurdles towards the effective deployment of AI in the AEC industry (Akinosho et al., 2020).

With the advancement in AI, there has been significant improvement in the development of Conversational AI (CAI) and Generative AI (GAI). Conversational AI deals with the application of NLP to enable computers to understand and interact with humans in a conversational way using natural language (Kulkarni et al., 2019). Generative AI deals with the creation of novel content such as texts, audio, and images (Gozalo-Brizuela and Garrido-Merchan, 2023). CAI improved human-computer interactions and led to the development of chatbots, virtual assistants and other conversational interfaces which often leverage GAI and can assist users in automating tasks, information retrieval, and customer services among others. Saka et al. (2023) reviewed the current applications of Conversational AI in the AEC industry and highlighted that the deployment of this emerging field is still limited. Few extant studies on the application of Conversational AI in the construction industry focused on information retrieval from BIM with limited functionalities. Majority of the developed Conversational AI agents in the AEC industry are based on the traditional approach to NLP, which requires time for processing the data, and users' interactions are often restricted as the agents are developed with the assumption of happy path users. Similarly, other studies have leveraged on machine learning for the development of Conversational agents such as Bidirectional Encoder Representations from Transformers (BERT) and the use of commercial platforms such as IBM Watson, Amazon Alexa, Google Natural Language AI, and Microsoft Azure (Saka et al., 2023). However, this approach often requires large data sets for training which are unavailable and expensive to gather in the AEC industry.

Furthermore, these machine learning approaches such as BERT are part of LLMs which came to the limelight in 2018 after the introduction of transformer-a model architecture which rely on attention mechanism and differs from recurrent neural networks - by Vaswani et al. (2017). LLMs are neural networks with large parameters and are trained using self-supervised learning and semi-supervised learning on large datasets. These LLMs have improved NLP and shifted the direction away from training with labelled data for defined objectives. Generative Pre-trained Transformer (GPT) models which are decoder blocks only from OpenAI which have gained significant attention and showed improved performance from GPT-2 (trained with 10 billion tokens) to GPT-3 (trained with 499 billion tokens) and recently GPT-4 released in 2023. The GPT models as a result of the large training dataset and large parameters have enabled few-shot (provide contexts and examples in the prompts), zero-shot (no example is provided in the prompt) learning capability (Wei et al., 2022). As a result, it has been widely deployed in many applications. GPT models have beneficial applications in healthcare for triaging, analysing electronic health records, translation, medical education, medical and diagnostic (Li et al., 2023). In bioinformatics, GPT model have been applied in sequence analysis, Genome analysis, Gene expression, proteomics, and in drug discovery (Zhang et al., 2023). In education, GPT could transform autodidactic experience by providing personalized support, increased accessibility, flexible learning, real-time feedback and guidance (Firat, 2023). Similarly, GPT can be leveraged in business and commerce for chatbots, virtual assistants, customer service management, sentiment analysis, financial analysis and forecasting, fraud detection and supply chain management (Zong and Krishnamachari, 2022).

Despite GPT models overcoming some of the extant challenges of developing AI applications in the construction industry and providing opportunities to improve productivity, there are few studies on GPT models in the AEC industry. Also, there are no reviews on the opportunities of these emerging LLMs in the literature. Consequently, this current study aims to critically review GPT models in the AEC industry with the following objectives:

a) To identify opportunities for the application of GPT models
b) To evaluate the limitations to the application of GPT models in the AEC industry
c) To validate a use case for GPT models in the AEC industry

Achieving these objectives would significantly contribute to the emerging body of knowledge on LLMs and Generative AI in the construction industry and provide research agenda for researchers. Also, this study highlights areas that would benefit from the application of GPT models and provides a case study validation for the use of GPT model in material selection and optimization. Similarly, inherent challenges of the application of GPT are presented to enlighten stakeholders about the possible pitfalls that can be encountered in the deployment of GPT models and to prevent health, safety, and business problems. The rest of the paper is structured into seven sections (Fig. 1) covering the literature review, methodology, findings, discussion, case validation and conclusion.

2. Generative Pre-trained transformer (GPT)

OpenAI's Generative Pre-trained (GPT) models have made significant contributions to the field of language generation. GPT models use transformer-based models that learn statistical patterns of natural language, enabling them to generate human-like language. The series started with GPT-1 in June 2018 and has since evolved to GPT-2, GPT-3, and GPT-3.5 (OpenAI, 2019; Radford et al., 2019). The latest addition, GPT-4, was launched in March 2023 and demonstrates significant advancements in generating coherent and understandable text. GPT models are trained using vast amounts of unstructured text data, enabling them to generate language almost indistinguishable from human-generated text (OpenAI, 2023a,b). Early NLP relied on rule-based systems that required explicit programming of grammar rules and syntax. However, these systems have limitations in programming complex languages and linguistic nuances, making them less adaptable to new domains or contexts and less scalable (Shaalan, 2010). The rise of data-driven approaches, such as GPT models, enabled machine learning algorithms to learn from large amounts of data and recognize complex patterns in natural language without explicit programming of rules. The GPT-3 API was introduced in June 2020 and made publicly available in November 2021 (Karhade, 2022; OpenAI, 2020). It brought significant advancements in NLP technology making GPT-3 widely accessible. In January 2022, InstructGPT, a version of GPT 3.5, which can handle more complicated instructions, was released. In 2022, speech recognition software Whisper and GPT-3.5 upgrade to text-davinci-003 were introduced in September and November, respectively (Karhade, 2022; OpenAI, 2023a,b; Radford et al., 2022). GPT-4 has further advanced the NLP after launching in March 2023, opening up new possibilities for industry-specific applications. The GPT models have transformed the field of NLP, enabling previously unattainable levels of fluency and coherence in machine-generated text (OpenAI, 2023a,b). Table 1 provides a chronological summary of significant milestones in the development and release of GPT models.

One of the main advantages of GPT models is their capacity to produce language that is cohesive, fluent, and nearly indistinguishable from text produced by humans. These models have been effectively used in a variety of applications, including chatbots, content generation, and machine translation. They can produce answers to open-ended questions, making them an important tool for natural language communication. The layers of GPTs' transformer-based neural architecture employ attention techniques to concentrate on particular areas of the input text (Neelakantan et al., 2022; Vaswani et al., 2017). The model can pick up on statistical patterns in natural language attributable to its architecture without having to explicitly program it with syntax or

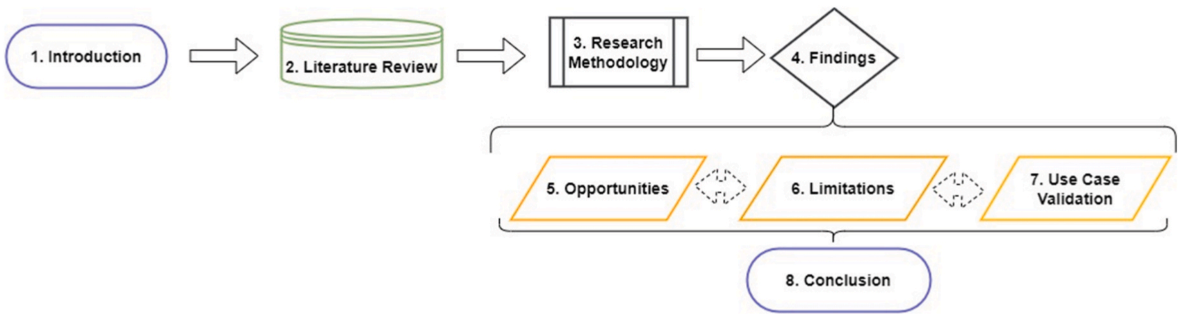

Fig. 1. Structure of the paper.

Table 1
The progression of OpenAI's GPT models from GPT-1 to GPT-4.

Date	Milestone	References
June 11th, 2018	OpenAI introduced GPT-1, the first model in the GPT series.	MUO (2023)
Feb 14th' 2019	OpenAI announced the release of GPT-2.	Radford et al. (2019)
May 28th' 2020	OpenAI published the initial GPT-3 preprint paper on arXiv.	Brown et al. (2020)
June 11th' 2020	OpenAI launched a private beta for the GPT-3 API.	VentureBeat (2020)
Sep 22nd' 2020	OpenAI licensed GPT-3 to Microsoft.	OpenAI (2020)
Nov 18th' 2021	The GPT-3 API was opened to the public.	VentureBeat (2020)
Jan 27th' 2022	OpenAI released InstructGPT as text-davinci-002, later renamed GPT-3.5.	OpenAI (2023)
Jult 28th 2022	OpenAI published a paper on exploring data-optimal models with FIM.	Bavarian et al. (2022)
Sep 1st' 2022	OpenAI reduced the pricing of the GPT-3 model by 66% for davinci model.	Decoder (2022), OpenAI (2022)
Sep 21st' 2022	OpenAI announced Whisper (speech recognition).	Radford et al. (2022)
28/Nov/ 2022	OpenAI expanded GPT-3.5 to text-davinci-003 with improved language generation capabilities.	Karhade (2022)
Nov 30th' 2022	OpenAI announced ChatGPT.	OpenAI (2022)
Mar 14th' 2023	OpenAI released GPT-4, the latest and highly anticipated addition to the GPT series.	OpenAI (2023)

Table 2
Search query.

Search Category	Search Query
Construction Industry	"Construction industry" OR "architecture engineering and construction industry" OR "AEC industry" OR "AECO industry"
GPT	"Generative Pre-trained Transformers" OR "Generative AI" OR "GPT" OR "GPT-1" OR "GPT-2" OR "GPT-3" OR "InstructGPT" OR "ChatGPT" OR "Transformer*" OR "GPT-4"

grammar rules. The transformer network creates coherent and fluent output while the attention mechanism enables the model to focus on pertinent portions of the input text (Zhang et al., 2022). Transformer networks, feedforward neural networks, and attention processes make up the building blocks of GPTs (Hernández and Amigó, 2021). Massive volumes of text data are trained during the pre-training phase of GPTs, allowing the model to learn broad language patterns that may be honed for particular tasks (Kotei and Thirunavukarasu, 2023). Pre-training often involves unsupervised learning without labels or annotations. After pre-training, the model is adjusted for a variety of tasks to increase the quality and accuracy of the text that is produced for that activity, such as language modelling, text categorization, or question-answering.

GPT models may be fine-tuned to accomplish a range of tasks with great accuracy (Ouyang et al., 2022; Wei et al., 2023). GPTs are capable of a variety of tasks such as language production, sentiment analysis, text categorization, and question answering (Brown et al., 2020). Language generation is the process of creating coherent and fluent text, whereas sentiment analysis is the examination of text sentiment, such as whether it is positive or negative. Text categorization entails classifying text into several groups, such as news articles or product reviews. GPTs are useful tools for natural language interaction because question-answering creates replies to open-ended questions (Brown et al., 2020). GPTs have revolutionized NLP by bringing remarkable fluency and coherence to writings produced by machines (Devlin et al., 2018; Radford et al., 2018). The potential bias available in the pre-training data, which could affect the precision and calibre of the generated text, is one of the main challenges. Moreover, there may be significant computational costs and challenges associated with the use and training of GPTs (Mantel, 2023). Future opportunities for more research will continue to fuel continuing efforts to improve the accuracy and efficacy of these models, which will drive the dynamic character of the GPT sector. For instance, there might be a decrease in the computational expenses related to creating and utilizing GPTs, which would make them more affordable for smaller businesses (Hussin et al., 2023; Paaβ and Giesselbach, 2023).

Table 3
Experts' demographic details.

Designation	Professional Background	Experience	Sector and Expertise
A	Architect	15 years	Research and Development with expertise in the deployment of Artificial Intelligence
B	Software Developer	14 years	IT with expertise in developing solutions for AEC companies
C	Civil Engineer	12 years	Research and Development with expertise in the deployment of Artificial Intelligence
D	Project Manager	14 years	Research and Development with expertise in construction project analytics
E	Computer Engineer	19 years	Research and Development with expertise in the deployment of Artificial Intelligence in the Construction Industry
F	Architect	19 years	Research and Development with expertise in business intelligence
G	AI/ML Engineer	10 years	IT with expertise in developing solutions for AEC companies

3. Methodology

A qualitative research approach is adopted in this research to achieve the aim of the study. This involved leveraging three sequential steps, as depicted in Fig. 2, including a literature review, critical review, expert discussion, and a case study.

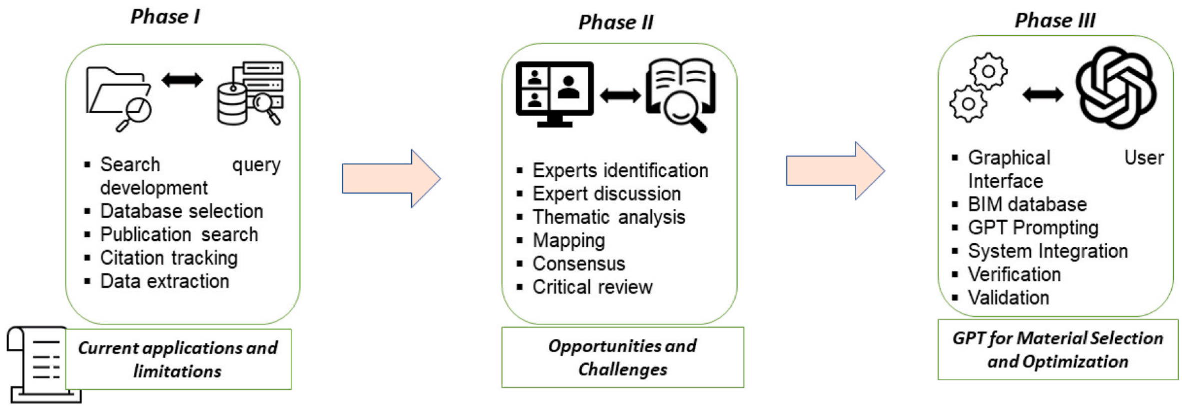

Fig. 2. Research approach.

i) Initial Exploration (Phase I): A search query (shown in Table 2) is developed and used in conducting a detailed search in Scopus, ACM, Web of Science, Science Direct, and Google Scholar databases. These databases were selected because of their capacity, and relevance to the subject matter and have been well-adopted in similar studies (Saka et al., 2023). The outputs from all the databases revealed that, although transformers have been gaining increased attention in the AEC industry, the application of GPT models is low. As such, only three publications were identified that specifically leveraged GPT models in the AEC industry. Furthermore, a subsequent search on arXiv database suggested that there are 3 related preprints – manuscripts that are yet to be formally peer-reviewed – available online. All the identified outputs were reviewed and citation tracking – getting previous studies from references - was used till saturation. These outputs are tabulated in an Excel file and considered to avoid publication bias. Lastly, the outputs were reviewed, and themes related to the objectives were identified and tabulated for usage in the subsequent research phases.

ii) Expert Discussion and Critical Review (Phase II): Based on the outputs of Phase I, expert discussion and a detailed critical review were employed to complement the few research studies. Expert discussion is a method of obtaining in-depth insights on a specific research theme by facilitating a structured discussion with a group of panellists with diverse backgrounds and experiences. It is a strong approach when the research area is new or ambiguous and there is a need for the generation of innovative ideas, identifying problems, develop recommendations and solutions to complex problems. It could take various forms such as a Delphi survey or Focus Group Discussion and involves a moderator to ensure group dynamic and round participation from all the experts (Hsu and Sandford, 2007; Jenkins and Smith, 1994). As such, the employed expert discussion is a modified classical Delphi survey with panellists who are selected based on predefined criteria - domain expertise in Artificial Intelligence and the AEC industry with a minimum of 10 years' experience. Ten experts were identified and contacted for the research discussion and only 7 accepted the invites and participated in the research. This is considered acceptable as a minimum of 7 is considered sufficient for the Delphi survey and this current study leverages the expert discussion to complement critical review and case study validation (Hon et al., 2011). Table 3 shows the demographic details of the experts who participated in the discussion. The experts were contacted virtually, and an average discussion of 25 min was undertaken on opportunities and limitations of GPT models in the AEC industry. Thematic analysis and mapping were conducted to identify specific opportunities mentioned by the experts. Opportunities and limitations were tabulated and pass across back to all the panellists for final review.

Following the expert discussion, a critical review was conducted on the identified opportunities and limitations of GPT models in the AEC industry. A critical review entails a detailed analysis and critique of the work with the view of providing an objective assessment of the work, implications, and insights. It is employed in this study to evaluate and identify the opportunities and limitations of GPT models in the AEC industry based on expert discussion and relevant extant studies.

iii) Use case (Phase III): One of the identified opportunities of GPT models in Phase II – material selection and optimization – is evaluated in this study. The system architecture is proposed for leveraging GPT for material selection and optimization which is subsequently verified and validated. Verification deals with 'building the product right' and validation deals with 'building the right product' (Boehm, 1984). The verification and validation process is done using checklists and case-testing approach (Saka et al., 2022). The checklist technique involves the use of specialized lists based on experience to check significant issues that are critical for product development whilst case-testing technique entails prototyping the developed products. As such, the employed techniques in this study fulfil the basic criteria of verification and validation processes – completeness, consistency, feasibility and testability (Boehm, 1984).

4. Findings

This section presents the findings from the literature search on the current applications of GPT models in the AEC industry and expert discussion on opportunities and limitations.

4.1. Current applications

GPT models are still new in the construction industry, unlike other LLMs such as BERT which has been gaining widespread applications in the AEC industry since 2020. Only 5 papers that have applied GPT models were retrieved and summarized in Table 4.

These extant studies have applied GPT models for question-answering, information retrieval from BIM model and for scheduling & sequencing tasks. There are inherent limitations as a result of the GPT models employed in the applications and limitations as a result of the development approach employed in the studies. GPT models work best with well-structured and clean data, which is often unavailable in the AEC industry; as such, there is a need to pre-process the data before usage in GPT. Unstructured data are parsed into readable formats like Plain text files (.txt), Comma-separated values (.csv), and JavaScript Object Notation (.json). For instance, Zheng et al. (2023) employed BSON (Binary JSON) format by extracting building objects and properties from BIM model which is subsequently cleaned and stored in

Table 4
Current applications.

S/N	Application	Purpose	Access and GPT model (Specification)	Limitations
1	BIM-GPT (Zheng and Fischer, 2023)	Information retrieval from BIM using natural language	API access and GPT-3.5-turbo (Temperature = 0)	No quantitative evaluation Single-turn conversation
2	RoboGPT (You et al., 2023)	Automate sequence planning of construction tasks in robot-based assembly	ChatGPT-4 API access (Not provided)	Blackbox High risk Unable to leverage visual information
3	Prieto et al. (2023)	Scheduling of construction tasks	ChatGPT-3.5 (Not provided)	Zero-shot learning No quantitative evaluation
4	(Uddin et al., 2023)	To support hazard recognition and construction safety education	ChatGPT-3.5 (Not provided)	Zero-shot learning No quantitative evaluation
5	Amer et al. (2021)	Integrating master schedules with look-ahead plans	GPT-2 (small version)	Large data set

MongoDB. On the other hand, Uddin et al. (2023), Amer et al. (2021), Prieto et al. (2023) and You et al. (2023) leveraged text for the application. Despite some of the limitations, the studies are important and contribute to the new area of GPT applications in the AEC industry and provide a basis for new studies to build on.

4.2. *Expert discussion*

Table 5 summarizes the opportunities for GPT models in the AEC industry as identified through expert discussion, and they are categorized into different phases of the project lifecycle.

Table 6 presents the challenges and limitations of deploying GPT models in the AEC industry. Some of these limitations are inherent limitations of GPT models, whilst others are industry-specific challenges facing the deployment of GPT models in the AEC industry.

The following Sections 5 and 6 provide a detailed discussion of the opportunities and limitations identified in the previous section. Opportunities and limitations of similar themes are synthesised and discussed. These opportunities require different levels of development and interaction with the GPT models ranging from zero-shot learning to finetuning and integration with different knowledge sources. Similarly, some of the limitations are inherent in the GPT models whilst others can be attributed to the construction industry context.

5. Opportunities

The opportunities are categorized into different phases of the construction project lifecycle – predesign, design, construction, operation & maintenance, demolition phase and value-added services. These opportunities are made possible by the inherent capabilities of GPT models, integration of GPT with existing systems and leveraging plugins/add-ins that extend the functionalities of GPT. The following subsections present these opportunities and how GPT models can be leveraged.

5.1. *Pre-design phase*

Pre-design construction activities serve as the foundation for project success, budgeting, and optimization. They comprise site study, programming, construction cost analysis, and value engineering. As seen in

Table 5
Categorization of opportunities by experts.

Phase	Opportunities	A	B	C	D	E	F	G
Pre-Design	Optimal design and construction techniques	✓	✓	✓		✓	✓	✓
	Procurement	✓	✓	✓	✓	✓		
	Project brief and client requirements	✓		✓				✓
	Lessons from project	✓	✓	✓		✓		✓
	Project execution planning	✓	✓					✓
	Project management and planning			✓		✓		✓
Design	Generation of design concept		✓		✓			
	Regulatory compliance		✓		✓			
	Material selection and optimization	✓			✓	✓	✓	✓
	Quantity take-off and costing	✓			✓	✓	✓	✓
	Improving energy efficiency analysis	✓				✓	✓	✓
	Design specification		✓				✓	
Construction	Scheduling and logistics	✓	✓	✓	✓	✓	✓	✓
	Regulatory compliance	✓	✓	✓	✓	✓	✓	✓
	Risk identification, assessment, and management	✓	✓	✓	✓	✓	✓	✓
	Progress monitoring and report	✓	✓			✓		✓
	Site safety management	✓	✓	✓	✓	✓	✓	✓
	Resource allocation and optimization	✓	✓	✓	✓	✓	✓	✓
	Change order management		✓		✓			✓
	Quality control and assurance					✓		✓
	Documentation	✓	✓	✓	✓	✓	✓	✓
	Dispute resolution	✓						
	Budgeting and cost planning		✓					
Operation and Maintenance	Predictive maintenance			✓			✓	
	Energy management and optimization	✓			✓			
	Incident and resolution	✓	✓	✓	✓	✓	✓	✓
	Lifecycle management of asset	✓	✓	✓	✓	✓	✓	✓
	Occupant communication and support	✓	✓	✓	✓	✓	✓	✓
	Regulatory compliance management	✓	✓	✓	✓	✓	✓	✓
	Space/facility management	✓	✓	✓	✓	✓	✓	✓
	Performance monitoring	✓			✓			
	Sustainability				✓		✓	
	Waste management and recycling	✓	✓					
Demolition	Demolition protocol	✓	✓	✓	✓	✓	✓	✓
	Waste management							
	Redevelopment plan	✓	✓	✓	✓	✓	✓	✓
	Regulatory compliance and permit	✓	✓	✓	✓	✓	✓	✓
	Costing				✓			
	Environmental impact analysis		✓		✓	✓		
	Material recovery				✓		✓	
	Risk assessment	✓	✓					
Value added	Knowledge management and training	✓	✓	✓	✓	✓	✓	✓
	Customer services	✓	✓	✓	✓	✓	✓	✓

(*continued on next page*)

Table 5 (*continued*)

Phase	Opportunities	A	B	C	D	E	F	G
	Stakeholder communication		✓	✓		✓		
	Business intelligence	✓	✓	✓		✓	✓	✓
	Conversational AI/ Chatbot	✓		✓	✓	✓		✓

Table 6
Limitations of GPT in the construction industry.

Limitations	A	B	C	D	E	F	G
Hallucination	✓	✓			✓		✓
Data	✓	✓	✓	✓	✓		
Expertise knowledge	✓	✓	✓	✓	✓	✓	
Intellectual property and confidentiality		✓		✓			
Safety	✓	✓	✓	✓	✓	✓	✓
Trust and acceptance	✓	✓	✓	✓	✓	✓	✓
Accountability and liability			✓				
Ethics	✓	✓	✓	✓	✓	✓	✓
Skills and training			✓	✓	✓	✓	✓
Interoperability and integration		✓					
Capital/cost	✓	✓	✓	✓	✓	✓	✓
Infrastructure requirements			✓			✓	✓
Scalability	✓		✓	✓			
Performance optimization		✓			✓		✓
Cybersecurity	✓	✓		✓		✓	
Interdisciplinary			✓				
Cultural and social consideration	✓		✓		✓	✓	
Latency issue							

Fig. 3, this section examines the status of pre-design in building projects and the potential benefits of utilizing GPT models.

5.1.1. Expert guidance on optimal techniques for design and construction

Stakeholders collaborate throughout the pre-design stage of construction to establish project objectives. Pre-design's purpose is to identify critical aspects and restrictions that will guide subsequent design and development processes. Currently, the predesign landscape is defined by a mix of traditional approaches and specialized technologies, each with its own set of benefits and drawbacks.

Due to cognitive biases and information overload, the traditional reliance on expert knowledge and experience might result in less-than-ideal outcomes (Levy, 2010). Extant studies have documented the importance of predesign in reducing project risk, optimizing resource allocation, and enhancing overall project success (Guo and Zhang, 2022; Lu et al., 2020). This phase can further be enhanced and transformed by GPT models, which provide expert guidance on the best design and building procedures, resulting in higher productivity, decreased costs, and improved sustainability (OpenAI, 2023a,b). Users may access the model using the user interface or API access to query its vast knowledge base on best practices in design and construction (Smith et al., n.d.). Also, effective prompts can be written using 'Act As' approach to engage the GPT model in providing technical information and clarification on optimal design and construction techniques. For instance, the 'Act As' was employed as shown in Fig. 4.

5.1.2. Procurement decision support

In the predesign phase, current procurement decision support procedures include techniques such as value engineering, life cycle costing, and multi-criteria decision-making (MCDM) (Tezel and Koskela, 2023). The efficacy of these strategies, nevertheless, is restricted as they rely on specialized knowledge, which is generally subjective and susceptible to human fallibility (Ratnasabapathy and Rameezdeen, 2010). Furthermore, previous studies have underscored the necessity for enhanced data processing and analysis to optimize decision-making, particularly considering the escalating quantity of project data acquired during the preliminary design stage (Budayan et al., 2015). As posited by McBride et al. (2021), GPT models present a fresh approach to augmenting procurement decisions in the preliminary design phase by surmounting the limitations associated with conventional methodologies. GPT models, with their powerful natural language processing and machine learning capabilities, can evaluate data, delivering insightful suggestions that encourage accurate, data-driven decisions (OpenAI, 2023a,b). GPT models also promote more efficient cooperation among stakeholders through real-time information and predictive analysis (Abioye et al., 2021; Momade et al., 2021). Prompts can be developed allowing procurement decision-makers to swiftly acquire important information, explore options, and make educated decisions. GPT models can be used in performing textual analysis to provide insights based on supplier reviews, and product description historical purchase data for informed decisions. Also, an integrated system can be developed with BIM, GPT model and procurement database. This integrated system can be leveraged for queries related to procurement and automating workflow such as order placements and status updates.

5.1.3. Development of project brief and client requirements

A crucial part of the predesign stage of the construction process is the development of the project brief and client requirements, often known as Employer Information Requirements (EIR) in BIM projects (Catenda, 2020; Kim et al., 2022). Creating a thorough project brief and outlining the client's requirements in detail are essential stages that provide the groundwork for the whole construction process at the pre-design stage of the project. Multiple methods and constraints, such as the use of templates, checklists, and questionnaires, are part of the existing ways of collecting design requirements (Assaf et al., 2023).

Numerous approaches and restrictions that affect the creation of the project brief and employer information requirements (EIR) have been highlighted by recent studies. By automating some procedures and fostering cooperation and communication between project teams and clients, the emergence of GPT models has the potential to completely transform the development of project briefs and EIRs (Shaalan, 2010).

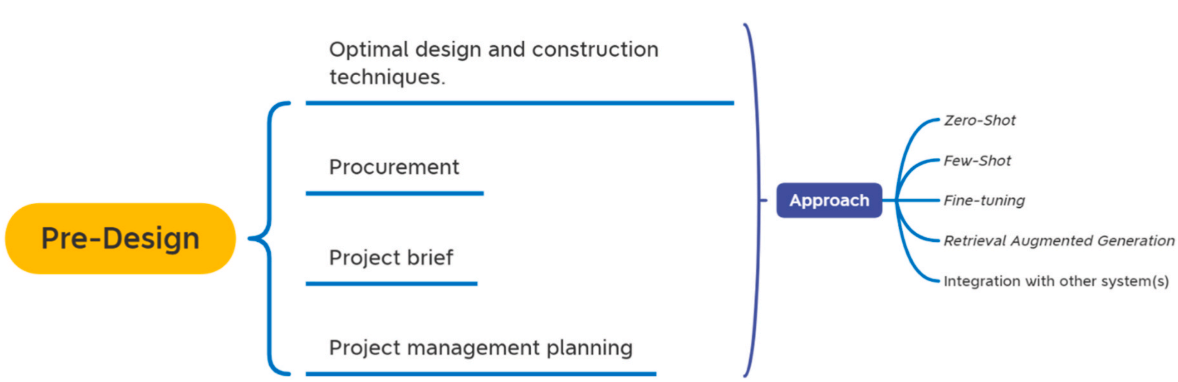

Fig. 3. Opportunities for GPT models in the Pre-design Phase.

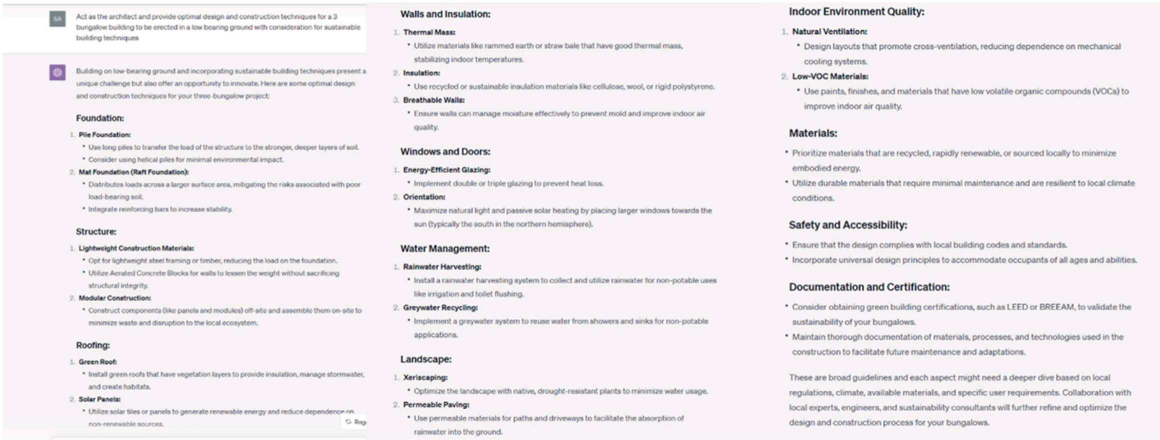

Fig. 4. Act-As prompting.

For instance, GPT model can be integrated with an existing system for interacting with and supporting clients in the development of initial project briefs (Saka et al., 2023). Fig. 5 shows the questions that the GPT model would ask the client in a conversational style to automatically develop the initial project brief. Based on the develop brief, the GPT model can provide design suggestions and technology recommendations. Also, the brief can be compared with regulatory compliances for non-compliance and potential risks can be highlighted in the brief.

5.1.4. *Project management planning*

Project management planning is vital to the successful delivery of projects, as poor planning could lead to cost & time overrun and quality issues (Asiedu et al., 2017). It entails inputs from project teams and stakeholders and sets out details of how the project is to be executed, monitored, and controlled. As such project management planning components are baselines for scope, schedule, cost, requirement management plan, change management plan, configuration management plan and process improvement plan (Globerson and Zwikael, 2002).

GPT models trained on corpus of database could be finetuned to support project management planning during predesign stage in scope definition, scheduling, resource allocation & estimation, risk management and decision support system. For instance, with prompting, GPT models can help understand the impact of diverse factors on projects and provide recommendations for effective management. Also, GPT models have been proved applicable in the identification of tasks and scheduling based on specific project requirements (Prieto et al., 2023; You et al., 2023). As such, GPT models could also be leveraged for analysing data and providing relevant insights to the project manager during the predesign stage. Similarly, with zero-shot learning, GPT can act as a repository for industry standards and lessons learnt from previous projects for stakeholders to make informed decisions.

5.2. *Design phase*

This section presents the opportunities for leveraging GPT models during the design phase of construction projects as shown in Fig. 6.

5.2.1. *Generation of design concept*

An essential step in the design process is creating design options that satisfy project requirements. In the past, architects and engineers have

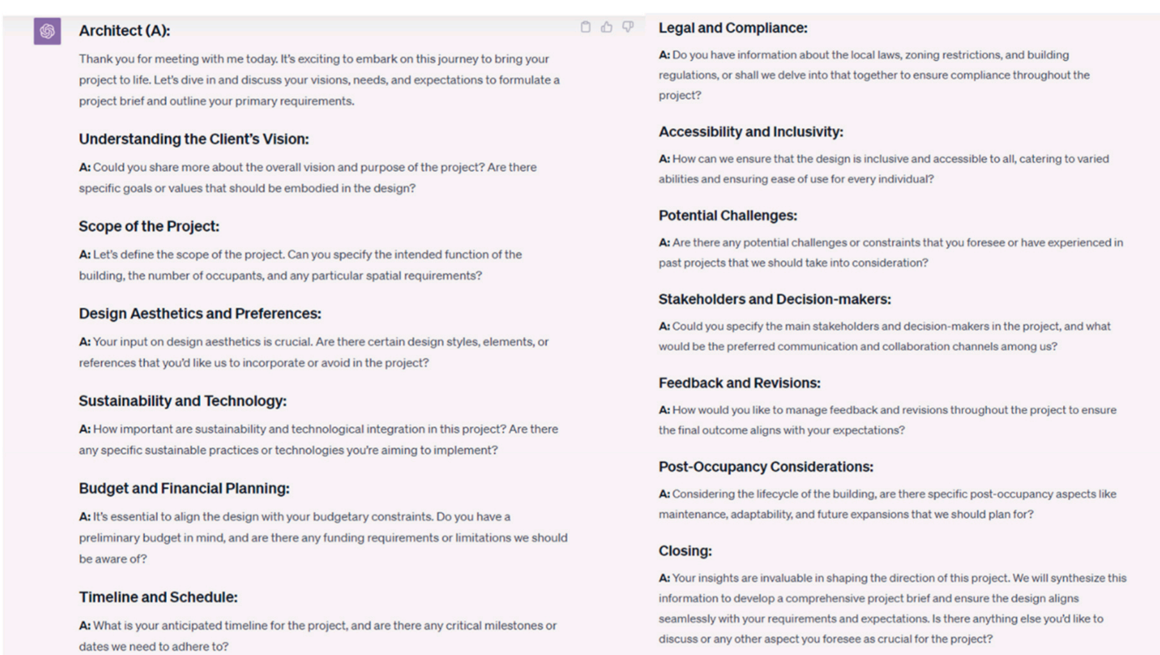

Fig. 5. Conversational development of Client's brief.

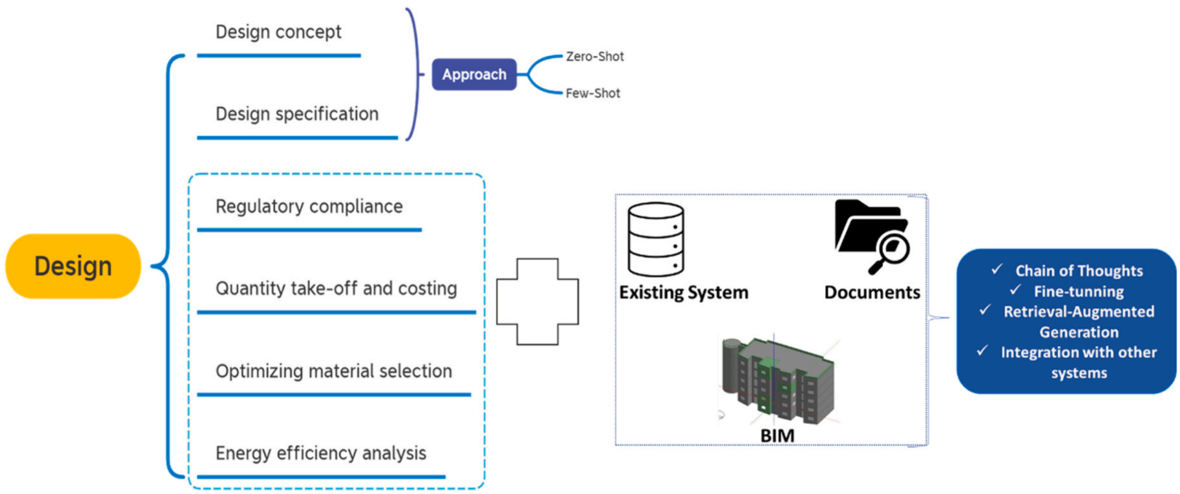

Fig. 6. Opportunities for GPT models in the Design Phase.

relied heavily on their personal knowledge and previous experience to manually develop design concepts, which can be lengthy and subjective (As et al., 2018; Lewis and Séquin, 1998). Recently, GPT have shown promise for accelerating and enhancing this process through their ability to generate coherent, context-relevant text and images after training on large datasets of domain-specific information. For example, by learning from architectural plans, construction codes, and design guidelines, GPT models can acquire construction industry language patterns and leverage that knowledge to automatically generate design ideas tailored to given constraints (Zheng and Fischer, 2023). Lastly, with the inclusion of DALL-E, GPT model can be used in generating design ideas with zero-shot learning as shown in Fig. 7.

5.2.2. Automated regulatory compliance

Complying with regulatory requirements is a critical aspect of the design phase, as failure to meet these standards can result in legal issues, delays, and safety hazards. The complexity and frequent updates of building codes and regulations make it challenging for design professionals to ensure compliance manually (Dimyadi et al., 2015). Nevertheless, GPT models can play a significant role in automating regulatory compliance checks, reducing errors, and streamlining the design process. This can be achieved by analysing architectural and structural designs and comparing them against relevant building codes. Conversely, the model can identify potential issues, allowing designers to rectify them before construction, thereby saving time and minimizing costly revisions.

5.2.3. Optimizing material selection

The construction industry consumes a lot of resources and contributes significantly to the green gas emissions. Material selection is one of the ways to reduce the environmental impacts of a project during its lifecycle. Factors such as cost constraints, location of the component, design consideration and environmental requirements are decision-making factors for material selection (Florez and Castro-Lacouture, 2013). During the selection, the designer would need to consider all these factors coupled with other subjective and objective measures to reach a decision which may not be the optimal solution. As such, extant studies have proposed the use of different optimization approaches such as mixed integer optimization, fuzzy logic approach, and Grey relational analysis to solve the problem (Emovon and Oghenenyerovwho, 2020). GPT models can be leveraged for optimization of material selection with detailed consideration of different factors and parameters. This can be integrated with BIM model to optimize material selection during design and to provide design alternatives. It would involve evaluating the material of building components (from BIM) based on material properties and performance database (from GPT) to fulfil predefined criteria. This is further demonstrated in Section 7 for validation.

Fig. 7. Image Generation from ChatGPT using DALL-E.

5.2.4. Quantity take-off and costing

Quantity take-off and costing form an integral part of successful project delivery, and the quantity surveyor is often saddled with this responsibility (Saka and Chan, 2019). GPT models can be leveraged for quantity take-off and costing of building projects by providing detailed information about the project – design, material and other specifications. This can be achieved by providing textual data for the model with necessary cost databases and estimation methods. Based on these, prompts can be developed for quantity take-off of the project with elemental breakdown and subsequent costing of the quantities. Also, GPT can be used to prepare bills of quantities and analyse past bills of quantities to draw insights and make predictions. Machine learning models can be developed in GPT model using past cost data which can then be used in predicting the cost of new projects. Lastly, GPT can be queried to provide steps to be followed using python in extracting quantities from IFC file for quantity take off.

5.2.5. Improving energy efficiency analysis

There has been a surge in energy demand with rapid development over the decades in the construction industry (Oluleye et al., 2022). The energy efficiency of buildings are is broadly based on the building envelope, which influences energy consumption and the rate at which energy is lost in the building (Abu Bakar et al., 2015). GPT models can be provided with information on standards, regulations, passive design principles, building facades optimization and renewable energy systems for it to be leveraged for improving energy efficiency analysis. As such, GPT models can provide guidance on selection of simulation tools, interpretation of results, identify opportunities for improvement (such as optimizing building orientation, insulation, energy systems) and analysing cost-effectiveness of proposed solutions. Also, life cycle analysis can be computed with prompts developed for usage on the finetuned model and documentations can also be prepared by the GPT models. Whilst some of these are possible with zero-shot learning, to get best output from the GPT models, there is need to fine-tune the model and integrate it with other BIM and energy efficiency analysis tools.

5.2.6. Design specification

As one of the largest industries with in-built complexities, design specification plays a crucial role in the success of any project within the construction industry. Design specification, being a technical document, provides all necessary information for the design phase of a construction process. The existing process for developing a design specification document entails manual work, which can be time-consuming and laborious. However, with the introduction of the GPT models, new prospects for automating the process of developing design specification documents have surfaced.

Since GPT models can generate logical, grammatically correct language (Brown et al., 2020), they have the potential to automatically construct complete design specification documents when provided with key inputs. Engineers and architects would simply need to feed the model the core information needed, and it could produce the full specifications (Hayman, 2022; Parm AG, 2023). This has the potential to greatly reduce the effort and resources required to develop specifications. Additionally, GPT-generated specifications may have higher accuracy and consistency than manual approaches.

5.3. Construction phase

This section presents the opportunities of leveraging GPT models during the construction phase as shown in Fig. 8.

5.3.1. Managing project schedule and logistics

The process of scheduling entails the development of a comprehensive plan that outlines the sequence of activities, tasks, necessary resources, and estimated time required for completion (Castro-lacouture et al., 2009). On the other hand, logistics management encompasses the deliberate formulation, implementation, and regulation of the transportation of individuals, resources, and machinery to and from the construction site (Dannoun, 2022). The successful execution of a construction project hinges upon the efficient handling of scheduling and logistics. Managing logistics and scheduling are difficult responsibilities since the supply chain is unpredictable and complex.

Previous research has employed a hybrid approach to connect mixed integer programming (MILP) and machine learning (ML) to address these difficulties, particularly emphasizing the utilization of long short-term memory (LSTM) models (Al-shihabi & Mladenović, 2022). However, GPT models exhibit certain advantages when compared to conventional techniques. Unlike MILP and LSTM models, which primarily operate on structured and numerical data, GPT models possess the ability to effectively acquire and analyse textual information, thereby facilitating a more comprehensive understanding of the complexities associated with construction project scheduling and logistics. In contrast to the mathematical optimization problems described in MILP models, GPT models leverage learned patterns and representations derived from the available data. This approach reduces the need for explicit mathematical modeling and enables a more flexible and intuitive approach to addressing scheduling and logistical challenges in construction endeavors. Furthermore, the utilization of GPT can be employed to implement the Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) by inputting the project schedule.

5.3.2. Automated regulatory compliance implementation

The intricacy of regulatory compliance is a significant barrier within the building business. It is of utmost importance for construction enterprises to ensure adherence to a multitude of legislative requirements and performance-based rules (Zhang and El-Gohary, 2016). The conventional approaches to regulatory compliance verification are characterized by their tendency to consume significant amounts of time, their susceptibility to errors, and their heavy reliance on resources. The emergence of artificial intelligence (AI), particularly GPT models, presents potential avenues for enhancing efficiency and automating the regulatory compliance procedure. GPT models possess the potential to streamline regulatory compliance in the construction sector by virtue of their natural language processing (NLP) capabilities and aptitude for comprehension. Beach et al. (2020) argue that these models establish the capacity to assess and isolate relevant information from textual information pertaining to construction regulations. This process involves changing the extracted information into logic clauses, which can then be utilized for automated reasoning. The implementation of automation in the compliance checking process can yield substantial reductions in time and effort needed for regulatory compliance evaluation. GPT models, in particular, have the potential to function as valuable aids in the realm of automated regulatory compliance.

5.3.3. Risk identification, assessment, and mitigation

The proactive identification and resolution of risks can effectively

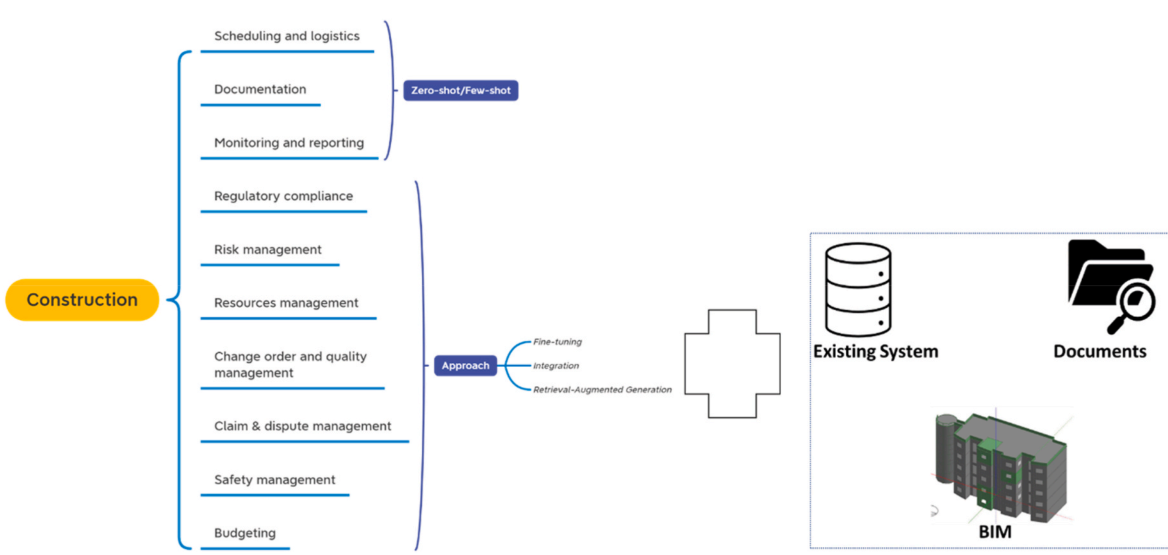

Fig. 8. Opportunities for GPT models in Construction Phase.

mitigate any negative impacts on project objectives. The potential hazards linked to a specific undertaking may involve a range of factors, including external factors, internal intricacies, technical challenges, or unforeseen situations. During the construction period, there exist various possible sources of dangers that may manifest. The factors encompassed in this context are project complexity, resource availability, safety threats, design modifications, and contractual considerations (Siraj et al., 2019). Risk management strategies play a crucial role in the construction sector, however they are not without inherent limitations.

Given these limitations, it becomes apparent that GPTs hold significant potential in augmenting the identification, assessment, and management of hazards within the construction industry (Mills, 2001; OpenAI, 2023a,b). GPT models provide the capacity to be employed for comprehensive and flexible risk identification and assessment by scrutinizing substantial project documents and historical data, while also being capable of integrating new information as the project progresses. The aforementioned skill enhances the current comprehension of the project's risk assessment (Miller, 2016; OpenAI, 2023a; Zheng and Fischer, 2023). Predictive analytics holds the capacity to anticipate and evaluate probable hazards and their associated consequences, hence augmenting the overall accuracy of risk profiles (Cornwell et al., 2022). In summary, it can be inferred that GPTs possess the capacity to automate the generation of risk reports and various types of communication. The implementation of this approach holds promise for improving the accuracy and consistency of risk communication, hence mitigating the risk of misunderstandings and exclusions.

5.3.4. Project progress monitoring and reporting

The act of monitoring a project during the construction phase is vital in order to ensure its effective culmination. The utilization of effective monitoring strategies facilitates timely interventions and adjustments, ultimately leading to improved results. Project reports play a crucial role in effectively conveying the present state, accomplishments, obstacles, and other significant facets of a project to stakeholders who possess a vested interest in its ultimate results (Ibrahim et al., 2009). However, conventional methodologies for monitoring and reporting project progress possess inherent constraints. These approaches often rely on human judgment, introducing subjectivity and potential mistakes into the process. Furthermore, it is important to acknowledge that these methodologies possess the capacity to need a substantial investment of time and may not provide instantaneous or current insights into the progress of the project. The absence of immediate access to information can hinder the ability to make proactive decisions, as emphasized by El-Omari and Moselhi (2009).

Prior studies have recognized that applying computer vision (CV) and machine learning (ML) models could potentially solve the problems related to progress reporting. The theoretical basis in question is substantiated by the empirical inquiries carried out by Ibrahim et al. (2009) and Kim et al. (2013). The utilization of sophisticated algorithms and image processing methodologies is a characteristic feature of these models, enabling the extraction of significant insights from construction data encompassing images, videos, and sensor data. GPT models exhibit a notable advantage in this specific field owing to their employment of robust language models that incorporate CV, ML, and NLP techniques. GPT models have demonstrated their capacity to comprehend, interpret, and proficiently generate text that closely resembles human language. Hence, it can be posited that these models possess the capacity to augment the effectiveness of progress monitoring and reporting through the examination of textual data pertaining to projects, encompassing project updates, documents, and reports. Therefore, GPT models can offer a complete solution for automating reporting and progress monitoring during the building stage.

5.3.5. Site safety management

The construction industry is associated with high rates of accidents and fatalities (Dolphin et al., 2021). Managing site safety is, therefore, vital during the construction phase to prevent accidents, reduce injuries, and ensure compliance with safety regulations. However, traditional approaches to site safety management can be time-consuming and labour-intensive (Tixier et al., 2016). The integration of GPT in site safety management presents new opportunities for improving safety practices during the construction phase. By leveraging the capabilities of GPT, construction companies can efficiently perform safety audits, automated risk assessments, and get insights into potential hazards (Porter, 2021).

GPT can also assist in identifying high-risk areas on construction sites by analyzing text-based data like project documents, safety reports, and worker feedback to identify potential areas of concern that may not be readily apparent. Also, image-based data can be evaluated by GPT to identify hazards on construction sites as shown in Fig. 9. As a result, propose mitigation measures based on these historical data, documented industry best practices, and regulatory guidelines (Ezelogs, 2023; Togal. AI, 2023). Moreover, GPT can play a crucial role in knowledge sharing and training. Construction workers can access GPT-powered platforms for interactive safety training, where they can receive personalized instructions and guidance on safe practices (Uddin et al., 2023). GPT's NLP capabilities enable effective communication and prompt responses to worker queries, enhancing the overall safety culture on construction sites. Additionally, GPT can facilitate incident reporting and analysis by automatically categorizing incidents, identifying root causes, and recommending preventive measures, thereby enabling proactive safety management.

5.3.6. Resource allocation and optimization

Resources on construction projects include plant, personnel, and items necessary to complete tasks. Resources allocation is important and can affect the delivery of projects in terms of cost, time and quality. The allocation of resources is dependent on the diverse features – nature of the project and other key attributes (Kusimo et al., 2019). Approaches such as genetic algorithm and particle swarm optimization have been applied in optimizing resource allocation and levelling. GPT models can also be used in resource allocation and optimization by providing detailed information about the project. The models can provide recommendations by taking cognisant of the project requirements, available resources, project duration, and critical path potential challenges. Also, scenario analysis can be conducted with the GPT model and documentation of the resources' allocation.

5.3.7. Change order and quality management

GPT models can assist the project team when there are changes in the project scope by providing aspects of the project such as cost, time and quality that could be impacted (impact analysis) (Abioye et al., 2021). The models can be employed in reviewing change orders to ensure they are consistent with the contract documentation and for highlighting discrepancies in the change order. Also, the models can be leveraged in the documentation of change order requests, communication and providing recommendations in the event of negotiation and dispute resolution.

Quality control and assurance ensure that the quality of a project is in tandem with objectives and established standards whilst also mitigating errors and defects. GPT models can be employed in planning and organizing inspection and testing activities based on defined project requirements and familiarization with principles (quality control and assurance in the construction industry). GPT can be used to identify anomalies in quality data, suggest best practices standards for preventive and corrective actions and assist in quality documentation (management, technical and general procedure manual and policy manual).

5.3.8. Construction project documentation

Managing project documentation requires significant effort to ensure that all the relevant documents are up-to-date, accurate, and accessible to all relevant stakeholders (El-Omari and Moselhi, 2009). This is often

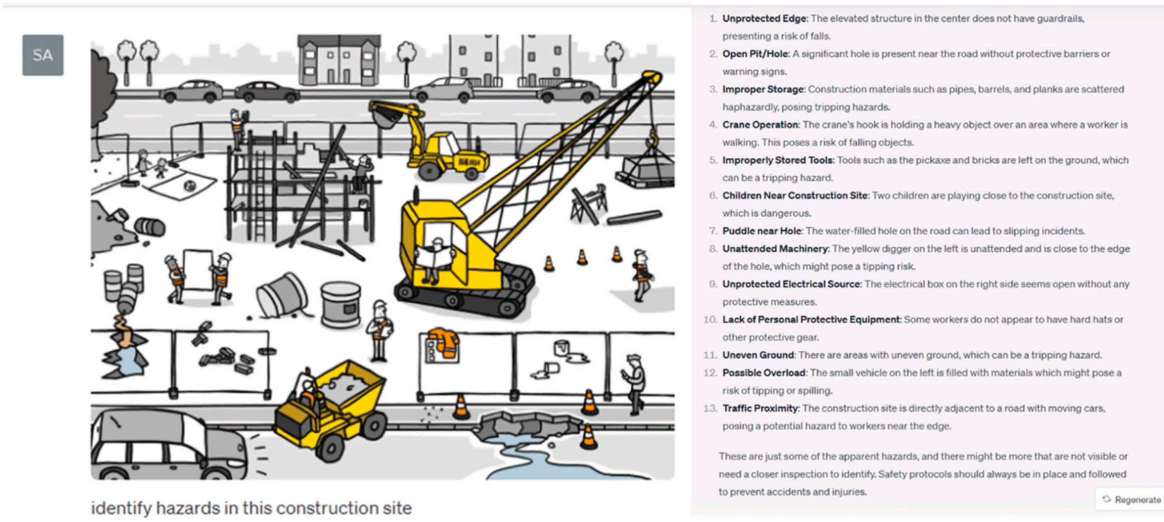

Fig. 9. Hazard identification using computer vision capability of ChatGPT.

done traditionally, which is largely dependent on human judgments, thereby resulting in the infrequent provision of accurate and timely construction data (Ibrahim et al., 2009). Hence, the experts have highlighted the adoption of GPT to mitigate this issue, as the models can be trained to recognize and analyse different types of documents or recordings, extract relevant information from them, and create a centralized database for easy access by all stakeholders. As such, progress reports or status updates can be easily generated based on the extracted data from the project documentation.

5.3.9. *Claim and dispute resolution*

The financial health and integrity of construction stakeholders can be affected by the occurrence of claims and dispute resolution; hence, it is a critical aspect in the construction industry that needs optimum attention. Disputes often arise due to various reasons, such as design errors, construction delays, or cost overruns, and can result in lengthy and costly legal battles (Dikbas et al., 2010).

Drawing upon past records, such as modifications to orders and schedules for projects, GPT models possess the capability to forecast the odds of encountering conflicts or claims in current or forthcoming projects. Additionally, these models can propose varied strategies for settling disputes tailored to the unique conditions surrounding the conflict. Achieving this is possible by educating the models on an array of methods for resolving disagreements, encompassing techniques like mediation, arbitration, and negotiation, thus equipping them to examine the particulars of a conflict and recommend suitable avenues for its resolution (Chaphalkar et al., 2015).

5.3.10. *Project budgeting and cost planning*

Efficient budgeting and cost planning are vital during a construction project's lifespan, as the industry is known for frequent overspending and budget deviations. These budget misrepresentations substantially impact finances and timelines (Wang et al., 2012). Traditional budgeting relies on expert judgment, which tends to be subjective and error-prone (Cheng et al., 2009). In contrast, GPT models have the capability to automatically generate accurate and data-driven financial forecasts and estimates based on historical records and industry norms. It should be acknowledged that the precision of the model depends on the prompt quality and the data employed.

5.4. *Operation and maintenance phase*

This section presents opportunities for leveraging GPT models in the operation and maintenance phase as shown in Fig. 10.

5.4.1. *Predictive maintenance*

A considerable challenge in the operational stage of a construction project lies in efficiently overseeing maintenance activities. Conventional practices in this area have been more reactive than proactive, acting only after an equipment breakdown. Such an approach frequently results in unanticipated periods of inactivity, increasing costs for repairs, and the suboptimal distribution of resources (Bouabdallaoui et al., 2021).

One of the ways that GPT models can transform maintenance practices is by enabling predictive maintenance. Predictive maintenance is a data-driven approach that can foresee equipment failures or performance problems before they happen (Taiwo et al., 2023). GPT models can analyse historical data, sensor readings, and other relevant factors to find patterns and indicators of potential failures, thus allowing maintenance teams to take preventive actions, plan repairs or replacements at the best times, and reduce the impact on operations. It can help to lower maintenance costs by preventing unnecessary repairs and prolonging the equipment's lifespan.

5.4.2. *Energy management and optimization*

Buildings and infrastructure heavily consume energy, and inefficient usage increases costs and environmental impact. Traditional manual energy monitoring methods are labor-intensive, resource-demanding, and error-prone (Hagras et al., 2008). However, GPTs can optimize energy management by analyzing large datasets - like historical usage, weather, occupancy, and equipment data - to identify savings opportunities (Zheng and Fischer, 2023). GPT-enabled energy management provides several benefits: real-time tracking to detect anomalies and waste quickly, predictive demand forecasting for resource planning, and customized recommendations for energy saving measures like adjusting heating, ventilating, and air conditioning (HVAC) settings, or equipment upgrades tailored to the building.

5.4.3. *Incident reporting and resolution*

In the operational and maintenance phases of construction activities, efficient procedures for reporting and resolving incidents are critical for the safeguarding of safety, asset functionality, and overall operational performance. Events such as equipment failures, safety risks, and interruptions in operation are not uncommon and necessitate immediate and judicious action to limit their consequences. Traditional methods for incident reporting and resolution often involve manual systems, paper documentation, and elongated communication channels, contributing to delayed responses and potential communication errors (Bach et al., 2013).

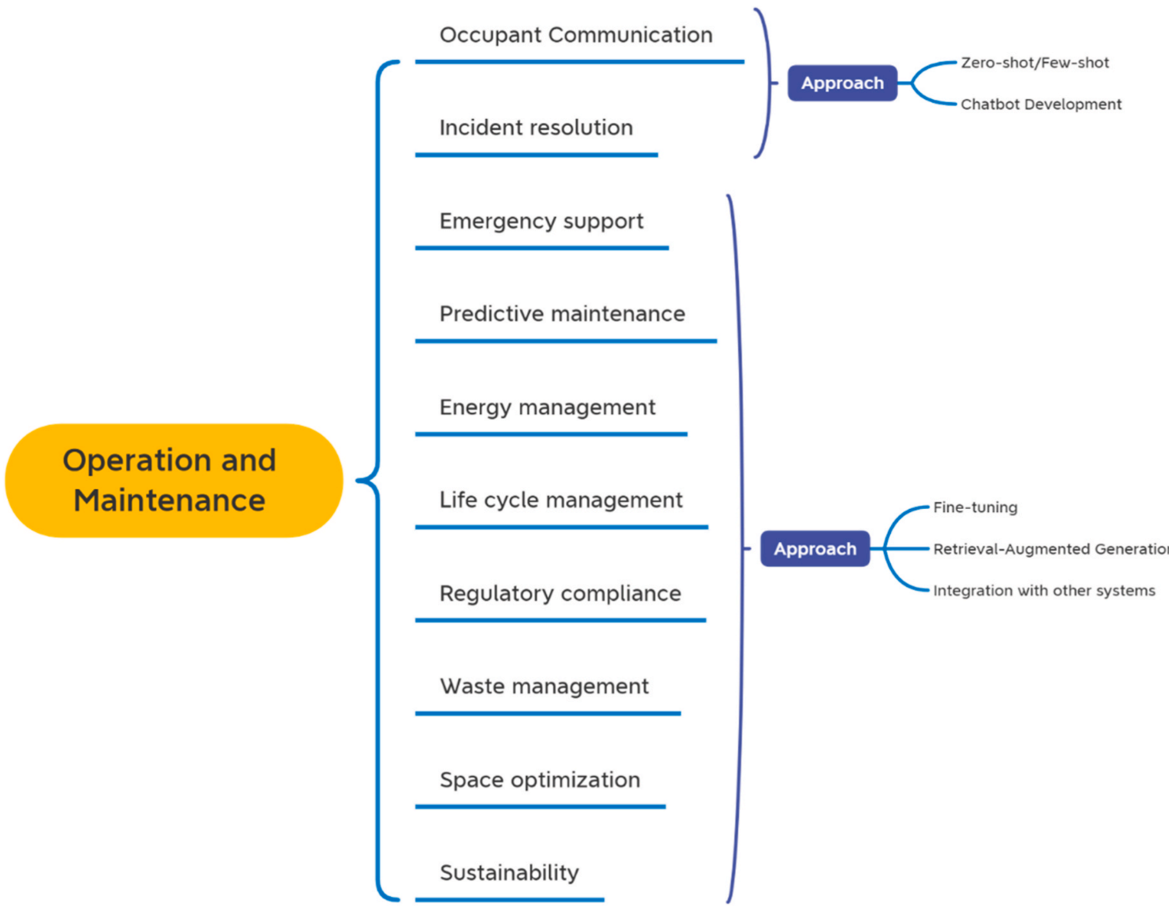

Fig. 10. Opportunities for GPT models in Operation and Maintenance Phase.

GPT models represent a promising approach for addressing these challenges. Exploring its NLP and ML functionalities, these models have the capability to efficiently evaluate incident reports, recognize recurring themes, and classify incidents based on their level of criticality and time sensitivity. Moreover, GPT models can facilitate the creation of standardized incident reports, thereby capturing essential details and enabling uniform documentation.

5.4.4. *Lifecycle management of asset*

Conventional asset management approaches tend to be intricate, time-consuming, and financially burdensome (Grussing, 2014). In this regard, GPT models offer a compelling solution by streamlining asset management through automated processes encompassing data collection, analysis, and decision-making. By harnessing the power of GPT models, it becomes possible to accurately predict an asset's remaining useful life, empowering maintenance teams to proactively schedule necessary maintenance and repairs, thereby mitigating the risk of unexpected failures. The proactive approach facilitated by GPT models significantly reduces the need for costly emergency repairs and minimizes downtime, resulting in substantial cost savings.

5.4.5. *Occupant communication and support*

GPT models can be employed as a conversational system between the occupant and the facility management (FM) department. These can be prompted to act as chatbots for communicating and supporting facility users in real-time whilst allowing the facility management personnel to attend to meet their requests faster and more effectively. For instance, GPT models can collect maintenance requests, general enquiries from facility users to ensure clear and consistent communication and necessary support. Fig. 11 shows ChatGPT prompted to serve as a Facility Chatbot to collect and sort occupant maintenance requests with zero-shot learning.

This can be deployed on the FM company's website or an automated voice assistant. For the automated voice assistant, Automatic speech recognition (ASR) and Text to speech synthesiser will be required. ASR will convert speech to text for interaction with the FacilityBot and TTS will convert the text from the system to voice (Saka et al., 2023).

5.4.6. *Regulatory compliance management*

GPT models can be trained with relevant compliance documents, guidelines, and reporting requirements to capture patterns and embedded knowledge. These models can be used in compliance evaluation of facility management activities by comparing new inputs with regulatory requirements to identify non-compliance issues. Similarly, the GPT models can be employed in documentation by highlighting non-compliance issues, providing recommendations, and creating standardized reports to save time and ensure consistency as shown in Fig. 12.

5.4.7. *Space optimization and performance monitoring*

GPT models can be leveraged to analyse information about spaces available in a facility to allocate the space for the best usage based on predefined objectives to maximize productivity and utilization. Similarly, data from sensors can provide information about real-time usage to identify peak periods, usage patterns, and congestion areas to optimize space layout, and streamline workflow. This would also enable FM personnel to make space reconfiguration decisions, plan for accommodating future growth, and adapt to seasonal changes and new work trends.

Key performance Indicators (KPIs) such as equipment uptime, user satisfaction, space utilization, energy efficiency, maintenance response

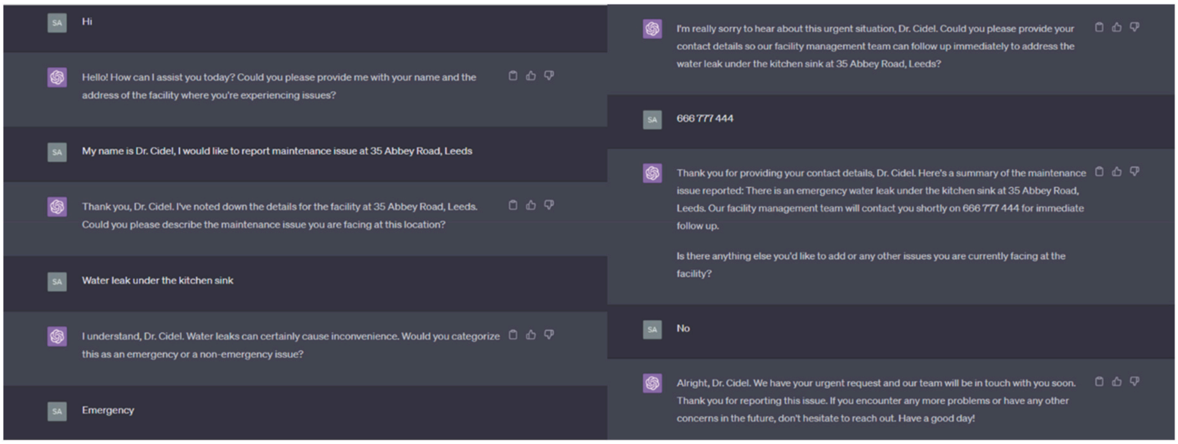

Fig. 11. Facility chatbot.

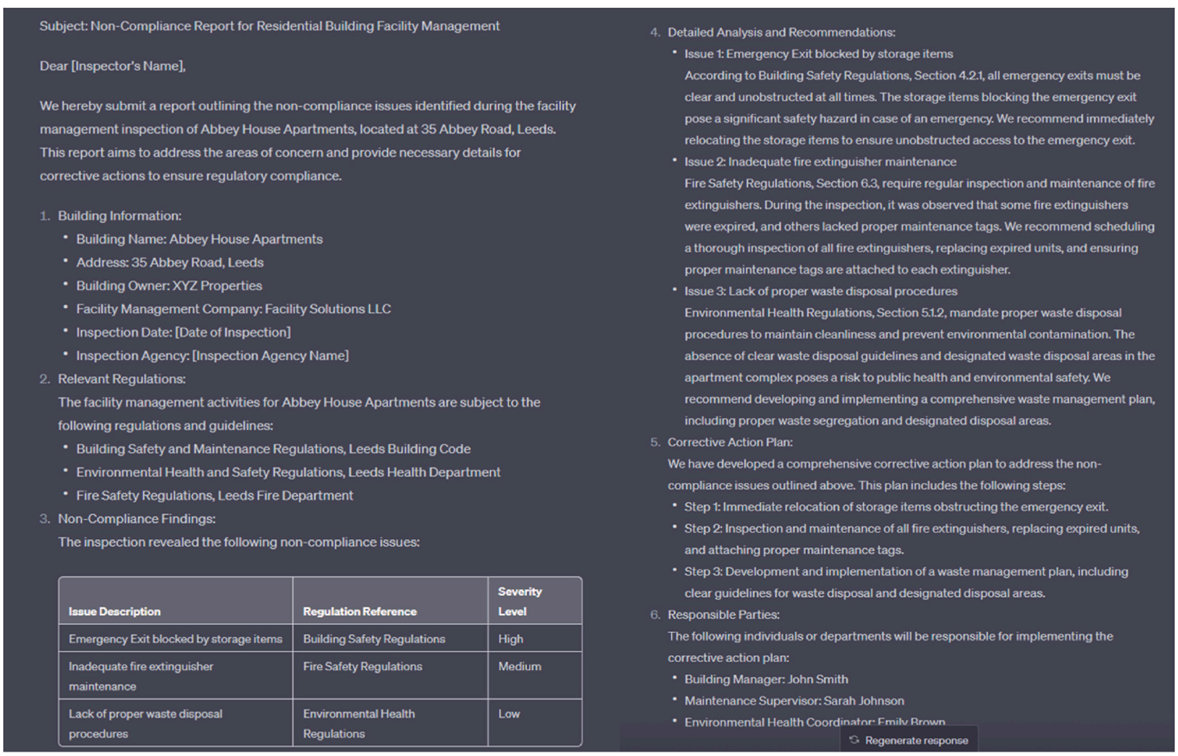

Fig. 12. Compliance report generation.

time and energy efficiency are some of the metrics employed to measure performance during the facility management phase of construction projects. Information such as maintenance records, equipment performance, energy consumption can be obtained from sensors, project management and energy management systems for usage of GPT models in performance monitoring. Also, real-time data would enable the FM personnel to track performance and deviations from desired performance levels. The developed KPIs can be compared to similar projects and best practices can be recommended by the GPT models. Similarly, performance forecast can be conducted based on historical performance data and GPT models can be leveraged for documentation of facility performance in accordance with defined standard to ensure consistency and saves time.

5.4.8. Sustainability reporting and improvement

Sustainability has become a paramount consideration in the construction industry, and stakeholders are increasingly focusing on measuring, reporting, and improving the environmental, social, and economic performance of buildings and infrastructure (Marjaba and Chidiac, 2016; Taiwo et al., 2023a). Nevertheless, thoroughly documenting sustainability practices and metrics is challenging due to extensive, complex data collection and analysis requirements.

GPT models could streamline sustainability reporting by extracting insights from large datasets - like energy use, occupant feedback, maintenance records and environmental monitoring data. When trained on sustainability rating systems like LEED or BREEAM (Yeung et al., 2020), GPTs would help generate automated reports, identifying performance gaps and recommending concrete improvements to facilities' sustainability.

5.4.9. Waste management and recycling

Effective waste management and recycling play a pivotal role in the operation and maintenance phase of the construction industry. Properly managing construction and demolition waste, as well as responsibly handling ongoing operational waste, is vital for minimizing environmental impact and fostering sustainable practices (Adedara et al., 2023). Nevertheless, waste management poses a challenge, demanding streamlined processes for efficient tracking, sorting, and disposal methods (Amaral et al., 2020).

Due to their intelligent decision support and optimization capabilities, the experts have identified GPT models to offer valuable contributions to improving waste management and recycling practices. By training these models on waste management regulations, best practices, and recycling guidelines, they can effectively analyse waste-related data and provide informed recommendations. An example of their utility is waste sorting and classification. GPT models can be adapted to analyse images or descriptions of waste materials and based on their training on extensive datasets of waste items and their appropriate recycling or disposal methods, the models can accurately identify the correct handling procedures for various waste types. This capability empowers facility managers to streamline waste management processes and enhance recycling rates, ultimately contributing to more efficient and sustainable practices.

5.4.10. Emergency response during fire or other hazards

During fire outbreaks or other hazardous incidents, the ability to respond swiftly and effectively is vital for protecting occupants, minimizing property damage, and restoring normal operations promptly. Emergency situations are often complex and dynamic, demanding rapid decision-making and coordinated efforts among stakeholders (Jiang, 2019).

These complex situations can be addressed using GPT models. This is achievable by training the models on diverse datasets, including information on past fire incidents, emergency protocols, and safety regulations. Subsequently, they can analyse real-time data and provide intelligent decision support to emergency responders. Leveraging their analytical capabilities, these models can assess the severity of the situation, identify potential hazards, and recommend appropriate actions such as evacuation, containment, or fire suppression. Their insights and guidance assist responders in making informed decisions and executing effective emergency plans. The post-incident management can also be enhanced by evaluating incident reports, witness statements, and other relevant documents to identify root causes, lessons learned, and opportunities for improvement (Beata et al., 2018).

5.5. Demolition phase

This section elucidates the potentialities for harnessing GPT models during the construction demolition phase, as visually depicted in Fig. 13.

5.5.1. Development of demolition protocol

The demolition phase of a building endeavour involves the careful and controlled removal of existing structures in a manner that ensures safety and security. Chew (2010) asserts that the achievement of project success is contingent upon the scrupulous formulation of plans and the flawless implementation thereof, while duly considering the welfare of labourers, the preservation of the environment, and the overarching objectives of the project. The establishment of a comprehensive demolition procedure is of utmost importance to provide guidance for demolition operations and effectively address potential hazards.

GPT models possess the potential to contribute significantly to the advancement of demolition protocols through their proficiency in data processing and risk assessment. The models possess the capability to effectively handle substantial amounts of data, encompassing project plans, site circumstances, and historical demolition records. Their primary function is to detect potential dangers, establish the most advantageous demolition sequences, and propose suitable safety measures. One possible application of GPT models is to predict and evaluate risks

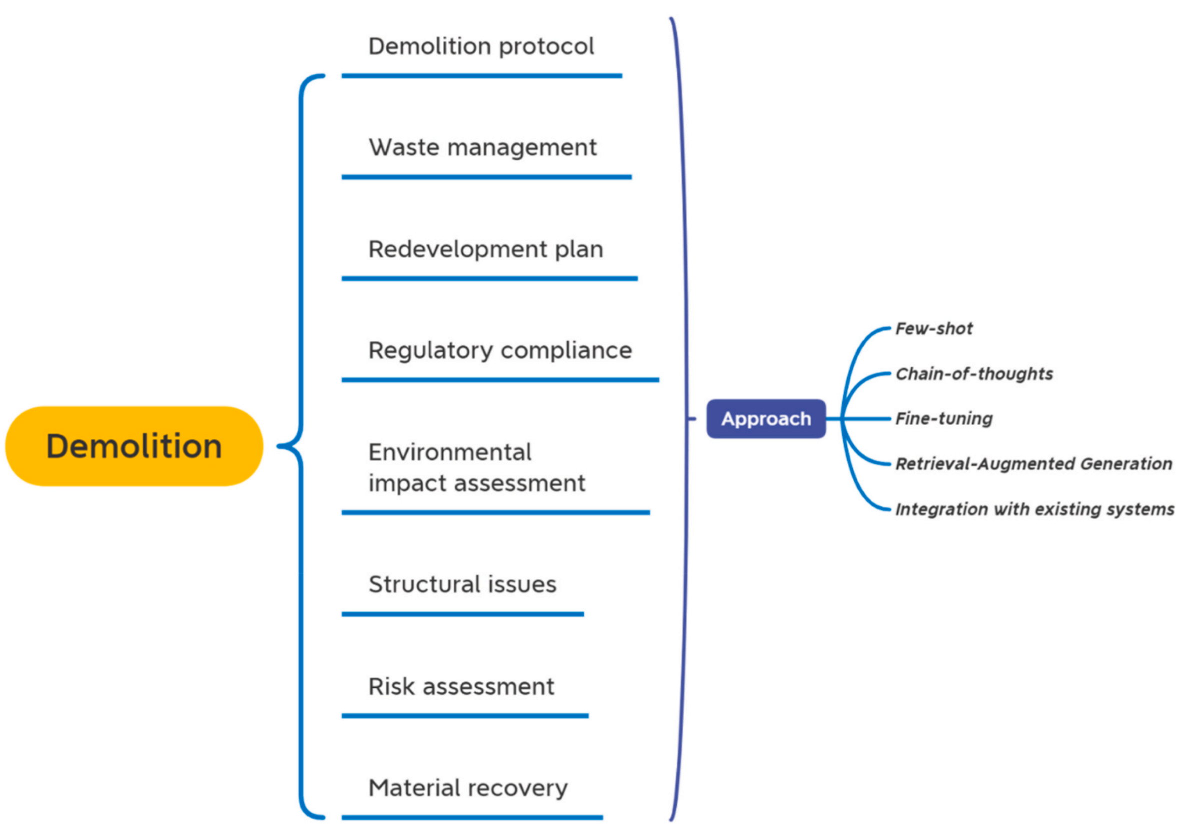

Fig. 13. Opportunities for GPT models in the Demolition Phase.

in various domains. Furthermore, via the incorporation of variables like as site accessibility, waste management techniques, and equipment utilization, these models have the capacity to develop demolition plans that effectively limit operational interruptions, mitigate environmental consequences, and optimize the allocation of resources.

5.5.2. Waste recycling and safe hazardous material disposal

Demolition projects yield a substantial quantity of refuse, including fragments, building components, and conceivably perilous compounds. Effectively handling of waste, in conjunction with the adoption of suitable recycling and disposal methods, assumes a pivotal role in advancing environmental sustainability and complying with regulatory obligations (Rahman et al., 2022). Conventional waste management practices frequently depend on labour-intensive sorting and decision-making procedures, which are recognized for their protracted duration, inefficiency, and susceptibility to human fallibility. The use of GPT has the potential to improve the existing waste and recycling process. Through the utilization of their proficiency in data analysis and pattern identification, these models have the capacity to enhance the efficiency of waste sorting, discern recyclable resources, and streamline the decision-making procedure pertaining to the appropriate disposal of hazardous substances.

5.5.3. Redevelopment plan

Following the dismantling of a physical edifice, a novel and auspicious occasion arises, presenting the potential for revitalizing and reutilizing the premises. The formulation of a successful redevelopment plan presents a formidable undertaking, necessitating meticulous examination of a multitude of factors including site conditions, market demands, and regulatory stipulations (Volk et al., 2018).

Traditionally, the formulation of these plans is dependent on manual methodologies that involve comprehensive research, rigorous data examination, and extensive engagement with relevant parties. The methods exhibit distinctive attributes including their protracted duration, substantial resource demands, and proneness to human biases. Furthermore, the complex and intricate nature of incorporating multiple variables and constraints frequently presents difficulties in ascertaining the optimal strategies for redevelopment. To effectively tackle this challenge, it is worth noting that GPT models have emerged as a valuable tool that can provide significant support in the formulation and implementation of well-informed and efficient redevelopment strategies. The models possess the capacity to effectively analyse extensive and heterogeneous datasets, encompassing market trends, demographic data, zoning regulations, and environmental factors. This analytical capability facilitates thorough evaluations of the site's inherent possibilities and the discernment of feasible alternatives for redevelopment. In addition, it is worth noting that GPT models possess the capability to effectively support scenario modelling endeavours. This attribute enables stakeholders to actively engage in the exploration of diverse redevelopment strategies, thereby allowing for a comprehensive evaluation of the potential outcomes associated with each strategy.

5.5.4. Regulatory compliance and permitting

The strict adherence to regulatory frameworks at various administrative levels, including local, regional, and national, assumes paramount importance in guaranteeing the secure implementation of demolition activities. This adherence serves to effectively mitigate potential risks posed to the environment, public health, and the occupational safety of workers engaged in such operations. The conventional methodology commonly involves the laborious implementation of manual procedures to ensure compliance with regulations and obtain necessary permits. The implementation of these procedures typically necessitates a substantial volume of paperwork, rigorous documentation practices, and intimate cooperation with regulatory entities (Macit İlal and Günaydın, 2017). The circumstances have the potential to lead to delays in project timelines and an increase in administrative duties for construction teams. Furthermore, it is crucial to recognize that the explication of regulations and requirements may give rise to variations, thereby resulting in inconsistencies and potential concerns regarding compliance.

GPT models exhibit an inherent capacity to perform thorough analysis and interpretation of regulatory documents, guidelines, and codes, thereby facilitating the timely provision of guidance and ensuring rigorous compliance with relevant regulations. These individuals exhibit the capability to facilitate the identification of the specific permits and approvals required for each demolition project, thereby expediting the permit application process. The utilization of GPT models in the examination of regulatory prerequisites presents a promising opportunity to rectify inaccuracies and augment the accuracy of adherence. The incorporation of automation into these models enables the streamlining of the process, resulting in an enhanced level of accuracy.

5.5.5. Environmental impact assessment

The demolition process has appreciable environmental kickbacks, in addition to the waste materials generation, the emission of pollutants, and the destruction of ecosystems. Hence, it becomes imperative to evaluate and address these repercussions to establish and uphold sustainable and ecologically conscientious methodologies (Uzair et al., 2019).

Conventionally, the undertaking of environmental impact assessments and the subsequent implementation of effective management strategies have been associated with a considerable allocation of human resources and temporal commitment. The research endeavors encompass a comprehensive process of data collection, rigorous analysis, and adherence to regulatory protocols. The evaluation of the environmental ramifications associated with a demolition undertaking presents a multifaceted endeavor, necessitating the consideration of diverse elements including atmospheric conditions, aquatic contamination, acoustic disturbances, and ecological diversity. This intricacy compounds the difficulties encountered by practitioners within the construction sector.

In the present context, it is evident that GPT models present auspicious prospects for the optimization and augmentation of environmental impact assessment and management procedures. The models possess the capacity to effectively analyse extensive quantities of data derived from a wide range of sources, encompassing environmental databases, scientific literature, and historical project data. By employing ML algorithms and employing natural language processing techniques, GPT models demonstrate the capacity to extract noteworthy insights, identify potential environmental hazards, and suggest appropriate measures for mitigation.

5.5.6. Establishment of structural issues

Before demolition commences, thoroughly evaluating structures is crucial for identifying issues and ensuring safe, efficient operations. However, manual inspection methods are subjective, prone to human error, and limited in analyzing extensive datasets - potentially missing concealed defects (Xia et al., 2021), leading to delays, costs, and safety issues. GPT models have the potential to strengthen structural assessments by uncovering concealed defects that human visual inspections may overlook. Examining historical data, maintenance records, and sensor data can allow GPTs to identify patterns and correlations. This enables them to highlight sections necessitating additional inspection or repair prior to demolition. Rather than depending entirely on subjective manual review, combining GPT analysis with current evaluation methods could offer more holistic insights into a structure's vulnerabilities.

5.5.7. Materials recovery planning and maximisation

Materials recovery and recycling is a significant considerations within the demolition phase, with immense potential to reduce waste and environmental impact (Akanbi et al., 2018). Manually developing detailed materials recovery plans is an arduous process requiring extensive data collection, quantification, and analysis. GPT models can augment this process through their ability to quantify recoverable materials and identify optimal recovery pathways. By leveraging their NLP and image recognition capabilities (Zheng and Fischer, 2023), these models can accurately identify materials such as concrete, steel, wood, and plastics (as shown in Fig. 14). This automation streamlines the process of materials identification, enabling efficient sorting and recovery operations. Another application of GPT in this area is the optimal allocation of the recovered material. The models can be integrated with data on market prices of materials, availability of recycling facilities, and environmental impact assessments. This will enhance the identification of high-value materials for resale, the determination of suitable recycling options, and the proper disposal of hazardous materials.

5.5.8. *Demolition risk assessment*

Processes such as structural dismantling, debris removal, and hazardous material management are associated with demolition activities (Akanbi et al., 2018). Conducting a thorough risk assessment is crucial to identify potential dangers, prioritize safety measures, and comply with regulatory requirements. Traditionally, the risk assessment is performed by relying on expert judgment, which may be subjective and time-consuming (Alipour-Bashary et al., 2022). Furthermore, they may not fully capture the complex interactions and dependencies between different risk factors.

The emergence of GPT offers a valuable solution to enhance demolition risk assessments. GPT models have the potential to analyse various risk factors and provide more accurate and objective assessments by leveraging their advanced NLP and ML capabilities. The training data may encompass demolition project records, structural characteristics, historical accident data, and safety guidelines. This enables the models to identify high-risk areas, predict potential failure modes, and recommend appropriate control measures to mitigate risks.

5.6. *Value-added services*

These are opportunities that are not directly related to a specific phase of the construction project lifecycle as shown in Fig. 15.

5.6.1. *Knowledge management and training*

Knowledge management and training are perhaps one of the common opportunities for which construction firms can leverage GPT models. Knowledge management deals with identifying, capturing, sharing and dissemination of knowledge and expertise within an organisation (Saka et al., 2022). There is corpus of construction-related information that were used in the training of GPT models, which enables these models to be used for knowledge base creation that could entail best practices, regulatory requirements, safety procedure, design guidelines and project documentation. GPT models enable quick and easy preparation of materials for training the construction personnel on diverse topics such as health and safety and project management. GPT can be deployed as part of the Chatbot system to provide education resources for construction personnel based on their queries, thereby, providing real-time education, personalized training and improving autodidactic experience (Saka et al., 2023).

GPT models can also be leveraged to capture tacit knowledge that is difficult to manage in the construction industry. The experience and expertise of construction professionals can be captured and preserved by using GPT models to gain insights and knowledge from historical data, and past project reports which would enable the creation of knowledge that would benefit new construction professionals. In addition, the construction industry is a global industry, and the construction site often faces language barriers. GPT models can provide multilingual support for knowledge management and training. As such, materials, documents and information can be translated into different languages in a global team and for effective dissemination across language boundaries. This is very important as language barriers often limit productivity and hamper effective health and safety on construction sites.

5.6.2. *Customer services*

GPT models can be leveraged to improve customer experience and satisfaction of firms involved in the delivery of construction projects. GPT models can be used as Chatbot to provide instantaneous assistance to customers and can handle requests and provide information about project progress, product pricing and other general inquires. GPT models can also be employed to provide tailored automated responses to customers' inquiries by identifying the customer's intent from their messages. Similarly, GPT models can enable better customer services across language boundaries and can also be employed in sentiment analysis of feedback from customers. Furthermore, GPT can provide suggestions about design and construction based on past data from clients thereby improving personalized interactions and overall customer services.

5.6.3. *Stakeholder communication*

Construction projects require stakeholders of diverse interests,

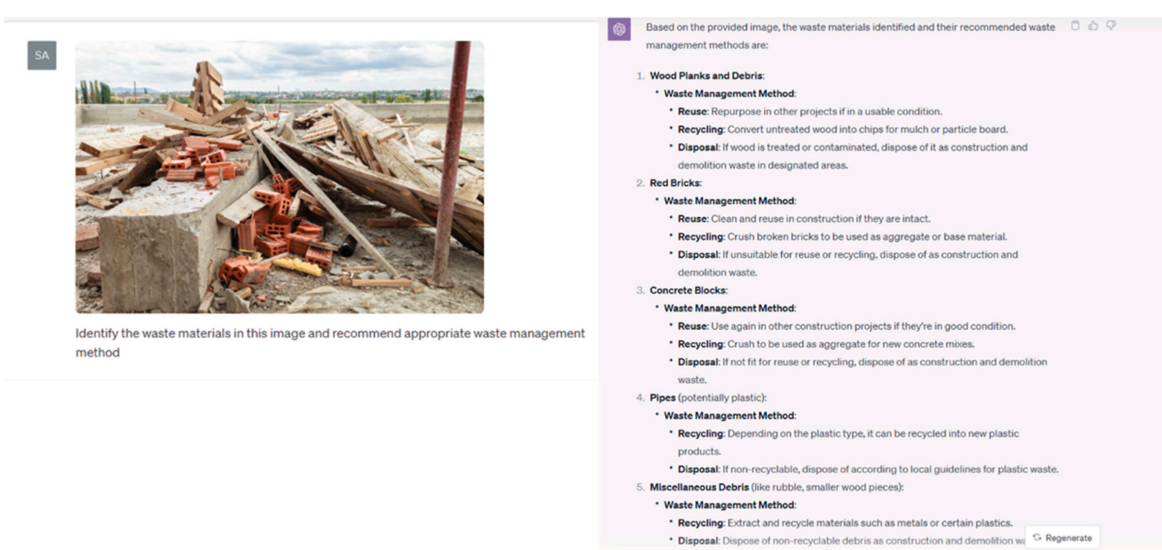

Fig. 14. Waste management using ChatGPT.

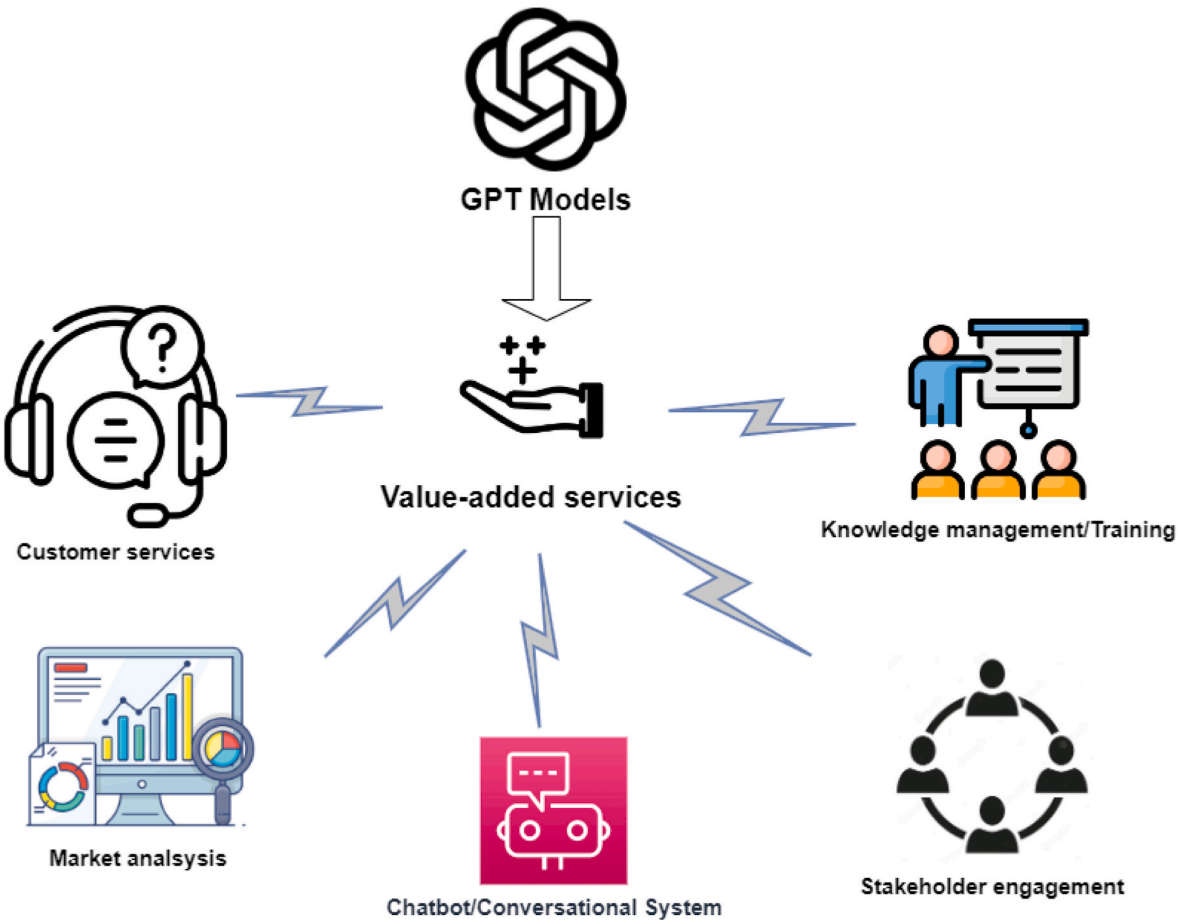

Fig. 15. Value-added services.

information needs and power to collaborate for effective delivery. GPT model can personalise project updates and reports for all the stakeholders to keep up with project developments and milestones. Similarly, GPT model can be integrated with the project database and other communication platforms to facilitate real-time interaction and engagement for the stakeholders. Also, GPT models are effective in summarization and can be leveraged in providing executive summaries of project-related documentation for effective communication with the stakeholders Lastly, communication between the project team and stakeholders can be analysed by GPT for sentiment analysis and multilingual communication can be facilitated towards effective stakeholders' management.

5.6.4. *Market analysis*

Leveraging the advanced data analysis capability of GPT models, trend identification and analysis can be done by integrating market data, reports and other relevant data into GPT. Also, insights about market dynamics, sentiment analysis of customers and market segmentation can be carried out to improve products and services. Similarly, they can provide a market analysis of competitors' services, products and marketing, and customer feedback to gain a competitive advantage and refine their market strategies. Also, based on the historical data market shift, potential market scenarios can be predicted. Lastly, GPT models can help with summarizing market intelligence reports to support strategic planning and organisational decision-making, and for monitoring industry news and updates.

5.6.5. *Conversational system/chatbot and low code/no code development*

GPT models can be leveraged in the development of conversational systems/chatbots for natural language recognition, intent classification and entity extraction, and natural language generation. As such, these models would enable conversational interaction via audio or text with the backup application. For instance, GPT models can be employed for information retrieval in BIM via natural language (Zhang et al., 2023) and can also be leveraged in the development of extant systems such as BIM-based AI voice assistant (Elghaish et al., 2022), Voiced-based virtual agents (Linares-Garcia et al., 2022). Leveraging GPT models in conversational system development would improve natural language generation compared to the pattern-based approach currently used in some systems which are rigid and susceptible to errors. Also, GPT models would limit data requirements and engineering expertise necessary for developing prototypes (Zhang et al., 2023) Similarly, with capabilities of GPT model to generate codes, the model can be leveraged in the development of low code and no code systems. For instance, platforms can be developed for developing applications for all professionals in the AEC industry usage without having technical expertise in coding. Drag & drop feature and natural language prompts will be employed by the users for interaction with the system, thereby increasing accessibility and significantly reducing the cost of development in the AEC industry.

6. Challenges

The challenges to the deployment of LLMs in the construction industry could be broadly classified into three categories – industry-related, LLM-related and a nexus of industry and LLM-related as shown in Fig. 16.

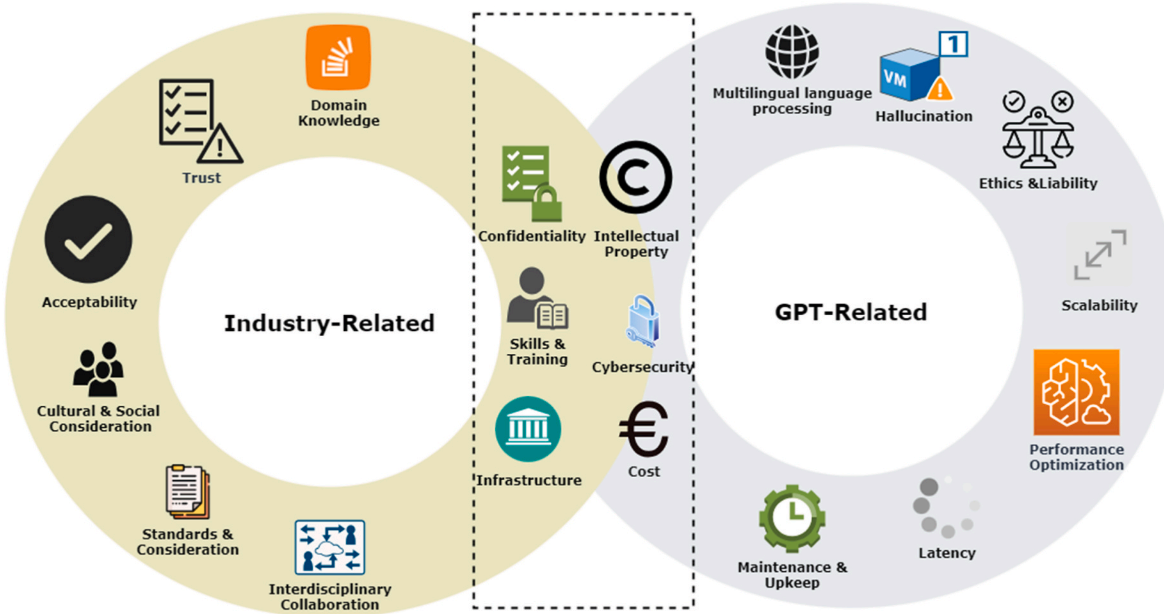

Fig. 16. Challenges of GPT models in the Construction Industry.

6.1. Hallucinations

Despite the improvement in NLP in GPT models, the models are prone to hallucination - giving sound and plausible information that is not true-which reduces system performance and users' expectations (Ji et al., 2023). This is highlighted as a major barrier to the application of GPT models in the construction industry by the experts because wrong information could endanger lives and properties and could also lead to profit loss by companies. For instance, relying on information from GPT models for health and safety management or for programming robotics sequences could lead to accidents on site. Similarly, relying on the hallucinated text on scheduling from GPT models could lead to project delay or cost overrun. A typical example of hallucinated text from the GPT model is shown in Fig. 17.

This sounds convincing but it is entirely false as there is no CIDEL electric shower from Triton Cara. Rather, CIDEL is a research laboratory 'Construction Informatics and Digital Enterprise Laboratory' at Leeds Beckett University.

6.2. Data and interoperability

Structured data is needed in the fine-tuning of GPT models which are often not readily available in the construction industry. Availability and quality of data have been a major challenge for the application of artificial intelligence in the industry (Abioye et al., 2021). Also, construction projects have unique attributes, and the industry is still slow in the adoption of digital technologies for data collection, leading to potential data loss. This is coupled with the heterogeneity of the data and the time-consuming & labour-intensive exercise in creating labelled data sets.

Furthermore, the cost of interoperability in the construction industry is enormous and ranges from millions of pounds (Shehzad et al., 2021). Datasets are available in different formats such as Portable document format (PDF), doc, hypertext markup language (HTML), Computer-aided design (CAD), Industry foundation classes (IFC) and others. Also, different software and digital tools employed have different formats that make seamless interoperability difficult. Data are often converted to a standardized form like IFC to improve interoperability but at a loss of watering down the richness of the data (Saka et al., 2023). GPT models currently only accept specific formats (Image formats, JSON, CSV, JSONL, TSV, or XLSX) which imply that leveraging construction data in GPT models or integrating GPT models with existing tools would involve conversion and pre-processing. For instance, converting BIM model to JSON format, however, not all the information in the BIM model can be converted which poses a challenge to the deployment of GPT models.

6.3. Domain-specific knowledge and regulatory compliance

Although GPT models are large language models and trained on large data sets, their ability to understand domain-specific knowledge is limited. This is a major barrier in the construction industry which requires a technical understanding of different principles, best practices and regulations. As such, there is a need for adequate fine-tuning of GPT models and the provision of context to improve their performance in a technical domain like the construction industry. Also, Retrieval-Augmented Generation (RAG) can be employed to improve the performance of the model. Similarly, the regulations in the construction industry are many, as it is one of the most regulated industries, due to safety and quality needs. These regulations vary from time to time and are based on different contexts such as countries with different environmental regulations, labour, and safety-related laws. Most importantly, these regulations are technically drafted and require technical knowledge and logical reasoning to understand. Consequently, there is currently a need for an adequate breakdown of the regulations for easy understanding of GPT models especially complex pictorial regulations and the need to update the understanding of the models as regulations change from time to time.

6.4. Confidential and intellectual property

GPT models are trained on large datasets, and these models improve their performance with interaction over time. In the construction industry, sensitive data such as project design, cost, contracts, and schedules are generated and could be used as inputs for GPT model applications. This raises the concern of confidentiality of GPT models generating output with sensitive information. Also, using data such as project designs and patented building techniques could infringe on the intellectual property owner and lead to ethical and legal issues. Lastly, the ownership of data has always been a problem in the construction

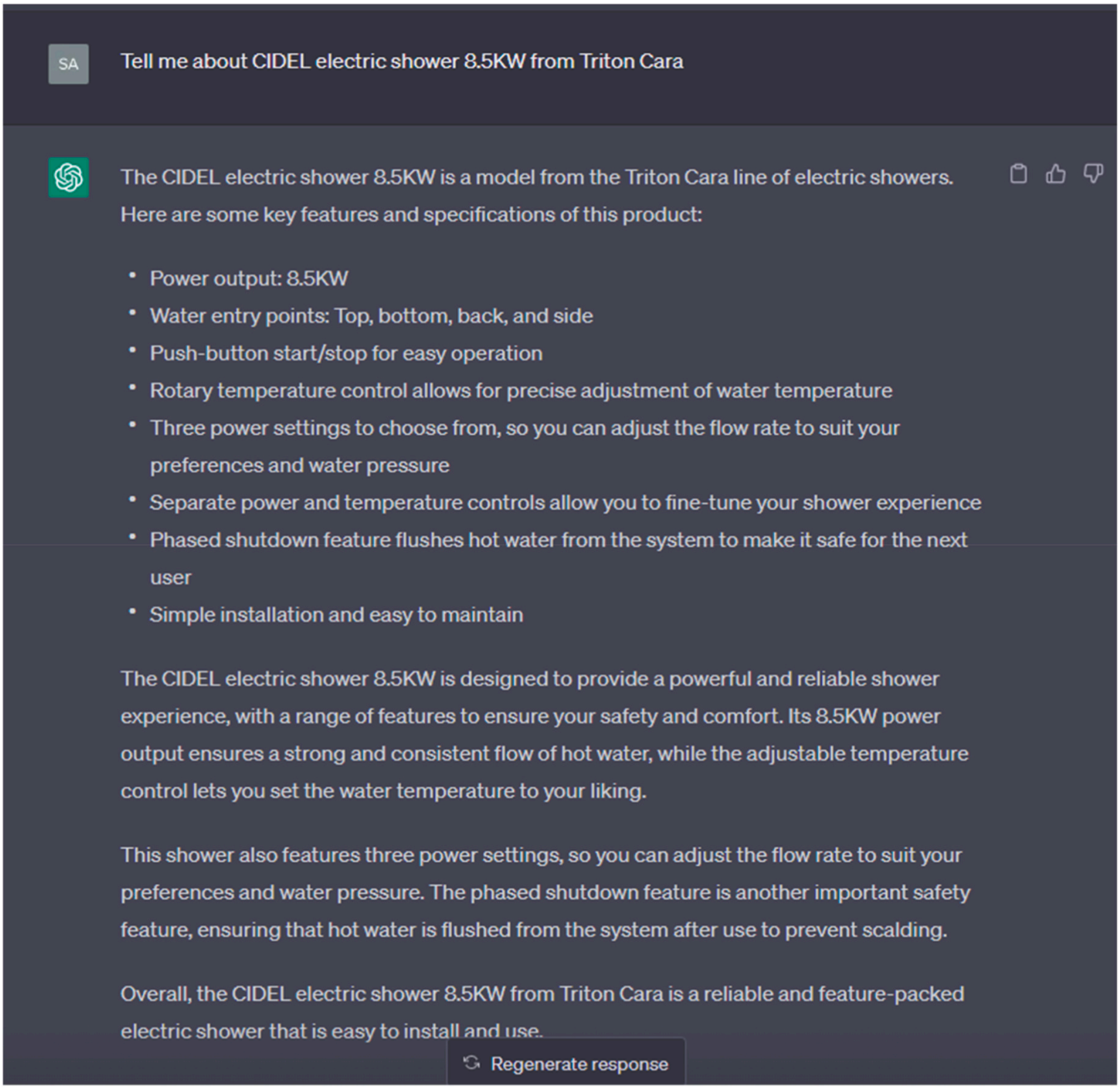

Fig. 17. Hallucinated outputs.

industry and the use of GPT models begs the question of who can use data created during the construction project for training large language models. Consequently, there is a need for a clear policy and guidelines for the use of GPT models in the construction industry to avoid confidentiality and intellectual property challenges.

6.5. *Trust and acceptability*

The construction industry is known to be slow in the adoption of innovation compared to other industries. There is often resistance to change in the industry, and digital technologies such as BIM have not been widely implemented as expected. With the growing application of AI in the construction industry, industry practitioners and stakeholders are sceptical about trusting and accepting it. Decisions by stakeholders have significant implications for cost, safety, quality and time of project delivery and relying on GPT models that are 'black box' is difficult. As projects often involve different parties, the issue of acceptance by some parties would hinder the deployment of GPT models on such projects and could also influence the unavailability of project data to fine-tune the models. Furthermore, LLMs do require access to large databases for training, with construction firms having concerns about the data usage, and are often unwilling to release such data. This is coupled with the fear that AI would take over jobs in the construction industry and the perceived complexity of digital tools. Consequently, trust and acceptability are inherent challenges in the construction industry that would hinder the applications of GPT models. There is a need to demonstrate the tangibility of GPT models and highlight their reliability through robust testing and validation. It is important to employ an inclusive approach which would involve all stakeholders in considering the usage of GPT models to have clear guidelines and to allay fears.

6.6. *Liability and ethics*

GPT can be leveraged for many opportunities at the design, construction, management, and demolition stages of construction projects. However, a growing area of concern in the use of AI like GPT models is liability and accountability challenges (McAleenan, 2020). GPT models are LLM trained on a large amount of data which influences what the models would generate during deployment. Bias, incomplete information and inaccuracies in the training data would affect the output generated by the models, and this could cause harm and business loss in the construction industry. Similarly, the inability of GPT models to fully comprehend various legal and regulatory requirements in the industry could lead to the provision of inaccurate and non-compliant advice and recommendations from the system. Additionally, the decision-making mechanisms within GPT models present challenges in interpretability, transparency, and explainability. Such obscurity undermines stakeholder trust and complicates accountability efforts. Individuals or entities depending on the outputs or recommendations generated by these models often find themselves in a position of uncertainty regarding the internal algorithms or systematic processes utilized. (You et al., 2023). These beg the question of who is responsible for the potential harm caused by wrong information generated from GPT models. There are currently no clear legal frameworks on accountability and liability for the harm caused by the application of AI in the construction industry, which could lead to exploitation and leave affected parties with no clear legal recourse. However, the optimal current approach to overcome liability and accountability challenges is to have clear policies and guidelines for the usage of GPT models, human oversight and to employ models as complement to the human personnel.

Similarly, the problem of ethical issues facing LLM affects GPT models in the construction industry. GPT models have the capability of amplifying biases and discrimination learnt from the training data set, can be used unethically, and could impact the labour market in the construction industry. As such, it is important, for the GPT models to be trained on unbiased and diverse datasets to ensure accurate and reliable results. During the deployment in construction organisations, it is important to have clear guidelines to prevent the model's misuse. In addition, there are economic impacts of GPT models in the industry which could lead to the loss of jobs, pose as a competitor, and replace repetitive tasks such as information retrieval from texts done by some low-skilled workers in the industry. It is thus important to take steps to evaluate the impact of GPT models in the AEC industry and mitigate negative effects.

6.7. Skills and training

Effective deployment of GPT models in the construction industry requires new skillsets and training programs to ensure that the professionals can leverage them properly. The most needed skill is 'prompt engineering' which deals with developing and optimizing prompts to effectively use LLMs (Liu et al., 2023). It is encompassing skills needed to build, interact, and develop new capabilities with LLMs. There are different techniques for prompt engineering such as zero-shot, few-shot and chain-of-thought (CoT) prompting (Wei et al., 2022). In zero-shot prompting, no examples are provided for the models to perform specified tasks whilst in few-shot prompting provide contexts and examples in the prompts for the model to perform better (Wei et al., 2022). On the other hand, CoT prompting provides a 'series of intermediate reasoning steps' which significantly boost the ability of LLMs to perform complex reasoning tasks. Further, there is a need to understand the fine-tuning process of GPT models and the use of RAG which enables the models to perform better than prompt design (OpenAI, 2023a,b). However, this requires structured training examples in specific formats (JSON, CSV, JSONL, TSV, or XLSX) which implies the need to have the skillsets to pre-process data. As such, skills, and training required for the proper deployment of GPT models in the construction industry serves as bottlenecks.

6.8. Infrastructure requirement and cost

Leveraging LLMs in the construction industry would require necessary infrastructure such as computing power, network connectivity and data storage. This poses a challenge for the small and medium-sized enterprises which represent about 80% of the organisation in the industry (Saka and Chan, 2020). Also, the current cost of web access for ChatGPT is $20/month with restricted traffic. Similarly, the development of applications that leverage GPT models is not free, as usage is billed per 1000 tokens (~750 words). This ranges from $0.09/1K to $0.18/1K (prompt and completion cost) for 8K and 32K GPT-4 model (OpenAI, 2023a,b). Gpt-3.5-turbo (ChatGPT) employed for use case validation cost $0.002/1K tokens (OpenAI, 2023a,b). Consequently, aside from the infrastructure requirement, the cost of leveraging LLMs are barrier to deployment in the construction industry. Chen et al. (2023) proposed strategies to leverage LLMs at a reduced cost with improved performance. The study highlighted prompt adaption, LLM approximation, and LLM cascade as strategies; and validated 'Frugal GPT' (LLM cascade) with 98% cost reduction.

6.9. Scalability and performance optimization

Whilst GPT models have overcome some of the scalability challenges inherent in the development of Conversational AI systems (Saka et al., 2023) via a generic model that can be personalized with a prompt design, the challenge of scalability of fine-tuned models persists. Fine-tuning improves learning of GPT models by training on more structured training data for a specific use case. This could be classification (e.g sentiment analysis, email categorization) or conditional generation (e.g entity extraction, chatbot for customer support) (OpenAI, 2023a,b) and would require different datasets. However, such specialization necessitates the use of disparate datasets and consequently limits the model's scalability across diverse tasks. For instance, a model fine-tuned for customer support chatbot functionalities would likely underperform in tasks related to information retrieval from Building Information Modeling (BIM). Similarly, while the performance of GPT models can be optimized by better prompt designs, other approaches such as self-reflection (Reflexion) require skilled personnel to improve the models (Shinn et al., 2023). Also, fine-tuning models to optimize performance requires structured data and infrastructure, which might be difficult for the majority of the organisations in the construction industry.

6.10. Cybersecurity

In an era of digital advancements, cybersecurity has become a critical concern across various industries, including the construction sector (Nyamuchiwa et al., 2022). As the construction industry embraces the potentials of GPT, it also faces significant cybersecurity challenges.

The utilization of GPT within construction processes brings forth fresh areas of vulnerability that can be manipulated by malicious individuals. The dependency on interconnected systems, cloud computing, and data exchange amplifies the likelihood of unauthorized entry, data breaches, and cyber-attacks (You and Feng, 2020). It is imperative for construction firms to confront these obstacles in order to protect sensitive information and uphold the steadfastness of their operations. Alongside external cyber threats, construction companies must also address insider threats. These can arise from unintentional errors or deliberate actions by employees who have access to sensitive information (Nyamuchiwa et al., 2022). Proper employee training and awareness programs are crucial to mitigate the risk of internal data breaches or compromises. It is vital for organisations to foster a cybersecurity-conscious culture and promote best practices among employees. Furthermore, construction companies need to invest in advanced threat detection systems, intrusion detection and prevention systems, and real-time monitoring tools. Prompt response to security incidents is crucial to minimize potential damage and prevent unauthorized access to critical systems or data.

6.11. Interdisciplinary collaboration

In the dynamic and complex landscape of the construction industry, successful project outcomes often hinge on effective collaboration among diverse disciplines (Oraee et al., 2019). Interdisciplinary collaboration involves the integration of expertise from various fields, such as architecture, engineering, construction management, and data science, to address the multifaceted challenges encountered throughout the project lifecycle (Fulford and Standing, 2014).

While the introduction of GPT in the construction industry brings promising opportunities, it also presents unique challenges to achieving seamless interdisciplinary collaboration. Professionals from different disciplines often use specialized language and terminology specific to their respective fields. GPT-generated outputs may include technical terms and jargon that might be unfamiliar to professionals from other disciplines. This can lead to misunderstandings, misinterpretations, and inefficiencies in collaborative efforts. For successful interdisciplinary collaboration, trust and acceptance among team members are crucial. The introduction of GPT may raise concerns and scepticism among professionals who are unfamiliar with its capabilities or who fear the potential displacement of their roles. Building trust and fostering acceptance of GPT as a collaborative tool can be a significant challenge, requiring effective change management strategies (Sezgin et al., 2022).

6.12. Cultural and social considerations

Construction projects are diverse and often take place in various cultural and social contexts, involving different stakeholders with distinct values, norms, and practices (Zuo et al., 2012). These cultural and social factors can significantly influence the acceptance, adoption, and effectiveness of GPT-driven solutions.

Due to their automation capabilities, the implementation of GPT in the construction industry may raise ethical and social considerations about the impact on employment and job security. The fear of job displacement and the potential loss of skilled labour can create resistance to adopting emerging technologies such as GPT models (Na et al., 2022). Moreover, concerns regarding data privacy, ownership, and security can undermine trust and hinder the widespread acceptance of GPT-empowered interventions. In order to mitigate these challenges, the relevant stakeholders can implement reskilling and upskilling programs to equip the workforce with new skills required to work alongside GPT systems and clearly communicate data handling practices to ensure compliance with relevant regulations.

6.13. Latency issue

The latency issue relates to the time lag that occurs between the input of data and the output of results (Yang et al., 2023). In the construction industry, latency can be especially problematic because of the time-sensitive nature of construction projects.

The GPT algorithms require to be fine-tuned on massive amounts of data to achieve their highest level of performance (Zheng and Fischer, 2023). Hence, the training process can be time-consuming. An additional factor contributing to latency stems from the insufficiency of processing capabilities in certain systems. GPT algorithms demand considerable computational resources, necessitating high-performance hardware for expedited processing. The financial burden associated with procuring such hardware may be unfeasible for smaller construction enterprises, thereby exacerbating latency challenges. Such delays can adversely affect various operations, including real-time monitoring of construction sites, collaborative design efforts, and the functioning of automated robotic systems.

6.14. Maintenance and upkeep

While GPT systems offer numerous benefits, ensuring their continuous operation and optimal performance over time requires diligent maintenance practices and regular updates (Zong and Krishnamachari, 2022). One of the primary challenges in GPT maintenance is system degradation and drift. Over time, GPT models may experience a decline in performance due to changing data patterns, evolving user requirements, or shifting industry standards. This degradation can lead to reduced accuracy, reliability, and relevance of generated outputs, impacting the overall effectiveness of GPT applications in construction processes. To address this challenge, continuous model training and adaptation are crucial.

The integration of GPT into construction processes involves a complex technical ecosystem comprising servers, databases, network infrastructure, and data processing systems. Coordinating and managing these components can be challenging, particularly as the scale and complexity of GPT applications increase. This challenge can be mitigated by putting in place dedicated IT personnel responsible for infrastructure management, regular system health checks, proactive troubleshooting, and prompt response to technical issues.

6.15. Multilingual language processing

In an increasingly globalized world, the construction industry is experiencing a growing need for multilingual language processing capabilities. With projects spanning across borders and involving diverse stakeholders, effective communication and understanding of multiple languages have become crucial (Kraft, 2019; Taiwo et al., 2022). Although GPT models are constantly being updated with more training datasets (Brown et al., 2020), models trained in limited languages may struggle to accurately comprehend and generate content in unfamiliar or less-represented languages. This variability poses a significant hurdle in achieving seamless multilingual communication.

Using zero-shot learning, Lai et al. (2023) conducted extensive experiments on ChatGPT (i.e., powered by GPT 3.5) to investigate its multilingual capacity using various NLP tasks such as summarization, question answering, named entity recognition, and part-of-speech tagging, amongst others. Their result indicated that ChatGPT underperformed in various languages except for English compared to task-specific models built in specific languages. This is due to the fact that a larger percentage of ChatGPT training data was in English (Koubaa et al., 2023). To address the challenge of language variability, it is essential to create and curate large-scale multilingual training datasets that encompass a wide range of languages, dialects, and domains specific to the construction industry. By incorporating diverse linguistic data, GPT models can better understand and generate content in various languages, enhancing their multilingual language processing capabilities.

6.16. Standards and variability

The construction industry involves diverse standards and requirements that vary significantly across countries, regions, and individual projects (Cheriyan and Choi, 2020). This poses a challenge in efficiently leveraging GPT models across the entire lifecycle of construction projects. Strategies to address this challenge include adaptive databases, customized fine-tuning, prompt conditioning, cost-effectiveness analysis, time management considerations and multilingual models. Firstly, instead of relying on a fixed corpus, GPT models can be trained on adaptive databases that are regularly updated with the latest standards, codes, and project specifications from different regions. This allows the models to account for geographical variations and changes over time. The databases can ingest structured data from BIM, project documents, and compliance repositories (Bilal et al., 2016).

Secondly, GPT models pre-trained on broad construction data can be fine-tuned on project-specific documents and asset data to adapt to the requirements of individual projects. This customization improves the relevance of the models' outputs for each unique project context. Similarly, Retrieval-Augmented Generation which provides a framework for improving LLM-generated responses by grounding LLMs on external verifiable information can be employed for the diverse standards and requirements. Lastly, Training multilingual GPT models on construction data from diverse regions can aid in overcoming language barriers and differences in terminology across geographies. This expands the applicability across international projects Lai et al. (2023).

7. Case study validation: material selection and optimization platform

To validate the practical application of GPT in the construction industry, we developed a material selection and optimization prototype. This prototype aimed to validate a use case for GPT in the design phase. To facilitate this, a simple BIM model containing 235 building elements was employed as a test case. The development process involves three key steps, each of which serves a specific purpose. Fig. 18 shows the system architecture for the use case validation.

7.1. Data retrieval module

The Forge Model Derivative API is used to translate and process the BIM models. The BIM file is uploaded to the forge cloud using the Data Management API and stored for access through the Model Derivative API (Fig. 19). The model was then translated into the SVF2 format, enabling the extraction of geometric and metadata information. The Forge Viewer renders 2D and 3D models for web-based access to BIM data. The Model Derivative API extracts data attributes and converts them to a searchable JSON format, including hierarchy trees, geometries, and properties such as component ID, type, and area location. The Data Retrieval module effectively extracts and cleans the necessary BIM data, making it useable for subsequent modules, such as NLP.

7.2. NLP prompt processing module

The prompt development for material selection and optimization using the ChatGPT API is a multistep process that involves constructing appropriate prompts and designing an interactive dialogue system. The goal is to guide users in selecting optimal materials for each element of the BIM model based on their requirements. The prompt manager connects to the OpenAI API with the ChatGPT model 3.5 turbo using AJAX asynchronous communication. A temperature value of 0.5 is set to reduce the level of randomness in the model's responses.

The prompt consists of two parts: the user prompt and the system prompt. The system prompt is concatenated with the properties of the element in context which is extracted from BIM JSON search before being sent to the ChatGPT API. User prompts serve as the initial input and should clearly express the user's intention, such as requesting assistance in finding the best material for a specific element in the BIM model. Providing sufficient context in prompts helps guide the conversation effectively (Fig. 20). System instructions play a crucial role in guiding the behaviour and responses of the ChatGPT. They leveraged the output from the BIM JSON search through the data retrieval module to refine prompts. For example, system instructions may direct ChatGPT to consider factors, such as moisture resistance, when suggesting materials for a bathroom door located at the entrance. These instructions, combined with the user prompts and BIM data search results, ensure that ChatGPT generates relevant and informed recommendations.

Prompt development is an iterative process that incorporates zero-shot and few-shot scenarios. The performance of the model is continually evaluated, and the prompts, instructions, and dialogue system are refined based on user feedback and real-world interactions. This iterative approach enhanced the efficiency and effectiveness of the system over time.

7.3. User interface and integration module

The user interface (UI) development for the material selection and optimization system involved the use of JavaScript, HTML, CSS3, and Bootstrap 5 (Fig. 21). These technologies were utilized to create a chat interface that seamlessly integrates with the forge viewer, which provides a library for visualizing cloud-based BIM. To facilitate smooth communication between the front-end interface and the prompt manager, an AJAX call was implemented. This allowed for the exchange of time-stamped natural language queries and answers as well as the retrieval of result IDs. Using these IDs, cloud-based BIM rendered

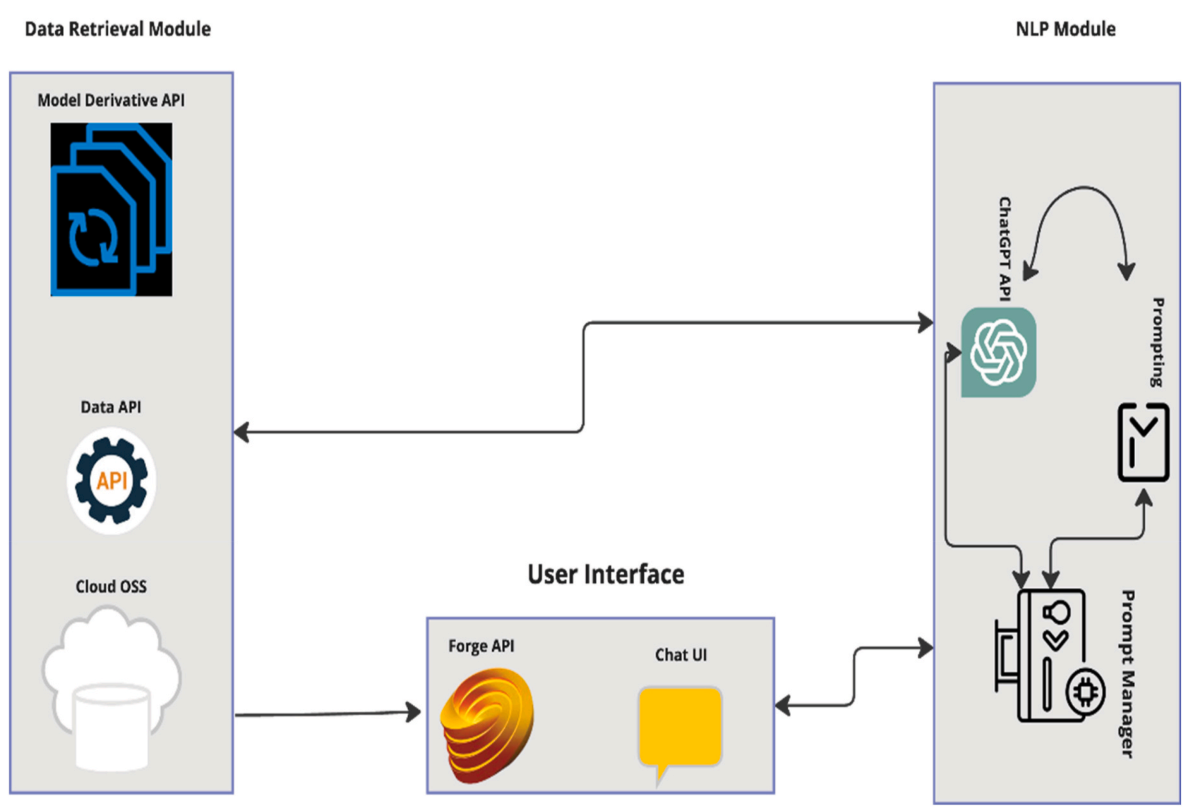

Fig. 18. System architecture.

```javascript
function onDocumentLoadSuccess(doc) {
  var viewables = doc.getRoot().getDefaultGeometry();
  viewer.loadDocumentNode(doc, viewables).then(i => {
    // documented loaded, any action?
    console.log("loaded");

    getAllLeafComponents(NOP_VIEWER, function (dbIds) {
      AllDbIds = dbIds;
      console.log('Found ' + dbIds.length + ' leaf nodes');
    });

    viewer.addEventListener(Autodesk.Viewing.OBJECT_TREE_CREATED_EVENT, async function (e) {
        //var props = await getBulkProperties(viewer.model, AllDbIds, {propFilter:null,needsExternalId:true,ignoreHidden:false,categoryFilter:null});
        var props = await getBulkProperties(viewer.model, AllDbIds, {propFilter:null,needsExternalId:true,ignoreHidden:false,categoryFilter:null});

      // var searchprops = await searchBulkProperties(viewer.model, AllDbIds, {propFilter:null,needsExternalId:true,ignoreHidden:false,categoryFilter:null});
      var searchprops = await searchProperties(viewer.model, keywords);
      var keywordSearchproperty = await getBulkProperties(viewer.model, searchprops, {propFilter:null,needsExternalId:true,ignoreHidden:false,categoryFilter:null});

      viewer.select(searchprops);
      viewer.fitToView(searchprops);

        //console.log(props);
       // console.log(searchprops);
      console.log(keywordSearchproperty);
        //console.log(AllDbIds);
    });

  });
}
```

Fig. 19. Extraction of element property from model derivative API.

```javascript
        // use JSON.stringify to encode myobject to JSON
        const elementpropertyjson = JSON.stringify(elementproperty)

        msgs = [
          {
                "role": "system",
                // You can change this part to be whatever you want it to be
                "content": `Your task is to help a builder select the best optimised material to be used for a selected element in a BIM model using the following step
-Determine if the user input is relevant to material selection for building components
-If No, reply only with "I apologize, but I am unable to handle your request as it is not related to material selection and optimization."
-if Yes then continue with the following steps
1.Element type and location: Determine the type and location of the element from the user input  json `+ elementpropertyjson +`
2.Properties: specify the required properties of the element, such as durability, moisture resistance, and
soundproofing using the location of the element for example doors of toilet require moisture resistance material.
3.Available materials: Evaluate the available materials possible that can be used for the element which includes
materials such as wood, glass, steel, and composite materials.
4.Material comparism: Compare the properties of the available materials to the required properties of the element.
 For example, if moisture resistance is a requirement, materials like PVC, fiberglass, and steel would be better
 options than wood.
5.Other factors: Consider other factors such as cost, sustainability, aesthetics, and energy efficiency when
 selecting a material.
6.Optimal material: Based on the evaluation of available materials and the required properties, choose the
optimal material for the element of the bathroom in the BIM model.
 \n`
            },
            {
                "role": "user",
                "content": user_request
            }
        ]
```

Fig. 20. Few-shot system prompt instruction.

different 3D contextual scenes of the relevant building objects in response to the user's query, enabling interactive exploration of the uploaded BIM model.

The web-based prototype was designed to be easily deployed to any cloud service provider, ensuring high availability and accessibility from various devices, including mobile devices. The UI seamlessly integrates BIM data available through the OpenAI API, providing a comprehensive and user-friendly experience for material selection and optimization.

7.4. Discussion

Fig. 22 showcases the developed prototype for material selection and optimization. The user interface provides seamless integration of user input queries and ChatGPT responses, both displayed on the right side of the interface. Additionally, the prototype incorporates a visual representation of the 3D model using the Autodesk Forge viewer.

The prototype was tested in 3 different scenarios zero-shot, few-shot with system prompting and edge case prompting scenarios.

7.4.1. Zero-shot prompting

To test the zero-shot capabilities, the prototype disabled the system role prompt in the payload of the ChatGPT API call, retaining only the user prompt and supplying BIM information as input.

Fig. 17 shows the response generated by chatGPT in response to a user query "Suggest the best material to be used for the door named 'Bois - Panneau de porteto' leading to toilet WC 15" at zero-shot scenario.

ChatGPT's response to the query was not specific as it responded with "*As an AI language model, I am not aware of the specific requirements of the door named "Bois - Panneau de porteto" leading to toilet WC 15*" as demonstrated in Fig. 8 above. However, it suggested common material for bathroom while laying emphasis on the specific requirements of the user and then recommending consulting professionals to determine the best material for the user's specific needs. The above scenario demonstrated that ChatGPT could not serve as an effective tool for material selection and optimization without proper prompt engineering.

7.4.2. Few-shot prompting scenario

Fig. 23 shows the response generated by ChatGPT in a few-shot scenario response to the same user query used in the zero-shot

```
send_request = function() {

    $("#status_message").html("<span class='sending'>Sending message...</span>")

    // The call to ChatGPT is made from this function:
    CallChatGPT()
};

 //Setup forge Viewer
 let divId = "MyViewerDiv";
 setupViewer(divId, documentId, tokenFetchingUrl, extensionArray);

// Wait for the page to load before we do anything
$("document").ready(function() {

    // Initialize the tabs:
    $("#tabs").tabs();

    // Set initial values from the sliders:
    $("#gpt_temprature_value").html($("#gpt_temprature").val())
    $("#n_gens").html($("#num_gens").val())
    $("#max_tokens").html($("#num_tokens").val())


    $(".min_max").click(function(){

        console.log("Clicked on min/max button")
        console.log("found elements: ", $(this).siblings(".wrapper"))
        // Toggle visibility of the sibling called ".wrapper":
        $(this).parent("h6").siblings(".wrapper").toggle();
    });

    // Capture change of sliders:
    $("#gpt_temprature").on("change", function() {
        $("#gpt_temprature_value").html($("#gpt_temprature").val())
    });

    $("#num_gens").on("change", function() {
        $("#n_gens").html($("#num_gens").val())
    });

    $("#num_tokens").on("change", function() {
        $("#max_tokens").html($("#num_tokens").val())
    });

    // If ctrl + enter is pressed anywhere on the page:
    $(document).keypress(function(e) {
        if ((e.keyCode == 10 || e.keyCode == 13) && (e.ctrlKey || e.metaKey)) {
            send_request();
        }
    });

    $("#send_button").click(function() {
        send_request();
    })

    // Hide the API settings and usage reference:
    $(".api_settings").find(".min_max").click();
    $(".usage_reference").find(".min_max").click();
});
```

Fig. 21. Interface set-up and Integration to ChatGPT.

scenario above with the user query: "Suggest the best material to be used for the door to toilet WC 15." ChatGPT successfully provides optimized material recommendations for a bathroom door, taking into consideration various factors. In contrast to zero-shot scenario, it carefully avoids suggesting wood as it is prone to moisture damage in bathroom settings and acknowledges the privacy concerns associated with glass, although glazed glass could provide a privacy solution. Instead, ChatGPT recommends steel and composite materials as viable options, owing to their moisture resistance and durability.

ChatGPT demonstrates its understanding of a specific door element and its location within the BIM model. It recognizes that a door to a bathroom, specifically WC15, is susceptible to water damage owing to its proximity to moisture sources. Based on the available data from the BIM model, ChatGPT analyses possible materials for the door, compares them using factors such as location, area of the component, and other relevant attributes. Furthermore, ChatGPT considers additional factors such as material availability, cost, and energy efficiency during the selection process. The user also has the option to specify the factor that holds the utmost importance, enabling ChatGPT to prioritize that factor in its final recommendation.

Fig. 24 displays another few-shot scenario where the user query “suggests the energy efficient wall named Maconnerie Isolant.” The BIM query, conducted through the data retrieval module, confirms that the wall in question is an external wall before calling up the ChatGPT API (GPT 3.5 Turbo model), which then analyses possible materials, taking into account the available data within the model, such as the external nature of the wall and the user’s requirement for energy efficiency to suggest an insulated concrete wall with an R-value of up to 20.

The few-shot scenario showcases the remarkable capability of ChatGPT as a valuable tool for guiding home builders in selecting the most suitable materials for their constructions. By leveraging both general information and user-defined preference parameters, ChatGPT offers informed recommendations that align with the desired characteristics of building components.

7.4.3. *Edge case prompting scenario*

In Fig. 25, when ChatGPT was prompted with a question ‘*What is BIM*’ that was not related to material selection and optimization, it responded with the message, "I apologize, but I am unable to handle your request as it is not related to material selection and optimization". This indicates that ChatGPT can be tailored to specific needs and deployed as an expert system in a particular field. The prototype allows for easy leveraging of the extensive language capabilities of ChatGPT by readjusting the prompts, without the need for technical experts as

Fig. 22. Zero-shot scenario.

Fig. 23. Few-shot scenario.

required by other NLP systems. This capability empowers construction practitioners to actively participate in rapid testing and prototyping processes, making the system more accessible and user-friendly for industry professionals.

7.5. Limitations

The prototype demonstrated the capability of selecting the best material for a specific component in a BIM model. However, it requires the identification of the component to provide accurate responses. Future studies would include enhancing the system by probing components and their properties in multiple conversations and leveraging the seamless NLP feature of ChatGPT. This involves guiding the user with a list of parameters to choose from, such as cost, geographical location, and aesthetics, to improve the selection process. Engaging industry stakeholders allows for the collection of query and response data, which can be used to fine-tune the ChatGPT model for better efficiency. In addition, the prompt development process will be evaluated and improved to minimize incorrect or irrelevant responses to user queries. These enhancements will enhance the overall performance and reliability of the material selection and optimization system.

8. Conclusion

Application of LLMs/Generative AI such as GPT models is still low despite these models overcoming some of the previous challenges that make the deployment of AI difficult in the construction industry. For instance, the time and expertise needed in the development of Conversational AI systems have been drastically reduced by the GPT models trained on large databases. Sectors such as education, medicine, and business have been leveraging these new large language models to improve their modus of Operandi. However, little is known about the opportunities and limitations of leveraging GPT models in the construction industry. Consequently, this study employed three sequential steps to identify and evaluate the opportunities and limitations of GPT models in the construction industry. A detailed preliminary study was conducted and reinforced with an expert discussion on the opportunities and limitations of GPT models. Based on the identified opportunities, a

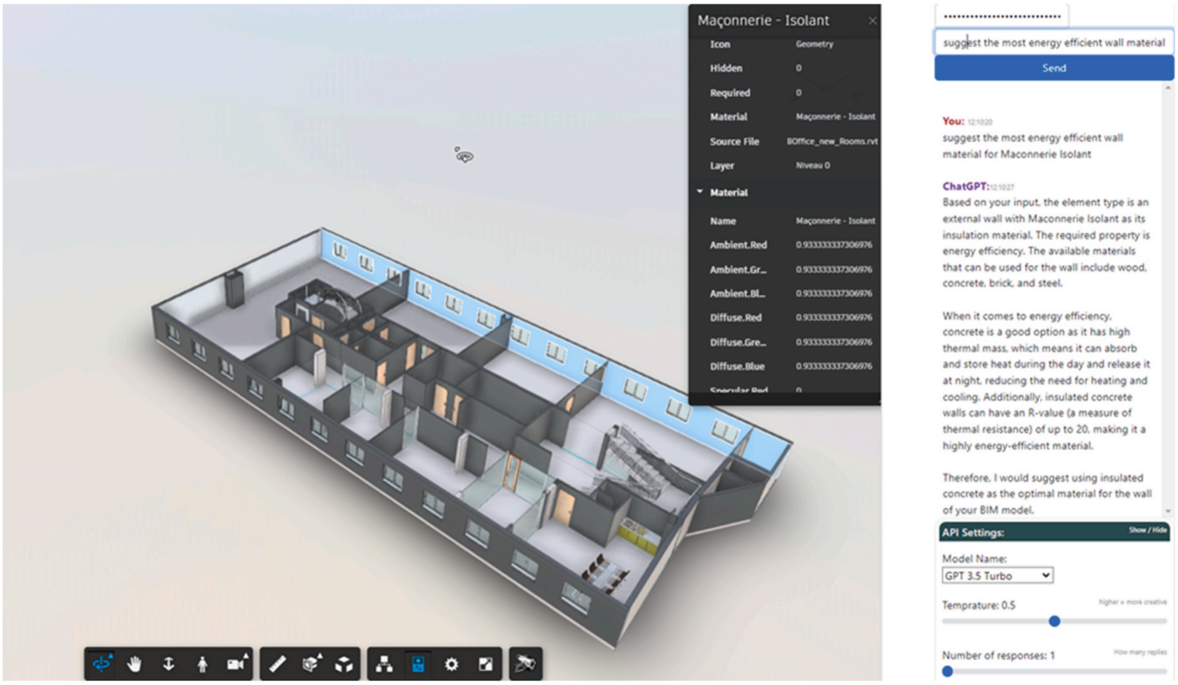

Fig. 24. Prompting (Happy path user).

Fig. 25. Prompting (Edge case).

use case was validated, and a prototype was developed for material selection and optimization by integrating BIM with a GPT model.

The study reveals that although large language model such as BERT has been gaining attention in the construction industry, GPT models are not well known in the industry until the recent launch of ChatGPT. The study highlights that current applications of GPT models in the industry are for information retrieval, scheduling, and logistics. Opportunities identified for the deployment of GPT models span the predesign, design, construction, and post-construction phases of the project. Also, value-added services are discussed as part of the opportunities for GPT models which include areas that are not directly related to a specific phase of the project lifecycle. These opportunities were discussed, and the findings reveal that the GPT models can be leveraged for some of the opportunities with zero-shot learning, few-shot learning, chain-of-thoughts learning via prompt designs or integration with existing systems. Similarly, some of the opportunities require the need to fine-tune GPT models with structured data to improve the performance of the models and leverage existing or external databases (RAG). However, despite these immense opportunities, the study shows that the deployment of GPT models in the construction industry would need to overcome challenges that are inherent in the GPT models and within the construction industry. Inherent limitations of GPT models such as hallucinations, accepted input formats, cost and reliability were highlighted in the study. On the other hand, challenges such as trust, acceptability, domain technicalities, skills, and interoperability which ensue because of the construction industry context were revealed. Furthermore, the study validated a use case with one of the opportunities – materials selection and optimization – by integrating BIM and

GPT. The data retrieval module, NLP prompt processing module, user interface and integration module were developed for the prototype. The study shows that leveraging the developed prototype would improve efficiency by providing the stakeholders with materials and optimizing the selection based on defined objectives such as the location of the components and cost.

In addition, there are limitations that serve as fertile grounds for further research. The preliminary search for literature was conducted in Scopus, google scholar, web of science and validated in other databases (ACM and Science direct) which could serve as a limitation. Similarly, the search query developed, and the inclusion criteria of the English language could have led to the missing of some publications. Also, the size of the expert recruited for the discussion could serve as a limitation; however, due diligence was observed to ensure the experts have the right experience. The developed prototype was also not subjected to any quantitative validation to evaluate its performance. Further studies can explore the different opportunities areas highlighted in this study by developing prompts, fine-tuning and integrating GPT models with existing databases and systems. Also, an advanced extension of the materials selection and optimization system is currently being developed by the researchers. This study contributes to the growing body of knowledge on the application of GPT models and provides research vistas for leveraging GPT models in the construction industry. It highlights the current limitations of LLMs and the need to overcome these barriers for the proliferation of LLMs in the construction industry. Its findings would be of benefit to researchers and stakeholders in the AEC industry.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors would like to acknowledge and express their sincere gratitude to Leeds Beckett University for providing financial support for this study.

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