Advanced Engineering Informatics 55 (2023) 101869

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Conversational artificial intelligence in the AEC industry: A review of present status, challenges and opportunities

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ARTICLE INFO

Keywords:
Artificial Intelligence
Conversational artificial intelligence
Conversational agents
Chatbot

ABSTRACT

The idea of developing a system that can converse and understand human languages has been around since the 1200 s. With the advancement in artificial intelligence (AI), Conversational AI came of age in 2010 with the launch of Apple's Siri. Conversational AI systems leveraged Natural Language Processing (NLP) to understand and converse with humans via speech and text. These systems have been deployed in sectors such as aviation, tourism, and healthcare. However, the application of Conversational AI in the architecture engineering and construction (AEC) industry is lagging, and little is known about the state of research on Conversational AI. Thus, this study presents a systematic review of Conversational AI in the AEC industry to provide insights into the current development and conducted a Focus Group Discussion to highlight challenges and validate areas of opportunities. The findings reveal that Conversational AI applications hold immense benefits for the AEC industry, but it is currently underexplored. The major challenges for the under exploration were highlighted and discusses for intervention. Lastly, opportunities and future research directions of Conversational AI are projected and validated which would improve the productivity and efficiency of the industry. This study presents the status quo of a fast-emerging research area and serves as the first attempt in the AEC field. Its findings would provide insights into the new field which be of benefit to researchers and stakeholders in the AEC industry.

1. Introduction

Artificial intelligence deals with the science of developing intelligent models and machines that can mimic human intelligence processes [1]. Its application has been transforming diverse fields and improving productivity [2]. The architecture engineering and construction (AEC) industry is not left out in applying AI to solve problems or improve conventional approaches. There has been a surge in the application of AI in the AEC industry over the last decades [1]. Consequently, studies have reviewed extant literature on AI in the industry [3–6]. A fast and emerging new research area in AI is Conversational Artificial Intelligence (Conversational AI) which is aimed at improving human–computer interaction. Per Kulkarni, Mahabaleshwarkar [7], Conversational AI is a "sub-domain of Artificial Intelligence that deals with speech-based or text-based AI agents and have the capability to simulate and automate conversations and verbal interactions". Conversational AI is brought about by advancements in Natural Language Processing (NLP) which has been revolutionising the way humans relate with computers. Hitherto, the review of Conversational AI in the AEC sector has not been presented in the literature.

Although Conversational AI became mainstream in recent decades, the idea of developing machines that can understand and converse intelligently with humans has been around since the 1200 s [8]. ELIZA was developed in 1966 at the Massachusetts Institute of Technology (MIT) Artificial intelligence laboratory by Joseph Weizenbaum who employed the pattern matching and substitution methodology to simulate chatbot experience [9]. It was the first program to attempt the imitation game proposed by Alan Turing to evaluate a machine's ability to behave intelligently in a similar way to humans [10]. Many other chatbots followed such as PARRY (1972) which was developed to

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https://doi.org/10.1016/j.aei.2022.101869
Received 12 July 2022; Received in revised form 30 November 2022; Accepted 27 December 2022
Available online 3 January 2023
1474-0346/

simulate paranoid schizophrenia behaviour, Alice (1995), Cleverbot (1997), Mitsuku (2005) and many others. Domain chatbots and Spoken Dialogue Systems emerged and were adopted by businesses to improve customer management. For instance, *How May I Help You (HMIHY)* spoken dialogue system was used by AT&T to attend to callers and to route them to the right destination, thereby reducing the cost of engaging human agents for such actions and allowing them to focus on more complex tasks [11]. Mercury was developed to provide phone-call access to a database of flights that includes schedules and prices to enable callers to plan itineraries independently without human agents [12]. With more complicated tasks and users' requirements, chatbots had to go beyond the use of scripted dialogues and need to be 'conversational', heralding the new Conversational AI [9]. This came of age in 2010 with the launch of Siri by Apple which is the first and most widely accepted virtual assistant. Consequently, many companies have launched different virtual assistants such as Amazon's Alexa, Microsoft's Cortana, Google Assistant, and Samsung's Bixby.

Popularity in the development of Conversational AI systems is a result of advancements in machine learning, the development of graphics processing units (GPU), and the involvement of big companies [13]. The success of these Conversational AI systems can be related to the improvement of human–computer interactions they brought about. It is not surprising that the Conversational AI global market size is expected to grow at a compound annual growth rate of 21.9 % moving from 4.8 billion USD in 2020 to 13.9 billion USD in 2025 [14]. Conversational AI is expected to change and support business models, supply chains, logistics, customer relationships, and improve productivity across industries [15]. Applications of Conversational AI systems are increasing in e-commerce (to attend to customers) [16], in the health care sector (for providing information to cancer patients, sex education, professional training, and chronic diseases) [17], in travel, tourism, and hospitality [18]. However, the application of Conversational AI in the AEC industry is still in the infancy stage compared with other sectors.

The AEC industry stands to benefit from the application of Conversational AI systems in its domain because of the current business models and the information-intensive nature of its ecosystem[19]. Also, the hands-busy and eye-busy nature of construction sites makes the use of Conversational AI systems a perfect fit to boost the productivity of the industry [1]. However, there is a lack of a general overview of the application of Conversational AI systems in the AEC industry. Consequently, this present study aims to achieve the following objectives:

i) Critically review the extant literature on Conversational AI systems in the AEC industry
ii) Identify and discuss applications and challenges of adoption of Conversational AI in the AEC industry
iii) Identify and discuss opportunities for Conversational AI in the AEC industry

The scientific contributions of this study are i) it presents an overview of an emerging research area which has not been addressed in the AEC industry ii) it provides a clear understanding of the status quo and trend which is necessary for further improvement and development of Conversational AI systems in the construction domain iii) it presents strategic areas in the AEC industry which can benefit from Conversational AI applications, thereby providing future research directions for the industry practitioners and researchers. Due to the numerous nomenclatures for Conversational AI in the literature, the term Conversational AI system would refer to any system or application that is text-based or speech-based with the capability to simulate conversation or interactions between AI agents and users. Thus, Conversational AI systems would be used as a synonym for chatbots, spoken dialogue systems and question-answering systems in this paper.

The rest of the paper is organised as follows: Section 2 presents related literature in the AEC sector and from other sectors. Section 3 presents the overview of Conversational AI with an emphasis on the system architecture and development approaches. Section 4 discusses the systematic research approach employed in this study. Section 5 presents a critical review of the identified literature, and a *meta*-synthesis of the studies to draw insights into current Conversational AI developments and Focus Group Discussion to highlight challenges and opportunities in the AEC industry. Lastly, section 6 presents the conclusion which entails the contributions of the study, significance, and limitations of the study.

2. Literature review

There has been an increase in the application of AI in the construction industry over the years. Consequently, there has been an increase in review studies on AI applications, challenges, and opportunities in the literature. Bilal, Oyedele [20] reviewed the prospects of big data in the construction industry and identified the opportunities, challenges, and future research direction. However, Darko, Chan [3] employed a scientometric approach and focused on the broader concept of artificial intelligence and reviewed the AI algorithms and application areas in the AEC industry. Abioye, Oyedele [1] adopted a systematic review and presented the trend in the applications of AI and identified the challenges hampering the widespread deployment of AI in the industry and future research opportunities. Akinosho, Oyedele [4] went further and specifically reviewed deep learning applications in the construction industry. Other studies have focused on the application of AI in specific domains in the AEC industry. For instance, Debrah, Chan [21] explored the applications in green buildings and Zabin, González [22] reviewed the applications of machine learning to BIM-generated data. Overall, these extant reviews (Table 1) of AI in the construction industry are important and improved the understanding of AI applications, challenges, and opportunities of AI in the industry. However, these studies are from a broader perspective of AI. None of these reviews has critically reviewed specific areas of AI applications, albeit these studies often highlight specific areas of AI for research opportunities e.g virtual assistant and Conversational AI. Conversational AI is an emerging area which has been gaining attention in the industry and practice but hitherto there is no overview of Conversational AI in the AEC industry.

Extant reviews on Conversational AI in the literature are from other sectors like business, health, commerce, tourism, and hospitality. For instance, Bavaresco, Silveira [23] presented an overview of conversational agents in the business domain and identified the areas of applications, goals of the agents, development of the agents, and future directions. Similarly, de Barcelos Silva, Gomes [24] reviewed studies on Intelligent Personal Assistant (IPA) and revealed the trends, areas of applications, development and future opportunities and proposed a taxonomy for the classification of IPA. Surprisingly, although the study adopted a general domain focus in the review, none of the 58 reviewed IPA/ studies is from the AEC industry as they are majorly from the health and education domain. In addition, Schachner, Keller [17] presented a systematic review of conversational agents designed for chronic diseases in the health sector by evaluating their development and type of chronic disease. Similarly, Mohamad Suhaili, Salim [25] reviewed extant studies on service chatbots to determine the research trend, development and evaluation of the chatbots.

Based on the review of relevant studies, it is established that current reviews on AI in the AEC industry have not addressed the Conversational AI field and there is no overview of Conversational AI systems that have been developed in the industry. The extant reviews on Conversational AI are majorly from the health and business sectors and do not address the AEC sector. Thus, this present study aims to explore and advance Conversational AI in the AEC industry which is a current gap in knowledge.

3. Overview of Conversational artificial intelligence systems

This section presents a summarized overview of Conversational AI

Table 1
Reviews of Artificial Intelligence in the AEC Industry.

S/N	Author(s)	Year	Method	Domain	Aim
1	Zabin, González [22]	2022	Scientometric	Building Information Modelling (BIM)	It reviewed applications of machine learning techniques for BIM-generated data
2	Debrah, Chan [21]	2022	Scientometric and Systematic Review	Green building	It reviewed studies on the applications of AI in green buildings.
3	Pan and Zhang [26]	2021	Scientometric and Systematic Review	Construction engineering and management	It reviewed the evolution of AI applications in the construction engineering and management domain
4	Abioye, Oyedele [1]	2021	Systematic Review	General domain	It reviewed AI applications and techniques employed in the AEC industry
5	Akinosho, Oyedele [4]	2020	Systematic Review	General domain	It reviewed applications of deep learning techniques in the construction industry
6	Darko, Chan [3]	2020	Scientometric	General Domain	It reviewed AI techniques that have been applied in the AEC industry
7	Elmousalami [27]	2020	Systematic Review	Cost Prediction	It reviewed the AI techniques for cost modelling
8	Hatami, Flood [15]	2019	Critical Review	Automated construction manufacturing systems	It reviewed AI methods for automated construction manufacturing
9	Panchalingam and Chan [28]	2019	Systematic Review	Smart Buildings	It reviewed studies on AI applications in smart building domains (maintenance, energy, design, safety, and comfort)
10	Bilal, Oyedele [20]	2016	Critical Review	General domain	It reviewed big data analytic techniques in the construction industry

systems which covers a brief history of Conversational AI systems, Conversational AI system development and system architecture of a typical speech-based Conversational AI system. This section is important as it introduces key concepts in Conversational AI systems. Also, an overview of these concepts is important for a better understanding of subsequent sections in this paper. Thus, terminologies, techniques and concepts introduced in this section would be referred to in subsequent sections.

3.1. History and categorization of Conversational AI systems

The dream of developing machines that can interact with man permeates time to the early ancient Greek creation of robots and the imagination of artificial life that is 'made, not born'[29]. With the emergence of ELIZA and many other chatbots that followed it in the 1900 s, Conversational AI came of age in 2010 because of advanced development in NLP. The Conversational AI domain has become an area of research interest and to say it is rapidly evolving is an understatement [9]. Conversational AI systems are referred to with different terms such as 'social robots', 'dialogue system', 'spoken dialogue system', 'conversational agent', 'chatbots', 'personal digital assistant', 'voice user interface'. Chatbots.org listed 161 acronyms used in referring to Conversational AI systems which signify the rapid level of development and attention the domain is getting over the years.

Per McTear [13] previously developed systems ranges from Text-based and spoken dialogue system, Voice user interface, Chatbots, Embodied conversational agent, to Robots and situated agents. Based on these previous studies, this study categorized the Conversational AI systems into different groups depending on diverse categorisation perspectives as shown in Fig. 1.

The categorization of the Conversational AI systems in this study is based on extant studies where different approaches, channels, objectives, modalities, initiation & turn, and communication method have been established. However, the categorization is not exhaustive.

Channel: Users can interact with Conversational AI systems via voice like Siri, text or a combination of both speech and text. Similarly, Conversational AI systems give feedback to the user via text, speech or visual or a combination of these different modes.

Objective: Conversational AI systems can be task-oriented for a particular task such as ordering food, booking a flight or making an appointment. These systems are also referred to as domain-specific or goal-oriented chatbots or task-oriented. The opposite categories are the non-task-oriented systems or open-ended chats that are chit-chat and do not result in the fulfilment of a particular task or objective.

Initiation and Turn: Conversational AI systems can initiate conversation and direct conversation flow by asking users questions or the user can initiate the conversation. This conversation can be directed by the system, users, or a mixed initiative where the user and machine can ask questions. Also, the conversation can be multiturn where the user and system converse for more than a turn or a single turn where the user or

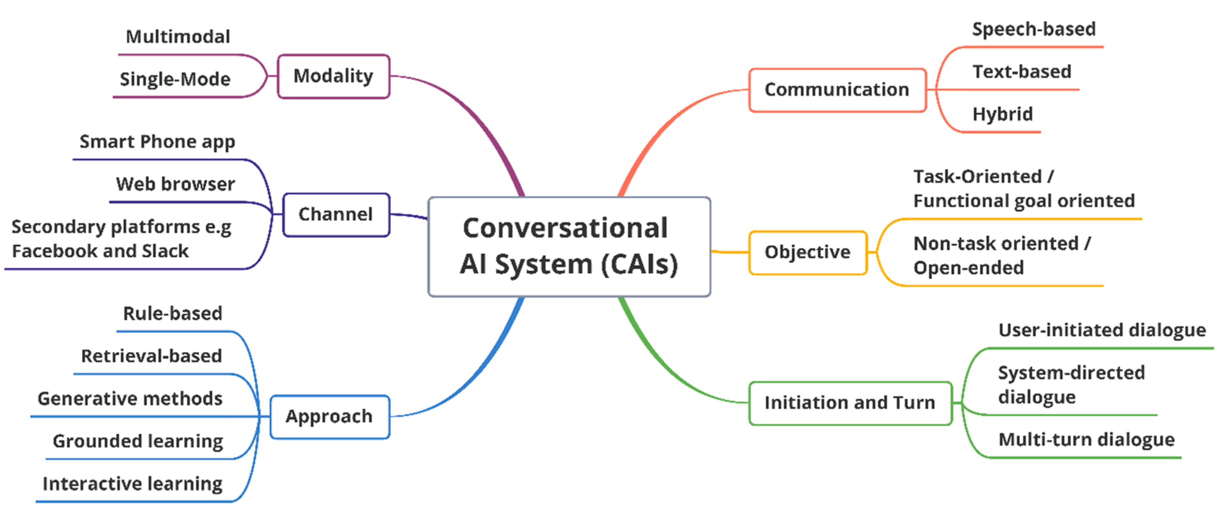

Fig. 1. Categorization of Conversational AI Systems.

machine interacts only once.

Approach: The dialogue management system is the central system of a spoken dialogue system as it interacts with the input from the user, using knowledge databases to determine the action to be taken in the dialogue. It can be developed based on different approaches such as rule-based, statistical data drive, end-to-end or hybrid. The DM can also be categorised as rule-based, retrieval-based, generative method, grounded learning, or interactive learning.

Modality: Communication goes beyond text or speech and includes gestures. Conversational AI systems can employ either text, speech or vision or a combination of these modes in conversation. Single modes such as text and speech and multi-modal such as text and speech are more common than multi-modal systems which combine speech, texts, and vision. This is because communication via vision which involves the use of facial expressions, and gestures are difficult [30].

Lastly, there are different approaches employed in the development of Conversational AI systems over the years. The earliest adopted approach is rule-based, followed by using statistical techniques and recently the use of deep neural networks.

3.1.1. Rule-based approach

This is the earliest form of dialogue management system in which the decision to be taken are anticipated and handcrafted as pre-scripted rules by the designers. Per McTear [13], the designers are certain that they have the system under control, however, there are many shortcomings of the approach. The system is time-consuming and costly in scripting, it is not scalable, and requires effort for maintenance. Similarly, although the designers have pre-scripted the rules according to best practice guidelines, however, the approach is not guaranteed to be optimal. Also, the system often struggles in 'edge cases' (where the user is not acting as expected, opposite of 'happy path'). This serves as motivation for employing a statistical data-driven approach.

3.1.2. Statistical data-driven approach

Based on the shortcomings of the rule-based approach, the statistical data-driven approach is employed in which the components of the system are modelled probabilistically [13]. The dialogue management system consists of dialogue policy and dialogue state tracking against dialogue control and dialogue context model in a rule-based approach [13]. Per McTear [13], the challenges of this approach are scalability, black box problem, and its optimization requires large data.

3.1.3. End-to-End neural approach

Although the previous approaches have been well employed in industry and academia, these approaches have shortcomings and there have been many extant and ongoing studies on improvement. Coupled with the highlighted shortcomings in the previous sections, the modularised structure of their architecture can lead to knock-on effects when a module is optimised leading to an adverse effect on the other modules. Thus, the end-to-end neural approach employs a sequence-to-sequence architecture. Although, the architecture employed in this system has an edge over knock-on effects as the whole system is optimised. However, this also serves as a pitfall of the system as it is difficult to pinpoint which part of the system is underperforming during evaluation known as the credit assignment problem[31]. Basically, the approach involves mapping user utterances directly to output using Deep Neural Networks (DNNs). Automatic speech recognition (ASR) and text-to-speech (TTS) operate separately from the system for taking in input in text and for sending out output in a spoken text when employed in a spoken dialogue system.

3.2. System architecture of a Conversational AI system

Fig. 2 presents an example of a Conversational AI system architecture. The components of a conversational interface are automatic speech recognition (ASR) which takes the speech input from the user for processing and conversion to text [8]. The Natural Language Understanding (NLU) component analyses the text from ASR to determine its meaning (intent classification and entity extraction) [7,13]. Based on the output from the NLU, the dialogue management system interacts with the knowledge sources to determine the action to be taken by the system. The direction given by the dialogue management system is then converted to text in the Natural Language Generation (NLG) component which is then transferred to the text-to-speech (TTS) component which converts the text into speech back to the user. Although this section presents the architecture for a voice-based Conversational AI system, the major difference between speech-based and text-based systems is the absence of ASR and TTS in the text-based systems.

3.2.1. Automatic speech recognition

This component deals with the conversion of speech input to text for further processing. It is made up of feature and signal extraction, acoustic model, language model and hypothesis search [32]. Previously, ASR employed Gaussian Mixture Models (GMMs), Hidden Markov Models (HMMs), Mel-frequency Cepstral Coefficients (MFCCs) and language models such *N*-gram language models, or finite state grammars. However, with the advancement in research, new techniques are gaining application in ASR. Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are now being employed in ASR which has shown improvement over the previous approaches. Also, companies and organisations have built ASR for use such as Google, IBM Watson, NVIDIA, Microsoft Azure, Microsoft Speech API, and Amazon Transcribe [33]. The ASR is evaluated with metrics such as word error rate (WER), Match Error Rate (MER), relative

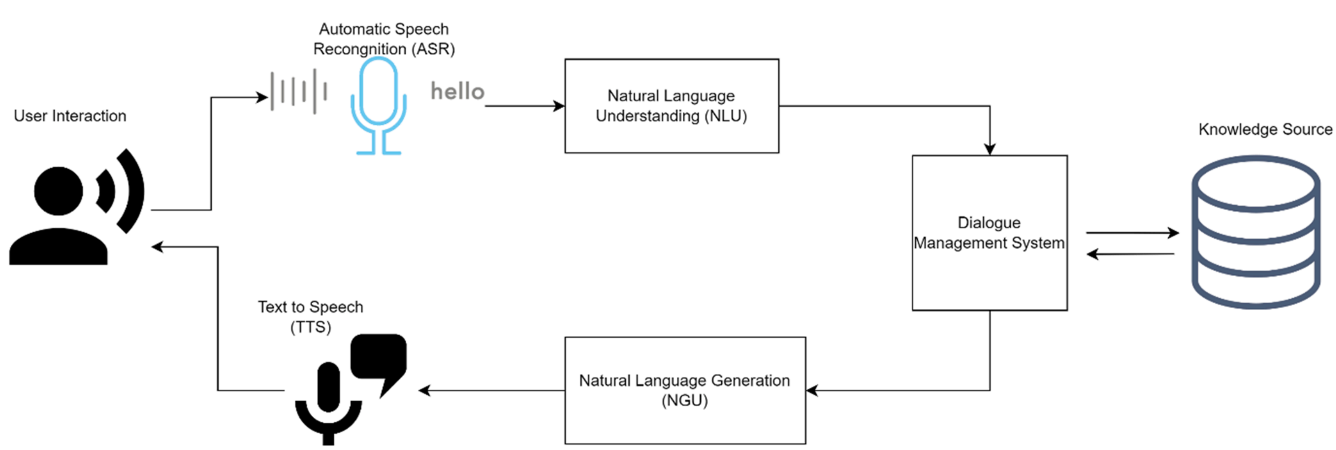

Fig. 2. An Example of a System Architecture for Conversational Artificial Intelligence System (Adapted from Kulkarni, Mahabaleshwarkar [7] and McTear [13]).

information lost (RIL), Hypothesis Per (Hp), references per (Rper), Position Independent Word Error Rate (PER), and word information lost (WIL) [33]. However, although the WER has many shortcomings, it is the most employed metric [34].

3.2.2. Natural language understanding (NLU)

NLU is a complex subdomain of natural language processing (NLP) that deals with the task of understanding human language. It involves intent classification and entity extraction from input [35]. Intent classification (IC) is the process of identifying the user's sentiment and determining the user's objective. Traditional IC models employed approaches such as Hidden Markov Models (HMM), Decision Trees (DT) and others. With the advancement in machine learning, deep learning is now employed for intent classifications. Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), bidirectional Long Short-Term Memory (biLSTM), and shallow feedforward networks are used to improve intent classification. Entity extraction or named entity recognition (NER) deals with extracting entities and classifying them into predefined classes. Conditional Random Fields (CRFs) were commonly employed for NER, and new approaches such as CNNs, and biLSTM improves entity extraction. The NLU component is evaluated by comparing output from the component with a reference representation. Metrics such as sentence accuracy, concept accuracy, confusion matrix, precision, recall and F1 [13].

3.2.3. Dialogue management system

This is the central system of the dialogue system which takes input from the ASR, and NLU and interacts with the knowledge source to determine the flow of the dialogue and follow-up actions. It is made up of a context model or dialogue state tracking or belief state tracking and a decision model or policy model [13]. The context model holds all the information to aid the dialogue and may include knowledge sources while the decision model decides the next stage of the dialogue based on the information in the context model. The decision taken depends on the approach employed in the dialogue system which can be a rule-based, statistical driven or neural dialogue system. The dialogue management system is evaluated based on how well it managed the dialogue and which can be measured via the number of system and user turns, how many times the system time out [13].

3.2.4. Natural language generation (NLG)

This component deals with outputting the system response to the user in a human language based on the output from the NLU and dialogue management system. The NLG is a sub-domain of NLP and refers to as response generation [25]. Its architecture can be said to consist of document planning, microplanning and realization module [36]. The different techniques employed in generating responses in CAIs include template-based, statistical approach, neural network approach or hybrid approach [7]. The template-based maps input into a predefined template, however, the predefined templates do generalize gender and number and make conversation boring [37]. Other approaches are the *N*-Gram generator, recurrent neural network (RNN), and sequence-to-sequence model [38]. The NLG performance can be evaluated based on several metrics such as comparing the output to human-generated responses, rating &judgement of the responses by humans, and task-based evaluation [39].

3.2.5. Text-to-Speech synthesis (TTS)

This component deals with converting the output from the NLG to speech and traditionally involves text analysis and waveform analysis [13]. When texts to be outputted consist of acronyms, they are converted to the full meaning and the whole text is transformed into phonemes and includes information about the rhythm, stress, and intonation. The transformed text is then converted into waveforms which are outputted as spoken text. With the advancement in machine learning, neural networks are now being employed in TTS to improve performance [40]. Per Wagner, Beskow [41], the evaluation for TTS can be classified into objective, subjective and behavioural assessment. The objective assessment involves scoring synthetic speech, while the subjective assessment involves assessing the users' interaction quality via a questionnaire. The behavioural assessment involves assessing aspects such as intelligibility and comprehensibility of the TTS output.

4. Research methodology

This study adopted a systematic literature review approach to achieve the set-out objectives per the Preferred Reporting Items for Systematic Reviews and meta-Analyses (PRISMA) approach and guidelines provided by Kitchenham and Charters [42]. Sequel to the systematic review, a semi-structured Focus Group Discussion (FGD) of Domain experts and Conversational AI experts was conducted to highlight and validate the challenges and opportunities of Conversation AI in the AEC industry. A systematic review is employed in this study as against scientometric review because the former is an approach to evaluating and interpreting available documents with a trustworthy and auditable methodology [42]. On the other hand, a scientometric review is the mapping of scientific knowledge [43] in a well-established domain – as it requires a large dataset. Also, it often involves the use of tools to map the trends and networks of keywords, authors, and references [44]. However, critical reviews also refer to as critiques involve presenting detailed commentary on and critical evaluation of texts. The systematic literature review has touches of critical review and provides methodological steps for reproducibility [42].

PRISMA is employed because it is 'evidence-based', the steps involved are auditable and has been well-established and used in the literature and similar studies [45]. Fig. 3 shows the data collection process via the PRISMA flow chart. The following sections discuss the process of the review.

4.1. Search strategy

The search was conducted in Scopus and Web of Science and then validated in IEEE Xplore (Institute of Electrical and Electronics Engineers), ACM (Association of computing machinery), Google Scholar, and Science Direct. These databases were selected because they host high-impact publications relating to the AEC industry and have been used in reviews covering similar themes [1]. The query was constructed based on terms in the literature and input from Conversational AI experts. Thus, the query was divided into three categories: Conversational AI systems, artificial intelligence and the construction industry as shown in Table 2. Also, the search was complemented with a citation tracking approach which involves checking the reference list of relevant publications to track other relevant publications. This approach was employed until the saturation point (i.e. where the track leads back to previous results).

4.2. Selection criteria

General search criteria: The developed search query was used in Scopus without year restriction with a focus on the subject areas of '*Engineering*' and '*Computer science*' and only documents available in the English language. Similarly, the search query was employed in the IEE Xplore database without restrictions (year and publication topics) and the *'Search within results'* option was used to sieve the outputs. Also, the Web of Science Core Collection was searched for the query and limited to '*Engineering Civil*' and '*Construction Building Technology*' without publication years and document type restrictions. The search in Science Direct was conducted sequentially because of the Boolean connectors' limitation in the search option; no year restriction and '*Engineering*' subject area were considered. Lastly, ACM digital library was searched with the developed query and research output reviewed for AEC-related

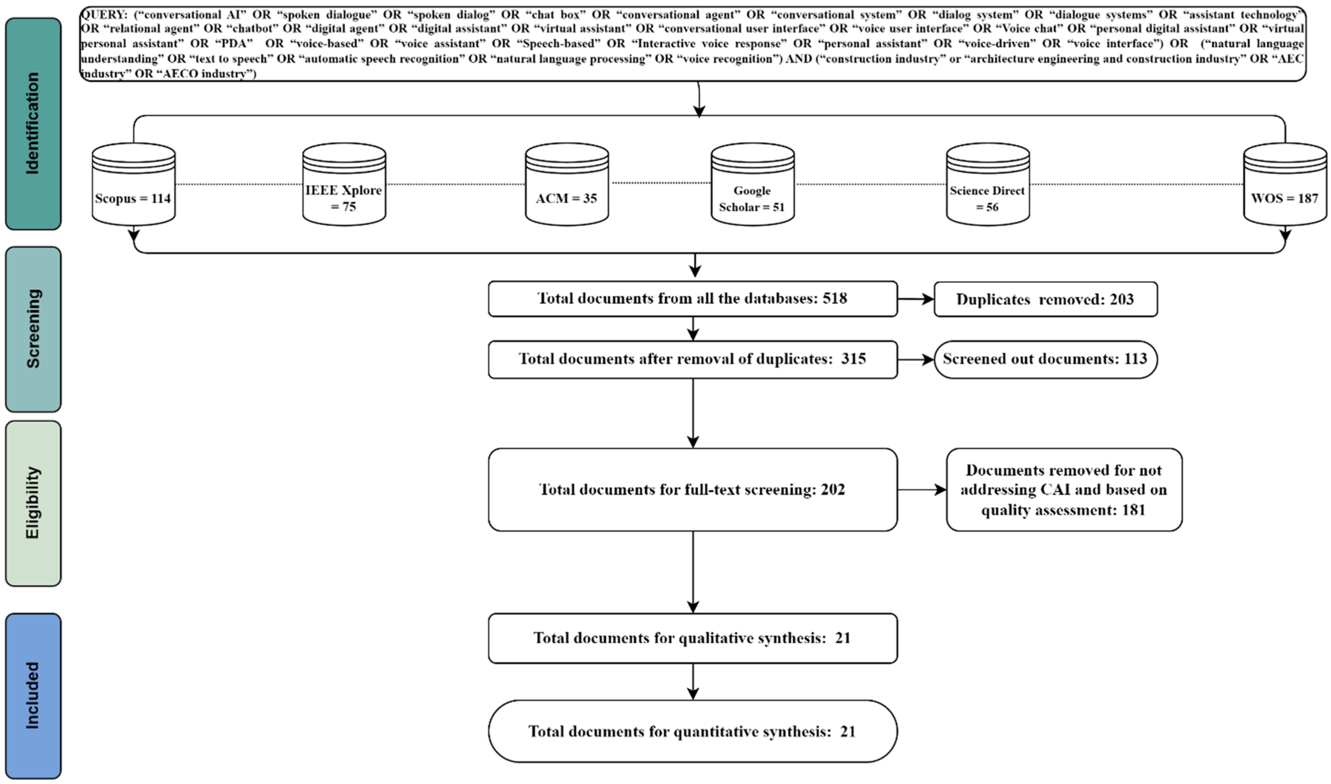

Fig. 3. Documents collection process (*Preferred Reporting Items for Systematic Reviews and meta-Analyses Flow Chart*).

Table 2
Search Query.

S/N	Search Category	Search Query
	Construction Industry	"construction industry" OR "architecture engineering and construction industry" OR "AEC industry" OR "AECO industry"
	Conversational AI	"conversational AI" OR "spoken dialogue" OR "spoken dialog" OR "chat box" OR "conversational agent" OR "conversational system" OR "dialog system" OR "dialogue systems" OR "assistant technology" OR "relational agent" OR "chatbot" OR "digital agent" OR "digital assistant" OR "virtual assistant" OR "conversational user interface" OR "voice user interface" OR "Voice chat" OR "personal digital assistant" OR "virtual personal assistant" OR "PDA" OR "voice-based" OR "voice assistant" OR "Speech-based" OR "Interactive voice response" OR "personal assistant" OR "voice-driven" OR "voice interface"
3.	Artificial intelligence	"natural language understanding" OR "text to speech" OR "automatic speech recognition" OR "natural language processing" OR "voice recognition"
4	Combined	1 AND 2 OR 3

literature.

Refining criteria: Studies were included based on these predetermined criteria: 1) studies that involved the application of Conversational AI in the AEC industry; 2) studies that involved the development of Conversational AI in the AEC industry; and 3) studies that involve the integration of Conversational AI to AEC domains. Similarly, articles were excluded based on these predetermined criteria: 1) studies that do not employ Conversational AI for application development; 2) review studies that mentioned Conversational AI but do not explore its applications; and 3) non-English studies. However, conference papers were considered because Conversational AI application is still an emerging area in the AEC and to avoid publication bias [46].

4.3. Selection process

The result from the refined search was input into an excel sheet and details (title and abstract) of each paper were populated in the columns. Duplicates were removed and a review was conducted by independent reviewers to assess if each paper meet the inclusion criteria. Cohen Kappa was computed to evaluate the inter-rater reliability between the reviewers [47]. In the case of disagreement between the rating of the reviewers, discussion till a consensus was employed to resolve such.

4.4. Data extraction and quality assessment

The result was further reviewed, and the following information was extracted from each publication: 1) Year; 2) Authors; 3) Title; 3) Publication type; 3) Aim; 4) Methodology; 4) and 5) Domain area. Per Kitchenham and Charters [42], quality assessment was conducted using the checklist provided in Table 3 as employed in similar studies [25,48]. Publications that passed 70 % of the checklist were considered for further evaluation in this study.

Table 3
Quality Assessment Checklist.

No	Checklist
1	Are the aim and objectives clearly stated?
2	Is the reporting logical and coherent?
3	Are the proposed technique well described?
4	Is the employed research methodology suitable for the objectives?
5	Are the methods for data collection adequately described?
6	Do the interpretation and conclusion hinge on the data?
7	Is there an incremental contribution to knowledge?
8	Are the aims and objectives fulfilled?
9	Is the research process well documented?
10	Is the study reproducible?

5. Results

This section presents the analysis of the 21 retrieved documents which included research articles and conference papers that meet the requirement and pass the quality assessment check conducted by the independent reviewers.

5.1. Document analysis

A total of 21 documents were considered for further analysis in this study which revealed that research on conversational artificial intelligence systems in the AEC is yet to be fully explored. These assertions are reinforced by 38 % (8 of 21) of the documents being conference papers from reputable conferences and 62 % (13 of 21) being articles published in peer-reviewed journals. Also, the recency of this research area can be deduced from the publications emanating between 2002 and 2022. The journal articles are from the *'Automation in Construction', 'Journal of Construction Engineering and Management', 'Advanced Engineering Informatics', 'Computer-Aided Civil and Infrastructure (CACIE)', 'Facilities',* and *'Journal of Computing in Civil Engineering (JCCEE')*. Similarly, the conference papers are from *'CIB W78 International Conference'*, *'Construction Research Congress (CRC)'*, *'International Workshop on Intelligent Computing in Engineering (EG-ICE)'*, *'International Conference on Computing in Civil and Building Engineering (ICCBE)'*, and *'International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA)'* as shown in Fig. 4. Lastly, the year 2022 has the highest number of publications which reflect corroborate recency of the research area and the increased attention given to the area in the construction industry.

AIC: Automation in Construction; JCEM: Journal of Construction Engineering Management (ASCE); I3CE: International Conference on Computing in Civil Engineering (ASCE); EG-ICE: European Group for Intelligent Computing in Engineering; ICCCBE: International Conference on Computing in Civil and Building Engineering; AEI: Advanced Engineering Informatics; CRC: Construction Research Congress (ASCE); CI: Computers in Industry; CAADARIA: Conference of the Association for Computer-Aided Architectural Design Research in Asia; JF: Journal of Facilities (Emerald); CACIE: Computer-Aided Civil and Infrastructure Engineering (Wiley); CIB W78: CIB Working Commission (W78) on Information Technology for Construction; JCCEE: Journal of Computing in Civil Engineering (ASCE).

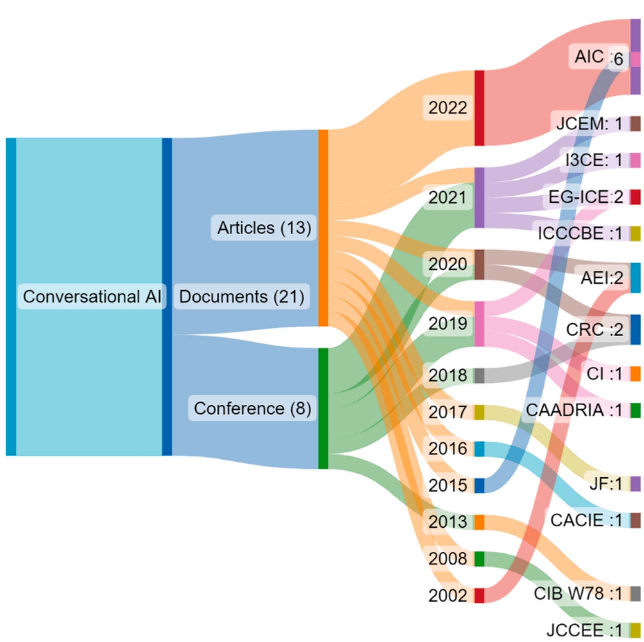

Fig. 4. Conversational Artificial Intelligence Documents in AEC Industry.

5.2. Application areas

The retrieved extant studies developed Conversational AI systems in various domains. However, most of the efforts have been on developing Conversational AI systems for information retrieval from knowledge sources such as building information models (BIM) and documents. The sections below discuss the domain areas and the various purposes the systems were developed for as summarised in Table 4.

5.2.1. Information retrieval/extraction

Information retrieval (IR) which is the science of searching for information from documents and searching for documents themselves has been evolving in the information-intensive AEC industry. The IR aims to provide users with relevant information from the databases in an efficient manner. 19 out of the 21 reviewed studies were built for information retrieval and extraction from different sources such as BIM models, BIM objects, BIM documents building regulations, design documents and project information. Asides from the different knowledge sources (database), the system differs in terms of the techniques. The majority of the systems were question/query answering systems [51,52,58,69] that extract relevant answers to queries posed by the users without further manipulation while others could manipulate the database[50,55,57].

BIM data mining is one of the earliest attempts of employing natural language to retrieve BIM objects and related information from BIM models and online sources. Lin, Hu [67], Gao, Liu [66], Lin, Hu [65] and Wu, Shen [60] developed search engines which employed natural language to interact with the knowledge source to extract BIM objects. IFC format was used in building the BIM object database for uniformity and the BIM object retrieval was conducted via keyword search from the queries and subsequent mapping with the related BIM objects. The results are presented to the users in visual and text format and does not provide further ontological reasoning and computation.

With the increased adoption of BIM in the industry, studies have progressed towards developing voice-based systems that would interact with BIM models. Elghaish, Chauhan [49] proposed an AI system for the retrieval of information from the BIM model via natural language and employed Amazon Alexa, Amazon Web Services (AWS) and Dynamo for the development. The developed system interacts with the BIM model and could perform tasks such as creating a room schedule without further computation or manipulation of the database. However, the proposed Conversational AI system by Shin and Issa [55], Shin, Lee [59] and Shin, Lee [57] focused on changing the materials of walls by interacting with the BIM model via natural language. Although these systems employed the BIM model as the knowledge source and interact with the model via Dynamo, the objective differs – information retrieval and manipulation. Also, Elghaish, Chauhan [49] converted the output to speech while the systems by Shin and Issa [55] and Shin, Lee [59] effect the request without speech feedback. These systems can be employed during all the phases of the construction projects for information retrieval and manipulation thereby saving the time required to execute tasks.

Furthermore, Intelligent Building Information Spoken Dialogue System (iBISDS) is the focus of Wang, Issa [56], Wang, Issa [53] and Wang, Issa [54] which proposed a Conversational AI system for retrieving information embedded in the BIM models using natural language. These studies represent incremental progress in developing a voice-based BIM query system and modularized and se2seq techniques have been explored. However, the extraction is still limited to property, geometric and basic model view information for architectural and structural BIM models. The Conversational AI system would enable skilled and unskilled users to query BIM models for information retrieval during the design, construction, operation, and demolition stage.

The IE focus of systems by Lin, Huang [51], Zhong, He [58], and Kovacevic, Nie [68] is providing answers to the queries from the users without complex reasoning. The systems were trained based on the

Table 4
Current Application Areas.

S/N	Source	Domain	Purpose	Construction Stage Relevance
1	Elghaish, Chauhan [49]	Information retrieval (BIM)	The study proposed a voice assistant system for the retrieval of information from the BIM model	Design, construction, and operation
2	Adel, Elhakeem [50]	Information retrieval and manipulation (Smart Contract)	The study proposed a chatbot for a Blockchain-based network in tracking work progress on construction projects	Construction
3	Lin, Huang [51]	Information Retrieval (BIM and artificial intelligence of thing)	The study developed a question-and-answer system for BIM and artificial intelligence of things-related questions	Design, construction, and operation
4	Linares-Garcia, Roofigari-Esfahan [52]	Information Retrieval (Assembly manual)	The study proposed a voice-based system for the retrieval of semantic knowledge during construction tasks	Construction
5	Wang, Issa [53]	Information retrieval (BIM)	The study proposed a modularized query-answering system for the retrieval of information from the BIM model using natural language	Design, construction, and operation
6	Wang, Issa [54]	Information retrieval (BIM)	The study proposed a natural language query answering system for information retrieval from the BIM model	Design, construction, and operation
7	Shin and Issa [55]	Information retrieval and data manipulation (BIM)	The study developed a modularised Conversational AI system for changing wall material in BIM models.	Design
8	Wang, Issa [56]	Information retrieval (BIM)	The study proposed a modularized Conversational AI system for extracting components of building elements in BIM	Construction and operation
9	Shin, Lee [57]	Information retrieval and data manipulation (BIM)	The study proposed a Conversational AI system concept to manipulate materials of components in BIM models	Design
10	Zhong, He [58]	Information retrieval (Building regulations)	It developed an end-to-end Conversational AI system for retrieving information about building regulations	Design, construction, and operation
11	Shin, Lee [59]	Information retrieval (BIM)	It proposed a framework for the integration of automatic speech recognition in BIM	Design, construction, and operation
12	Wu, Shen [60]	Information retrieval (BIM objects)	It proposed a search engine for the retrieval of BIM objects	Design
13	Sheldon, Dobbs [61]	AR	It proposed the integration of voice control and hand gestures in AR	Design
14	Zhoui, Wong [62]	Information retrieval (BIM)	It presented a framework to enhance natural language interaction with BIM for navigation during an emergency (fire).	Operation
15	Eiris-Pereira and Gheisari [63]	AR	It presented the concept of simulating a conversational construction site for educational purposes	Construction
16	Motawa [64]	Information retrieval (BIM)	It proposed a Conversational AI system for knowledge management to aid facility management	Operation
17	Lin, Hu [65]	Information retrieval (BIM)	The study developed an information retrieval system via natural language in the BIM model	Construction
18	Gao, Liu [66]	Information retrieval (BIM)	The system developed a search engine for the retrieval of online BIM documents	Design
19	Lin, Hu [67]	Information retrieval (BIM)	It presented a framework for data mining in BIM via natural language	Design, construction, and operation
20	Kovacevic, Nie [68]	Information retrieval (Web)	It proposed a question-and-answer system for construction-related questions	Design, construction, and operation
21	Cheng, Kumar [69]	Information retrieval (Project management applications)	A question-answering system was developed to provide project information details based on outputs from project management applications	Design, construction, and operation

likely questions and answers and extracted answers from users' queries based on similarity. Kovacevic, Nie [68] proposed a system for general construction-related questions and answers were extracted from a list of specified web pages. However, Lin, Huang [51] and Zhong, He [58] proposed systems for providing answers to BIM Artificial intelligence of things and building regulations-related questions respectively. As such, the answers were extracted from texts about BIMAIOT and building regulations. Although these proposed questions and answers are limited and domain-specific, they are of benefit in providing domain-specific answers to users and save time.

Similarly, Linares-Garcia, Roofigari-Esfahan [52] and Zhoui, Wong [62] systems were developed from a question-answering technique, however, the systems aimed to provide instruction to the users. Linares-Garcia, Roofigari-Esfahan [52] proposed a voice-based agent for providing an audio instructional guide to construction workers whilst completing tasks and validated the system with an assembly task. On the other hand, Zhoui, Wong [62] developed a framework for providing navigational instructions to facility occupants during fire emergencies. These systems provide instruction to task-specific queries from users and synthesize the instruction to speech which helps to improve productivity – saves time in consulting documents [52] – and safety [62].

Lastly, Conversational AI systems could be developed as an interface

Table 5
Current Conversational AI Systems in the AEC Industry.

Conversational AI System	ASR	NLU	Knowledge Source	Dialogue Management	Natural Language Generation	Text-to-Speech Synthesis
BIM-based AI voice assistant [49]	Alexa Skills Kit (ASK)	ASK	BIM Model (rvt format)	Amazon Alexa + Dynamo + Revit	Template-based	ASK
Blockchain-based network (BBN-Chatbot)[50]	IBM Watson Assistant (IBM WA)	IBM WA	Blockchain-based smart contract	IBM WA + IBM Blockchain platform	Template-based	–
BIM AIOT QnA System (BIM Artificial intelligence of things Question and answer system)[51]	–	Bidirectional Encoder Representation from Transformers (BERT)	3334 text paragraphs = 10,002 questions	BERT	–	–
Voice-Based Intelligent Virtual Agents (VIVA)[52]	Google Actions	Google Actions	Expected questions and appropriate semantic knowledge	Google Actions + Semantic knowledge source	Template based	Google Nest Smart Speaker
QA system for BIM IE (Query-answering system for BIM information extraction) [53]	–	Semantic and Syntactic Analysis = identification and classification of keywords	BIM model (IFC-STEP file)	Vectorization	Template based	–
QA (Query answering) System for BIM [54]	–	Bidirectional Encoder Representation from Transformers (BERT)	BIM model (IFC-STEP file)	Vectorization	Template based	–
BIM Automatic Speech Recognition (BIMASR) [55]	Google speech recognition	Syntactic + Ontology Semantic Analysis = SQL	BIM Model (rvt format)	BIM-to-relational database management system (RDBMS) + SQL = BIM model (via Dyanmo)	–	–
Intelligent Building Information Spoken Dialogue System (iBISDS) [56]	Google speech recognition	Syntactic + Semantic Analysis = Keywords	BIM model (IFC-STEP file)	IFC entity types + Keywords = result (attribute word, name phrase, extracted data and unit)	Template-based	Google Text To Speech
Shin, Lee [57]	Smart devices (iPhone's Siri or Amazon's Alexa)	Syntactic and Semantic analysis = SQL	BIM model (Relational Database Management System)	Dynamo Interface	–	–
QAS4CQAR [58]	–	Syntactic and Ontology Semantic Analysis	19 Chinese building Regulations	BidirectionalEncoder Representations from Transformers (BERT)		–
Shin, Lee [59]	smart devices (iPhone, Galaxy, iPad, and Alexa)	Syntactic and Semantic analysis	BIM model	Relational Database Management System (RDBMS) + SQL in Dynamo	–	–
Wu, Shen [60]	–	Syntactic and ontology semantic analysis	BIM Object Database	Keyword extraction + semantic query expansion + mapping	–	–
Sheldon, Dobbs [61]	–	Leap-Motion/Visual Studio	3D Models	Unity software Engine		–
Zhoui, Wong [62]	Google speech recognition	Syntactic + Ontology Semantic Analysis	BIM model (3D spatial and facilities location information)	Visibility Graph (VG) and Dijkstra's algorithm	Template-based	voice synthesizer tool (eSpeak)
Eiris-Pereira and Gheisari [63]	–	Virtual People Factory	Database (spatiotemporal contextual script)	Virtual People Factory + Unity's game engine	Template-based	–
Motawa [64]	Google speech recognition	–	case-basedreasoning (CBR) knowledge module + BIM module	Nearest neighbour technique	Template-based	–
Intelli-BIM [65]	–	Syntactic + Semantic Analysis	IFC-based BIM data (MongoDataBase)	Graph-based path search method	–	–
BIMSeek [66]	–	Ontology semantic analysis	15,176 BIM documents	Keyword extraction + semantic query expansion + pruning + similarity evaluation (Vectorization)	–	–
Lin, Hu [67]	–	Syntactic + Semantic Analysis	BIM Model (IFC-based database)	Graph-based path search method	–	–
Kovacevic, Nie [68]	–	Syntactic + Semantic Analysis	Domain-specific websites	Lucene System (Vector space model)	–	–
Cheng, Kumar [69]	–	Syntactic + Semantic Analysis	ifcXML files (Outputs from Primavera, MS Project and Vite SimVision)	XQuery + ifcXML files	Template-based	–

to interact with users in fulfilling diverse tasks such as facility management, project management and contract management. Motawa [64] developed a spoken dialogue system for providing solutions to maintenance-related challenges in buildings via natural language interaction. A case-based reasoning BIM system is employed to capture experts' experience in maintenance problems to solve new similar problems in the facility. Cheng, Kumar [69] developed a question-and-answer system to extract knowledge from the outputs of project management tools (Primavera Project Planner, Microsoft Project and Vite SimVision). The developed system enables users to pose natural language questions to retrieve information relating to the work schedule, tasks, and sequence of tasks based on the processed outputs of the project management tools. Adel, Elhakeem [50] developed a chatbot as an interface for interacting with a smart contract on a Blockchain-Based Network. These Conversation AI systems serve as a platform for interacting with backend applications and improving users' experience. Such systems could be deployed in different domains in the construction industry and throughout the project lifecycle to improve users' experience and improve productivity.

5.2.2. Augmented reality and virtual reality

Sheldon, Dobbs [61] proposed a workflow for the integration of voice and hand gesture control in AR for interacting and modifying 3D designs. The proposed system would enable the designers to interact with models and edit models in real-time via voice commands and hand gestures. Similarly, Eiris-Pereira and Gheisari [63] proposed a conversational system where virtual agents are incorporated into a virtual BIM-based environment for the interaction of students with construction tasks and professionals. The proposed system enables students to interact with virtual agents (construction professionals) in the simulated construction site to learn about the construction processes from the comfort of their classroom.

5.3. Critical review of identified conversational AI system development

This section presents a summary of the development of the Conversational AI systems in the reviewed document which includes components and evaluation. This section is important to provide an overview of the current techniques and components employed in the AEC industry for the development of Conversational AI systems. Table 5 shows a review of the components and techniques employed in the identified Conversational AI systems.

The components have been categorised into ASR, NLU, Knowledge source, Dialogue management, NLG, and TTS. However, not all Conversational AI systems employed these components in their development depending on the approach and objective of the system. A Modularized system used different components for different tasks while the seq-2-seq employed one component for more than one task. The ASR which takes in the users' input and converts the speech to text is employed in 7 of the studies with audio-enabled input. Most of these studies rely on Google Speech Recognition API, however, some of the recent systems are employing the Google Actions platform, IBM Watson Assistant and Amazon Alexa for developing the Conversational AI system which is inclusive of the ASR [49,50].

The NLU Unit is critical and relies on the success of the ASR to convert the speech into text from which it derives the request of the users. This process involves syntactic and semantic analysis. The syntactic or syntax analysis also referred to as parsing deals with breaking down the input to check its correctness per grammar rules. Semantic analysis on the other hand deals with drawing meanings from the words to identify the request from the users and it often employs domain ontology or knowledge base. The use of domain ontology in the NLU enables the system to have a field understanding of the meaning of the word before the generation of queries. However, developing a domain ontology is time-consuming and difficult to maintain. As such only, a few of the studies [55,58,60,62,66] employed domain ontology and the common approach for its development is the Seven-Step method [70]. On the other hand, for platforms such as Alexa and IBM Watson the Conversational AI System skill (different tasks or actions to be performed) are customised or prebuilt with the ability to detect the users' requests[49,50]. Similarly, Google Actions employed Natural Language Processing Algorithms embedded in its platform to conduct NLU[52].

The knowledge source components of the reviewed Conversational AI systems are needed for information retrieval. Knowledge sources in the construction industry are often in different formats such as CAD, IFC, PDF, XML, images, documents, and sheets. This makes the development of Conversational AI systems complex as the knowledge source should be accessible by the systems to meet the users' requests. Thus, one of the first hurdles in the development of Conversational AI systems is making the knowledge sources available in processable formats. Where documents serve as the knowledge source, they are processed and converted to an accessible database. For instance, Lin, Huang [51], Linares-Garcia, Roofigari-Esfahan [52], and Zhong, He [58] employed extraction of information from BIMAIOT-related documents, assembly guide, and building regulations to the developed knowledge database. The development and extraction of the information from these documents are done manually and limit the tasks that could be completed by the system. Conversational AI systems that are related to the BIM model rely on the IFC format for data use and this limit the information that could be retrieved from the database. In recent times, it is possible to develop Conversational AI systems as an interface for the usage of other applications in the background. For instance, Adel, Elhakeem [50] proposed a chatbot as an interface for a smart contract. Thus, it is possible for the knowledge base to be a background application.

Furthermore, as the aim of most of the reviewed systems is information retrieval, the DM manages and directs the process of retrieving the correct information from the database based on the users' request. For instance, some systems employed mapping of the search keywords to the database and vectorization. This could be directed on a developed platform based on pre-coded scripts and include interaction between more than one component, for instance, the interaction between the BIM model and Dynamo [49,55,57] for data extraction and manipulation of the BIM model. Sequel to the completion of the tasks, the feedback is relay to the users as texts, visual presentations, or speech. The response often employed a template to provide feedback to the users. For instance, Wang, Issa [53] developed a response pattern based on English grammar syntax which could generate feedback such as The W(height) of the Y (second floor) is Z (10 feet). Also, the response could be extracted directly from the knowledge source as predefined feedback. For instance Lin, Huang [51], Kovacevic, Nie [68] and Ding, Zhong [71] without further computational reasoning. Similarly, the response from search engines developed by Gao, Liu [66], Wu, Shen [60], and Lin, Hu [67] employed visual presentation of the BIM objects. Lastly, the generated natural language response is converted to speech and relay to the users using components such as eSpeak Google Text to Speech or IBM WA and ASK.

5.4. Insights into the current state of Conversational AI systems in the AEC industry

A critical review of the identified systems also revealed that most of the developed Conversational AI systems in the AEC industry rely on Google Speech-to-Text and smart devices in capturing the user's speech. This is related to the improvement in Google's speech recognition which employs neural networks and WaveNet from DeepMind to synthesise natural language to text. Also, Google's speech recognition API has been reported to outperform IBM Speech to Text and Wit by having the highest accuracy and lowest error rate [33].

The current approaches employed in the extant applications for understanding the users' request involves syntactic and semantic analysis. The syntactic analysis involves segmentation, tokenization, removing stop words, part-of-speech tagging, stemming and lemmatization. These steps deal with breaking down the users' requests (in text) to ensure their correctness per grammar rules. On the other hand, semantic analysis deals with drawing meaning from the words to identify users' requests. Developed parsers such as Sandford parser and libraries such as OpenNLP (Java) and NLTK (Python) are employed in the NLU phase. Search queries and requests of users in the AEC industry differ from that of users from other sectors and often require the use of domain ontology in the NLU. This enables the system to have a field understanding of the words through ontology semantic analysis. Libraries are often compiled to provide frameworks in mapping between the inputs and technical jargon used in the field e.g Industry Foundation Class (IFC) and International Framework for Dictionaries (IFD) (for BIM-related applications), compilations of common lexicons and synonyms in application areas. However, ontology semantic analysis still poses difficulty in the AEC industry because of the time involved in developing and maintaining domain ontology. Thus, some of the developed systems did not employ ontology semantic analysis which could have enhanced the efficiency of the developed systems.

Interestingly, there is a growing use of Pretrained Language Models (PLMs) in the development of Conversational AI systems in the AEC. Bidirectional Encoder Representations from Transformers (BERT) which is a deep learning framework for NLP is employed in Lin, Huang [51], Wang, Issa [54] and Zhong, He [58]. However, the availability of data sufficient for the training in the AEC still poses the main challenge for the deployment of PLMs. Thus, transfer learning could be leveraged and models like Robustly Optimized BERT Pertaining Approach (RoBERTa), Decoding-enhanced BERT with disentangled attention (DeBERTa), and StructBERT (extension of BERT with incorporation of language structures into pre-training) can be employed [72].

5.4.1. Validation and evaluation of the systems

Table 6 shows the breakdown of the validation, evaluation, and limitations of the reviewed Conversational AI systems. All the reviewed studies were validated except for the proposed framework in Sheldon, Dobbs [61]. The proposed Conversational AI systems are in the early stage of development and validated in a controlled environment with the assumption of happy path users – testing with expected inputs and receiving expected responses. The validation involves testing with a case study, a task, a set of queries or a set of questions depending on the aim of the system. However, no details are provided about the performance of the system in edge cases – where it encountered unexpected inputs – except in Cheng, Kumar [69] where a generic statement - '*Sorry, we cannot find the answer in the knowledge base*' – is scripted as a response for edge cases.

Most of the proposed systems were evaluated via user experience, performance evaluation or comparison with extant systems. The user's experience evaluation involves the users providing feedback (satisfaction, efficiency, and effectiveness) based on their usage of the system via a set of questions which could be in tandem with established standards such as ISO 9241–11:2018 and NASA-TLX questionnaire. On the other hand, performance evaluation involves using established metrics to compare the system's output with ground truth or known benchmarks. For instance, in Adel, Elhakeem [50], the system was evaluated based on the effectiveness of the system in completing tasks (blockchain base network's writing and reading latency and the storage size). Metrics such as accuracy precision and recall is/are employed by Lin, Huang [51], Wang, Issa [53], Wang, Issa [54], Wu, Shen [60], Kovacevic, Nie [68] and Gao, Liu [66]. Similarly, other studies [58,60] compared the performance of the proposed system with the extant system performing the same tasks.

Furthermore, as the proposed systems in the reviewed studies are in the early stage of development, there are limitations hindering the effective implementation and deployment of such systems in practice. The assumption of happy path users constitutes a limitation for the studies because edge cases would occur during deployment outside the laboratory. Also, the approach employed in the development of the

Table 6
Validation, Evaluation and Limitation of Extant Studies.

Conversational AI System	Validation	Evaluation	Limitation
BIM-based AI voice assistant [48]	The system was validated with a single-case mechanism experiment	Evaluated via user's experience (usability test)	• Requires centralised server Functionalities are limited to data retrieval without further processing Requires dynamo scripting for different tasks It assumed happy path users The user queries must conform for intent extraction
Blockchain-based network (BBN-Chatbot)[50]	The system was validated with a record of progress for a non-residential construction project	Evaluation via system performance	• Limited to the exchange of textual and numeric data without further analysis It assumed happy path users Queries must conform for functions and parameters identification Functionalities are limited to CRUDQ (Create, Read, Update, Delete and Query) No text to voice module to improve the user experience
BIM AIOT QnA System (BIM Artificial intelligence of things Question and answer system) [50]	The system was validated with 10 questions	Evaluated system performance	• Requires scripting of likely questions for the training of the system It assumed happy path users No text to voice module to improve the user experience Credit assignment problem
Voice-Based Intelligent Virtual Agents (VIVA)[52]	The system was validated with two experimental steel assemble tasks	Evaluated via usability test	• Requires providing embedded context to function well It assumed happy path users Requires scripting of likely questions and answers for all tasks to develop the semantic knowledge Requires onsite presence of the smart speaker Single modal interaction and no repeat functionality User queries must conform for intent extraction
QA system for BIM IE (Query-answering system for BIM	The system was validated with 127 queries from	Evaluated via system performance	• Information extraction limited to property, geometric and

(continued on next page)

Table 6 (*continued*)

Conversational AI System	Validation	Evaluation	Limitation
information extraction)[53]	7 building models		basic model view information for architectural and structural BIM models No ontological reasoning for the information extraction Knock on effect No text to voice module to improve the user experience
QA System for BIM [54]	The system was validated with 100 generated queries	Evaluated via system performance	• Limited to attribute information retrieval of building elements and spatial structure elements No ontological reasoning for the information extraction Credit assignment problem Queries should conform for content word identification
BIM Automatic Speech Recognition (BIMASR) [55]	The system was validated with two case studies (BIM models)	Not reported	• The system comprises three separate platforms: Revit (BIM model), Oracle (Database), and Dynamo (Data processing) No text to voice module to improve the user experience Functionalities are limited to manipulating basic building element data only It assumed happy path users Not applicable on mobile phones/ Tablets Knock-on effect
Intelligent Building Information Spoken Dialogue System (iBISDS) [56]	A prototype was developed and validated with a case study	Not reported	• The functionalities are limited to extracting only the attribute of the building element without further processing The user query is not flexible as it requires the use of tags It assumed happy path users
Shin, Lee [57]	The study proposed the system without validation of the approach	Not reported	• It proposed separate platforms for the development No validation No text to voice module to improve the user experience Not applicable on mobile phones/

Table 6 (*continued*)

Conversational AI System	Validation	Evaluation	Limitation
			Tablet Knock-on effect
QAS4CQAR [58]	The system was validated with 100 questions	i) Compared with the search engine (Baidu) and extant database. ii) Assessed by experts for ease of use, quality of responses, time of response and the system's overall performance.	• Functionalities are limited to text-based clauses in the used regulation documents Black-box problem It assumed happy path users Credit assignment problem
Shin, Lee [59]	The study proposed the Conversational AI system framework but not validated	Not reported	• It proposed separate platforms for the development No validation No text to voice module to improve the user experience Not applicable on mobile phones/ Tablet Knock-on effect
Wu, Shen [60]	The system was validated with 50 queries	Evaluated via comparison with extant system and system performance	• Developed domain ontology is limited Retrieval is limited to the BIM object database Query must conform for keyword extraction It assumed happy path users
Sheldon, Dobbs [61]	Not validated	Not reported	• It proposed separate platforms for the development No validation
Zhoui, Wong [62]	The system proposed validation in a VR-based environment	Evaluated navigation query, BIM-based navigation model and voice navigation command generation	• Hypothesized happy path users Assumed users can send navigation requests during emergencies
Eiris-Pereira and Gheisari [63]	The proposed system was validated using a crane hoisting operation	Not reported	• It assumed happy path users The conversations are pre-scripted
Motawa [64]	The proposed spoken dialogue system was validated	Evaluated via users' experience (facility management professionals)	• Used keyword No reasoning or further computation on the data retrieved The responses are limited to the stored cases in the system Hypothesized happy path users No text-to-speech synthesis
Intelli-BIM [65]	The system was validated with a case study	Not reported	• Used keyword It assumed happy path users No text to voice

(*continued on next page*)

Table 6 (*continued*)

Conversational AI System	Validation	Evaluation	Limitation
			module to improve the user experience
Gao, Liu [66]	The system was validated with search queries	Evaluated via system performance	• Ontology analysis is limited to the developed IFC ontology which does not fully cover all BIM information retrieval No text to voice module to improve the user experience The employed query expansion could lead to irrelevant results
Lin, Hu [67]	The system was validated with a case study	Not reported	• Used keyword It assumed happy path users No text to voice module to improve the user experience
Kovacevic, Nie [68]	The developed system was validated with questions from professionals and students	Individual modules and the relevance of the generated outputs were evaluated.	• Knock-on effect The responses generated are limited to the data source of the crawler which might not be the best answer No text to voice module to improve the user experience
Cheng, Kumar [69]	The system was validated with a case study.	Not reported	• Functionalities are limited to work schedule, description of schedule and relationship between activities. No text to voice module to improve the user experience Not applicable on mobile phone/ Tablets

system could serve as a limitation in optimizing the system. Modularized architecture could result in knock-on effects when a module is optimised leading to an adverse effect on the other modules while the end-to-end neural approach could result in a credit assignment problem. Similarly, most of the systems still employed the traditional approach to NLP with few leveraging on PLMs which are deep learning models and perform better. Also, the information extraction is limited to certain functionalities and some of the proposed would require further scripting to perform a different task [49,50,52,58].

5.5. Focus Group discussion (Conversational AI and domain experts Validation)

The FGD was conducted with two AEC professionals and two Conversational AI experts with development experience in the AEC industry. The discussion centred around the challenges of Conversation AI system development and opportunities in the AEC industry. All the participants in the discussion have PhD and over 7 years of experience in construction and AI-related research. Thus, they have the right knowledge and experience which align with aim of the FGD.

5.5.1. Insights into the challenges of Conversational AI systems in the AEC industry

Based on the reviewed studies and the conducted FGD, the challenges facing the development of Conversational AI systems in the AEC industry are highlighted in Table 7.

5.5.1.1. Development. The development of conversational artificial intelligence systems involves the natural language processing (NLP) domain which is considered a challenging and demanding area in computer science [73]. The efficiency of Conversational AI lies in its ability to correctly understand and process the natural language queries from users of diverse backgrounds. These users often have different languages and accents which serves as a major hindrance in the development of Conversational AI systems. Albeit there are now improvements in ASR to recognize diverse different languages and accents, the users' speech can be mixed and difficult to recognize, thus failing to recognize users' intent correctly. The Conversational AI systems also suffer either from knock-on effects in the case of modular architecture systems or credit assignment problems in the case of sequence2sequnce architecture. In addition, background noise which is common in construction sites often makes voice recognition on-site difficult. Thus, aside from the innate challenges of languages & accents and improvement in relation to architecture, the development of the Conversational AI systems in the AEC needs to be cognizant of domain problems such as background noise on construction sites.

5.5.1.2. Data. *'Data is the new oil'* and large datasets are crucial in the development of models [74]. Although, much data set is not needed in the rule-based approach of the Conversational AI system as it involved the scripting of rules, however, data is required in the statistical-driven and end-to-end neural approach. This has particularly limited the applications of machine learning-based approaches in named entity recognition for NLU in the AEC industry. The problems of data for the development of Conversational AI systems include data availability and data accessibility. Despite the huge volume of data available in the construction industry, the data are often difficult to access due to the structure of the data, missing data, noise and cost of data collection & pre-processing [75]. Interventions such as data augmentation and transfer learning[72] can be employed to tackle the challenge of data availability in the AEC industry. Data augmentation involves position augmentation techniques such as cropping, flipping, rotation and colour augmentation techniques to increase the data set and is widely used in computer vision [4]. On the other hand, transfer learning is the technique of adapting previous knowledge from different data sets to solve related new problems [76].

5.5.1.3. Cultural barrier. The major challenges to the application of Conversational AI in the AEC industry are related to cultural barriers. The cultural barriers make the adoption of innovation difficult, and slow because of the lack of willingness of the stakeholders to embrace change [77]. Some of the stakeholders have the perception that the status quo is sufficient and there is no need to employ new approaches. This is often because of the fear of the unknown, resistance to change and characteristics of the innovation. Consequently, it is the harbinger of a lack of top management support, lack of funding, and trust which discourages the application of Conversational AI [1].

5.5.1.4. Funding. The Conversational AI systems like other applications of AI require high initial cost in the development which often serves as a bottleneck in the AEC industry where the majority of the firms are small and medium-sized enterprises [4]. The cost of development entails the cost of powerful machines for building, training and testing the models and the cost of engaging the services of experts in the development and deployment. Anumba [19] asserted that there is a lack of coherent strategy in the IT investment approach of the AEC. This often leads to

Table 7
Challenges of Conversational AI systems in the AEC industry.

Source	Development	Data	Cultural Barrier	Funding	Ethics	Privacy and security	Scalability	Expertise
Elghaish, Chauhan [49]	✓							
Adel, Elhakeem [50]	✓							
Lin, Huang [51]	✓							
Linares-Garcia, Roofigari-Esfahan [52]	✓							
Wang, Issa [53]	✓	✓						
Wang, Issa [54]	✓	✓						
Shin and Issa [55]	✓							
Wang, Issa [56]	✓							
Shin, Lee [57]	✓							
Zhong, He [58]	✓	✓						
Shin, Lee [59]	✓							
Wu, Shen [60]	✓	✓						
Sheldon, Dobbs [61]	✓							
Zhoui, Wong [62]	✓							
Eiris-Pereira and Gheisari [63]	✓							
Motawa [64]	✓	✓						
Lin, Hu [65]	✓	✓						
Gao, Liu [66]	✓	✓						
Lin, Hu [67]	✓	✓						
Kovacevic, Nie [68]						✓		
Cheng, Kumar [69]	✓							
FGD	✓	✓	✓	✓	✓	✓	✓	✓

duplications and works of limited industrial impact. It is also noteworthy that the increased awareness and adoption of Conversational AI systems was because of the interests of big companies such as Apple, Google, Microsoft, Facebook, Samsung, and others [13]. The involvement of these big companies led to an increase in investment and funding of projects in Conversational AI systems which is lacking in the AEC industry.

5.5.1.5. Ethics, privacy, trust, and security. With the advancement in AI, there has been a surge in the discussion of ethical concerns in the development of AI systems. Per Hagendorff [78], extant issues on ethics in AI cover accountability, safety, data bias, security, privacy and explainability. These ethical guidelines are meant to serve as moral principles and obligations of the AI and its developers [79]. For instance, the General Data Protection Regulation (GDPR) deals with data protection and security in the European Union and covers 7 principles which are: i) processing the data in a lawful, fair and transparent manner ii) solely processing data for the legitimate purpose of the data collection iii) Only the smallest data that are necessary for the purpose should be collected iv) ensure accuracy of the data v) there should be justification for the data retention period vi) ensure integrity and confidentiality of the data vii) there should be accountability and compliance to ethical principles [80,118]. These ethical concerns are necessary considerations in the development of Conversational AI systems in the AEC industry. For instance, in developing Conversational AI systems for the mental well-being of construction workers, data can be accumulated from individuals, however, ethics and privacy are necessary consideration for such Conversational AI systems.

In addition, some artificial intelligence systems suffer from the black box problem and often hampers people's trust in the developed systems [131,141,142]. The issues of trust and privacy are critical and often affect the acceptability of Conversational AI systems in conservative industries like the AEC. Stakeholders are often reluctant to trust the 'new' approaches offered by the Conversational AI systems over the traditional tested approach employed over the years. Similarly, although there has been improvement in security for AI applications over the years, data breaches and security are still major challenges, and Conversational AI systems are susceptible.

5.5.1.6. Scalability and expertise. Conversational AI systems are often task-oriented as they are deployed for specific tasks. Thus, Conversational AI systems developed in other industries such as healthcare, and tourism are not scalable to the AEC industry. Conversational AI systems in some domains of the AEC industry are also often not scalable to other domains because of contextuality which serves as a challenge. Furthermore, there is a growing demand for AI experts across industries, however, there is a shortage of supply of these experts. The supply is lower in the AEC industry compared to other industries where there has been widespread development of AI systems. The challenge of lack of Conversational AI expertise is also compounded by the dearth of AI experts with AEC domain knowledge or professional experience in the industry which makes development easier and faster [4,117]. Thus, there is high demand and job opportunities for AI experts in the AEC industry and there is a need for the professional bodies and curriculum of built environment-related courses to rise to the tasks.

5.5.2. opportunities and future research direction

Based on the extant studies, areas are deduced and projected as the opportunities and future research direction for Conversational AI systems in the AEC industry. The proposed areas were subjected to the review of 2 domain experts and 2 Conversational AI experts (with experience in the AEC industry) for validation and categorisation during the FGD. The identified areas were categorised into the design, construction and post-construction phase and value-added areas as shown in Fig. 5.

5.5.2.1. Design phase. Current Conversational AI systems in the design phase are focused on information retrieval and manipulation from BIM models via natural language queries. Thus, the following areas are identified and projected for further development:

Conversational-BIM for design

Conversational agents can be implemented in BIM to improve productivity during the design stage. This will enable users to communicate with the Conversational AI systems in natural language as against the current usage of mouse and keyboards for input. Consequently, designers can modify (change or delete) components in the BIM model via speech. Voice 360 plugin enables voice recognition and command in Revit; however, the functionalities are limited to forge viewer commands and require the use of keywords. Similarly, Shin and Issa [55] proposed BIM Automatic Speech Recognition (BIMASR) for components modification, but the functionalities in the developed system are limited and implementation is done across different platforms. Similarly, Elghaish, Chauhan [49] proposed a Conversational AI system for interacting with 3D models to perform tasks such as creating a schedule.

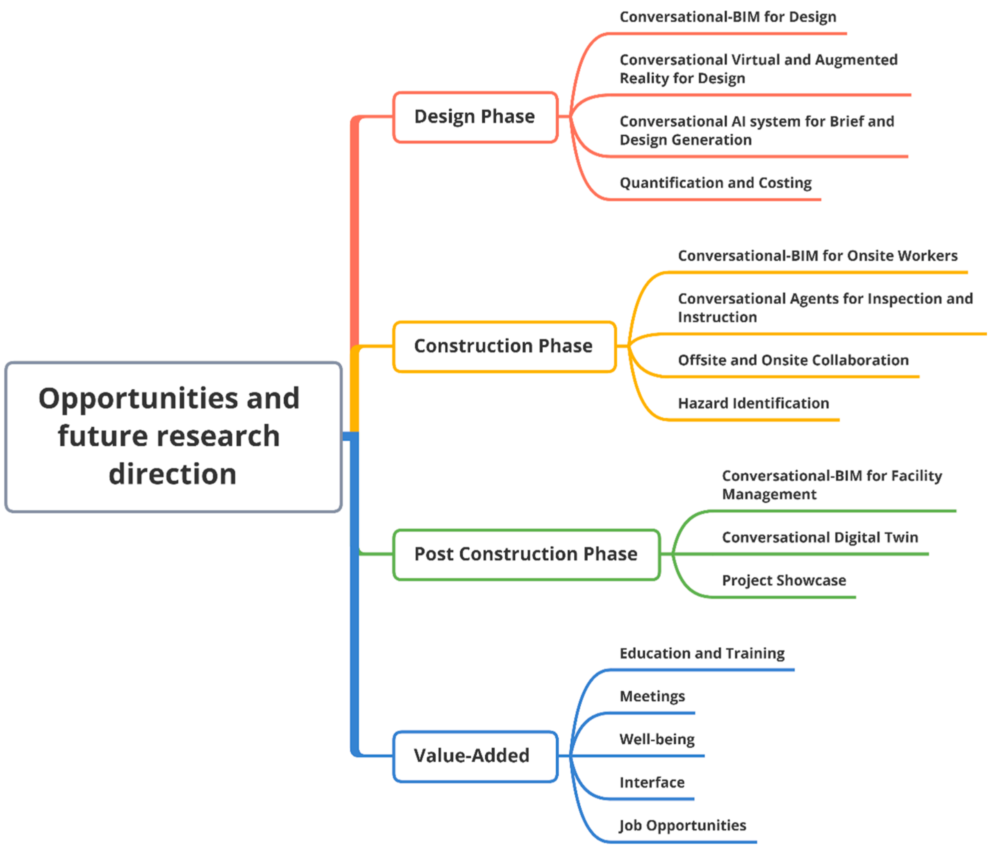

Fig. 5. Opportunities and Future Research Direction of Conversational AI in the AEC Industry.

The future of conversational agents for BIM in the design phase is the development of a proficient Conversational AI system that would interact with BIM models during design via speech, texts and even hand gestures without prior expertise in BIM [61]. Such systems would be integrated into a single platform and available to users via the web and accessible on mobile phones and tablets as proposed by Wang, Issa [56]. The benefit of such systems lies in their improvement of productivity and improving designer and computer interactions [112,113]. It would enable designers to generate design alternatives faster via natural language. Non-expert stakeholders such as clients [137] can communicate with the system to provide different design alternatives by changing various components of the model. The cost estimation of different design alternatives can be computed to make informed decisions during the design stage. Similarly, other simulations such as energy, waste, daylight, and environmental analysis can be performed on the different alternatives with little effort [81,123,124,134,135].

Conversational virtual and augmented reality for design

Visualization functionalities offered by Virtual reality and augmented reality can be enhanced with conversational agents to improve project design [115]. Sheldon, Dobbs [61] proposed the integration of voice and hand gestures into VR, however, the system only employs keywords for interaction. The use of natural language queries can be adopted in conversational AI-enabled VR to modify and interact with BIM [114]. Designers would be able to visualize and modify models beyond using forge view commands [148]. Conversational AI systems also have the potential to improve collaborative and engaging model design with stakeholders to make informed decisions.

Conversation AI system for brief and design generation

The briefing is an essential task where the client makes his project requirements known to the relevant professionals for the delivery of the project [138]. It is a task that can mar or make the project and influence the clients' satisfaction at delivery [82,139]. Briefing done poorly can significantly affect the cost, time, and quality of the project in the long run [83,121]. Thus, ensuring the client expresses his requirements clearly and understands the implications is essential to project delivery [120]. The extant traditional approach of the briefing is time-consuming and increases the budget [140], the implementation of client-oriented conversational agents can provide an interface to serve as a midwife in birthing the essential details of briefing documents. Task-oriented Conversational AI systems would provide an interactive platform for shaping the client requirements and improving project definition clarity. This would reduce the time spent in the traditional approach and provide support for the professionals in understanding the key requirements of the clients [127].

In addition, with the advancement in deep learning [126,133] and big data [125], generative design can be employed in generating design alternatives for consideration based on initial objectives [4]. Generative adversarial networks (GANs) and autoencoders can be implemented in conversational agents for the generation of realistic designs [84,85]. Generative design conversational agents can then subsequently be deployed for the usage of clients and design professionals.

Conversation AI system for quantification and costing

The Quantity surveyors are saddled with the responsibilities of proving material quantification and cost implications for design during the briefing, concept design and spatial coordination stages [86]. With the advent of Conversational AI, auto material quantity take-off functionalities can be improved with natural language engagement between the users and the system [87]. This would improve decision-making by shortening the time required for such activities and improves users' interaction. Similarly, costing of such quantities can be queried from the system along with the lifecycle costing implications and carbon emission in per with International Construction Measurement Standard (ICMS).

5.5.2.2. Construction phase. The following areas are projected for opportunities and future research areas:

Conversational-BIM for onsite workers

Unskilled workers on construction sites often have to refer to BIM models with the assistance of skilled professionals leading to time loss. BIM conversational agents can be implemented for the usage of non-skilled workers' easy access via natural language. Most importantly, the hand-busy and eye-busy modes of construction work make voice interaction a viable means of communication. Workers can communicate and receive feedback via speech. Professionals on sites can query the BIM model for components faster and easier to make informed decisions. The conversational-BIM access via mobile phones and tablets would improve the interaction of onsite workers and BIM, thereby boosting productivity.

Conversation agents for onsite construction tasks (Inspection and Instruction)

According to Li, Xue [88], a considerable amount of time is spent on checking BIM models and reading instructional guides to complete installation tasks. The time spent during interaction with the tools is more than the actual time to complete the assembly or installation resulting in productivity loss [89,119]. Extant BIM tools are expert-oriented and not practicable for onsite frontline workers because of the required expertise and time to undertake onsite operations via BIM. Abioye, Oyedele [1] corroborated that the current access mode could constitute distractions resulting in hazards. Consequently, a Conversation AI-enabled Augmented reality can be integrated into BIM to support construction operations. The construction workers can easily visualize the BIM model using the headset and query for instruction guides for current onsite tasks. A model of the proposed component for installation or assemblage can be projected onto the real physical spot in AR to guide installation [90]. Linares-Garcia, Roofigari-Esfahan [52] proposed a voice-based system to support the assembly tasks in the construction phase by providing an audio instructional guide to workers. However, the usage requires providing contexts for the request, no repeat functionality and the feedback is limited to speech.

Hazard identification

Hazard identification is a fundamental aspect of construction safety management and aid in the prevention of hazards or reducing the severity of hazards [91,129]. The traditional approach involves the use of construction statements, safety regulations, design drawings, past accident records, and expert knowledge in preparing safety measures and identifying potential hazards which often do not reflect the dynamic nature of site reality [143–145]. The V/AR has been employed in creating the construction environment for the identification of hazardous scenes. Hadikusumo and Rowlinson [92] proposed using a virtual model of construction components and processes to identify and assess safety hazards involved in the project. Similarly, Perlman, Sacks [93] proposed a virtual reality-enabled system for hazard identification and risk assessment in a simulated construction site. Albeit extant systems using AR/VR have improved safety hazard identification, the deployment of Conversational AI to such systems would bring conversational interface to enable the users to query the construction environment and get more information about likely hazards related with the different tasks and scenes on site.

Furthermore, Fang, Ma [94] presented the use of computer vision, ontology model and knowledge graph for hazard identification on construction sites. However, the system does not offer real-time hazard identification during construction. The deployment of Conversational AI systems employing knowledge graphs, ontology models, and real-time video feeds from the construction site as against images would enable the identification of hazards and alert potential victims. Park, Kim [95] proposed a similar system but employed Bluetooth location technology, BIM, and a cloud communication platform.

Offsite and onsite collaboration

Diverse activities are being carried out on the construction site simultaneously which involve different construction workers [146]. There is a need for seamless collaboration between the onsite activities and offsite offices [147]. Onsite activities such as site monitoring and site management are important to the successful delivery of projects [122]. Albeit, these activities are onsite, there is a need for the integration of offsite personnel [130]. The emergence of digital tools has improved the collaboration between the two categories. Kimoto, Endo [96] reported the use of personal digital assistants (PDA) to ease the management of construction sites. Similarly, Chen and Kamara [97] proposed a framework for information management using mobile computing on construction sites. With the advent of conversational agents, conversational artificial intelligence platforms can provide improved remote access to construction sites. The site office provides the database for the site monitoring details (images, videos, and reports) that can be accessed via conversational agents remotely by the client or offsite construction office. The Conversational AI system would evaluate the query from users to identify the entity and intent, then the necessary information is extracted and presented in the user interface.

5.5.2.3. Post-construction phase. The following are areas of opportunities for Conversational AI systems in the post-construction phase:

Conversational-BIM for facility management

Per Gallaher, O'Connor [98], two-thirds of $ 15.8 billion lost annually is borne by the owners and operators with the majority occurring during the post-construction stage. The BIM model holds promise for creating value for owners and facilities management organizations where the information generated during design and construction could be beneficial for a variety of facility management practices [132]. BIM conversational agents would enable the facility management organisations to have access to BIM models without the need for technical expertise. Motawa [64] proposed a spoken dialogue system to proffer maintenance solutions based on previously resolved maintenance problems. An improved Conversational AI system would enable the facility managers to query BIM models when there are maintenance issues. Sequence2sequence Conversational AI system can learn from past maintenance records and associated BIM components to resolve new maintenance issues. Similarly, Mo, Zhao [99] proposed a model to automate the assignment of staff with the right skills to building maintenance tasks. Such a system can be incorporated with BIM models and Conversational AI for the usage of facility managers and end-users in reporting maintenance problems and automatic assignment of staff. In addition, BIM conversational agents can be used for fire emergencies for providing navigation routes to trapped occupants during fire [62]. The system would enable facility users to report fire emergencies to the facility managers and the fire department. The geometric and spatial information on the BIM would enable safe navigation to be generated, and combustible components to be identified and avoided in the navigation path. Lastly, conversational-BIM can be queried by the users to inquire about the location of different components in the facility for easy access.

Conversational digital twin

There has been an increase in awareness and research on digital twin (DT) in the construction industry [100,116]. Per Pan and Zhang [101] DT 'is a mirror and digital depiction of the actual production process, which can imitate all aspects of physical processes under the integration of physical products, virtual products, and relevant connection data'. The components of a DT are the virtual, data and physical components [102]. The physical components generate the raw data for the processing of the virtual component; the processed data is subsequently relayed back to the physical component [116]. Several technologies are deployed in DT such as data-related, edge computing, and 5G technology. The Integration of a conversational artificial intelligence system would enable users to query the system in natural language with the DT serving as the knowledge source for the response generation.

Project showcase

Conversational AI systems can be used for customer services to attend to customers whilst enabling humans to attend to other critical tasks and improving productivity. Conversational AI systems are being deployed in the business sector such as tourism, aviation and banking in attending to customers. Cassell [103] developed an embodied

Conversational AI that can engage in a multimodal and real-time conversation as a real estate agent (REA). The conversational agent can answer questions about the properties and show the customers around the properties. The system is displayed on a projection screen for the interaction and is capable of sensing verbal and non-verbal input [104]. With the advancement in Conversational AI, the Conversational AI system can be deployed with the use of immersive virtual reality to give the real estate clients the feel of the properties whilst engaging in a natural language with the system.

5.5.2.4. Value-added areas. These areas of opportunities and research directions could not be categorised into a specific phase of the project cycle:

Education and training

VR/AR offers the platform for the training of professionals and students in a simulated and risk-free construction environment [115]. Eiris-Pereira and Gheisari [63] presented a BIM-based virtual environment coupled with virtual agents to enable students to learn about construction events and converse with virtual agents in the natural language. Students can watch construction operations whilst observing the spatiotemporal details of such tasks and asking questions about the operations from the virtual agents. Such systems leveraged VR/AR and conversational agents to improve the traditional learning approach and stimulate cognitive learning [105]. Similarly, Conversational-BIM can be employed in teaching BIM modules for students in a more interactive manner than the traditional approach. Conversational-BIM would enable students to query the model via natural language and visualize all the components in the model.

In addition, the development of question-answering systems can improve the training and education of students and professionals by providing access to information via natural language queries from the users [115]. The systems shorten the time required in sorting and processing data by focusing on the relevant information from the user's query. Kovacevic, Nie [68] developed a question-answering system for construction-related queries from the internet and Cheng, Kumar [69] proposed a similar system to provide answers to questions about project schedules from the output of project management applications. Similarly, Zhong, He [58] proposed a system for responding to questions relating to building regulations in the Chinese construction industry. Also, Lin, Huang [51] proposed a similar system for BIMAIOT-related questions. Conversational AI systems can be developed in different construction domains to aid students and professional learning. For instance, a safety management question-answering system would provide users with answers to any questions asked relating to safety.

Meeting

Several meetings are held with many stakeholders during project delivery in the construction industry [128]. At the end of such meetings, the minute of the meeting is written which entails details of the meeting, milestones and to-do lists that resulted from the meeting [136]. The development of such documents is done manually at the end or during the meetings. With the advancement in Conversational Artificial Intelligence, Conversational AI systems can be developed and deployed to facilitate meetings whilst ensuring a group dynamic, providing a structured communication flow, and improving decision-making processes. Also, these Conversational AI systems would generate meeting outputs and prioritize the to-do lists. Shamekhi [106] proposed a Conversational AI that would manage multi-party conversations in group meetings, that could be scalable to the construction domain.

Well-being

Extant studies have explored construction workers' well-being and different interventions have been proposed in the literature. Antwi-Afari, Li [107] proposed a method for identifying bad working postures in construction workers for the prevention of musculoskeletal disorders. Campbell and Gunning [108] reported that there are major health problems in the construction industry, however, stigmatization worsens the case and makes it difficult to combat. Digital tools are now being employed in ameliorating the health problems of construction workers. Nwaogu and Chan [109] employed wearable devices to collect sleeping data and heart rate variability of construction workers to evaluate the impact of work stress on the health of the workers. However, the use of conversational agents has not been explored for construction workers' well-being. Kimani, Rowan [110] proposed conversational agents to support well-being and productivity in the workplace while Morris, Kouddous [111] developed a conversational system to provide emotional support to improve mental health. Albeit these systems are beneficial, they are often not scalable to the construction industry domain. Consequently, there are opportunities for the development and deployment of conversational agents in relation to the extant system for construction worker safety and well-being. For instance, a Conversational AI system can be developed to alert construction workers at risk of musculoskeletal disorders during construction operations and provide support for their mental well-being. Also, the conversational agent can manage schedules and track the activities of the workers.

Interface development

Conversational AI systems could be employed to serve as an interface for different background applications to interact with the user and the background process. Albeit all Conversational AI systems are conversational interfaces to improve human–computer interaction, this category is highlighted for other emerging areas that are not categorised in the previous sessions. For instance, Adel, Elhakeem [50] developed an interface for smart contracts on a blockchain-based network to track the work progress of construction projects. As such, the smart contract serves as the background application and the developed chatbot provided access to it. Similar chatbots could be proposed for different domains in the construction industry such as risk management, contract administration, assessment of modern methods of construction in organisations, tender evaluation and others.

Job opportunities

Increased adoption of technologies in the AEC industry has led to a loss in some low-level skilled opportunities and the creation of new job opportunities [3]. The advent of CAD led to the loss of jobs for draughtsmen and the creation of new jobs for CAD modellers and managers. Also, BIM led to the creation of BIM managers, BIM modellers, BIM coordinators, BIM Engineers, and BIM specialists in the industry [149]. Deployment of artificial intelligence in the AEC industry also requires a set of construction AI researchers, trainers, engineers and testers [1]. Similarly, the development and deployment of conversational artificial intelligence in the construction domains would lead to the creation of job roles such as researchers, AI engineers, trainers and testers in the industry and academia [13].

6. Conclusion

Conversational Artificial intelligence has been improving the interaction between humans and computers over the years. Many industries have deployed Conversational AI systems in their domains to boost productivity. However, the applications of such systems in the AEC industry are still at the germinating stage. Existing studies on Conversational AI in the AEC are few and focused on limited domains. The information-intensive nature and the eyes-busy, hands-busy mode of operation on construction sites make Conversational AI a good fit for the industry and the construction sites. Thus, this study employed a systematic review of Conversational AI systems in the construction industry with the view of identifying the current application areas, development of the Conversational AI systems, opportunities, and challenges. A systematic search in Scopus, IEEE Xplore (Institute of Electrical and Electronics Engineers), ACM (Association of computing machinery), Web of Science, and Science Direct resulted in a total of 21 studies on Conversation AI systems in the AEC industry. These were retrieved and critically reviewed in this present study. These studies emanated from journals, and conference papers between 2002 and 2022.

Most of the Conversational AI systems in the reviewed studies employed a modularized architecture save one that employed the seq2seq approach. Similarly, most of the systems with ASR employed Google Speech Recognition System. The current applications of Conversational AI systems are majorly for information retrieval and information extraction. Extant Conversational AI systems focused on retrieving or extracting information from building information models, websites, project schedules, and building regulations. These systems are all tasks oriented and deployed for use by designers, facility managers, facility users, educators, and construction workers. These Conversational AI systems are aimed at improving users' experience, improving productivity by reducing interaction time, and improving cognitive learning. These AEC Conversational AI systems are however still limited in their functionalities and are often not evaluated. Only a few of the developed systems are evaluated and the evaluation is done via users' experience. This could be related to most of the systems still being in the improvement and development stage and not yet ready for usage beyond the laboratory/controlled environment.

Based on a focus group discussion, this study highlights the challenges of Conversational AI system deployment and validates opportunities and future research direction for Conversational AI in the AEC industry. The development of Conversational AI would boost productivity and improve users' experience in the deployed domains. One of the ripest areas for Conversational AI applications is the BIM, conversational-BIM would change the BIM from an expert-oriented system to a user-oriented system. Its applications would cut across the lifecycle of the project and improve the acceptability of BIM with unskilled and skilled professionals. Other Conversational AI systems can be deployed in the design, construction, and operation phase and in educational institutions in the built environment. This study also highlights the opportunities for deploying conversational agents in the AEC industry for meetings, briefing, hazard identification, training, collaboration, well-being, facility management and customer service. In addition, the development of these systems would lead to the creation of job opportunities in the industry. Also, these opportunities are not exhaustive as conversational artificial intelligence can provide a platform for any existing systems, thereby improving the users' experience.

Despite these immense opportunities for conversational agents in the industry, this study revealed that the applications are currently low because of a myriad of challenges. These challenges stem from the conservative culture of the industry in relation to innovation. Thus, there are funding, development, data, ethics, privacy, trust, scalability, and expertise challenges in the AEC industry. These challenges are surmountable, and this study presented some interventions to the challenges. With the advancement in deep learning techniques, conversational agents in the AEC can leverage PLMOs, Generative Adversarial Networks (GANs), CNNs, LSTM, Deep Belief Networks (DBNs) and RNNs in an end-to-end neural approach.

Lastly, despite the contributions of this study, there are limitations. The study employed data from Scopus and Web science which is subsequently validated with IEEE Xplore, ACM, and Science Direct database. Thus, the coverage of these databases could serve as a limitation to the study. Similarly, the search queries used in the search and the selection criteria could also serve as a limitation. However, best practice guidelines were employed in conducting the systematic review. Hence, this research is significant as it is the first attempt to the best of the authors' knowledge to provide an overview of Conversational AI in the AEC industry. Its findings would benefit researchers and stakeholders in the AEC industry to better understand Conversational AI, challenges, and unexplored areas for Conversational AI deployment.

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

No data was used for the research described in the article.

Acknowledgements

The authors would like to acknowledge and express their sincere gratitude to the Engineering and Physical Sciences Research Council (EPSRC – EP/S031480/1) for providing financial support for this study.

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