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Cloud computing for chatbot in the construction industry: An implementation framework for conversational-BIM voice assistant

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ABSTRACT

This study presents a structural framework for selecting cloud services for the Conversational AI system implementation in the construction industry using Design Thinking Methodology. A focus group discussion approach was used to obtain user requirements from construction workers to implement the Conversational AI for BIM. This resulted in five factors: finance, speed of operation, privacy, estimation, and interface. The user specifications were mapped into technical modules, which were used to select cloud services employed to implement the virtual assistant for the construction industry. The study thus presented the comprehensive requirements for the different categories of construction workers to implement the Conversational-BIM Chatbot (Conversational-BIM) system. Furthermore, the study presented the architecture of Conversational-BIM using Amazon Web Services. The study is useful to researchers and IT developers in implementing chatbots for the construction industry as it presents the relevant considerations for conversational AI applications in the industry.

1. Background and introduction

Voice user interfaces employ voice-based commands [1] to exhibit hands-free and eyes-free interaction with great intuitiveness and flexibility [2]. According to Ruan et al. [3], humans speak faster than typing. Also, Lee and Nass [4] opined that hearing synthesised speeches as responses created a strong social presence to users. No doubt, voice-based technology's speed, efficiency, and convenience is leading towards the less screen-interaction era [5]. Thus, this is not surprising that the adoption of voice-based technology is soaring, with about 3.25b digital voice assistants in use in 2019 and a forecast of 8b users by 2023 [6]. Digital Voice Assistants, also called Chatbots or Conversational Artificial Intelligent systems [7], have recorded successful applications across retailing [8], marketing [9], education [10] and healthcare ([11] & [12]) sectors. In addition to carrying out business operations like administration, billing, payroll, amongst others within an office, construction industries also carry out several operations on sites. No doubt, the construction industry is daily evolving and desiring to benefit from the latest technological innovation for maximum operational efficiency. However, the industry is slow in adapting to change, especially adopting advances in IT [13,14]; nevertheless, this tide appears turning nowadays. As the construction industry has been benefitting from emerging technologies, i.e., from BIM [15,16], Digital Twins [17], Artificial Intelligence [18], Big Data [19,20,21], IoT [22], Machine Learning [23,24], Deep Learning [25–27], Augmented Reality/Virtual Reality [28,29], Robotics [30,31] to Cloud Computing [32], the industry is also poised to benefit from the recently developed digital voice assistant technology. In practice, voice-based technologies enable construction workers to perform diverse activities on sites using voice command with hands-free and eye-free operations [7]. Furthermore, voice-based technologies can improve site worker's productivity as interacting with voice is more natural [33], unlike other mediums of interactions like the keyboard and mouse.

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hands-free and eyes-free interaction with great intuitiveness and flexibility [2]. According to [3], humans speak faster than typing. Also, Lee and Nass [4] opined that hearing synthesis speeches as responses created a strong social presence to users. No doubt, voice-based technology's speed, efficiency, and convenience is leading towards the less screen-interaction era [5]. Thus, this is not surprising that the adoption of voice-based technology is soaring, with about 3.25b digital voice assistants in use in 2019 and a forecast of 8b users by 2023 [6]. Digital Voice Assistants, also called Chatbots or Conversational Artificial Intelligent systems, have recorded successful applications across retailing [8], marketing [9], education [10] and healthcare ([11] & [12]) sectors. However, the construction industry is slow in adapting to change, especially adopting advances in IT [14]; nevertheless, this tide appears turning nowadays. As the construction industry has been benefitting from emerging technologies, i.e., from BIM [15], Big Data [19,20], IoT [22], Deep Learning [26], Augmented Reality/Virtual Reality (Delgado et al., 2020), Robotics (Delgado et al., 2019) to Cloud Computing [32], the industry is also poised to benefit from the recently developed digital voice assistant technology. In practice, voice-based technologies enable construction workers to perform diverse activities on sites using voice command with hands-free and eye-free operations. Furthermore, voice-based technologies can improve site worker's productivity as interacting with voice is more natural [33], unlike other mediums of interactions like the keyboard and mouse.

BIM is a modelling tool comprising 3D visualisations, time and cost projections to result in 5D designs (Eastman et al., 2008). BIM is a shared database containing specialised documentation on architecture design, landscape design, construction and installation design, scheduling, bills of quantities, and cost estimates [34], accessible for collaboration by stakeholders to produce complete project documentation. The use of BIM software on construction sites has become an established routine. Meanwhile, interacting with BIM with the traditional keyboards and touchscreens has slowed down the adoption of the technology [35]. This slow adoption is due to inconvenient methods of interaction, thus limiting the use of the technology. Construction workers are already working with hands on site; however, using hands to hold tools and interact with BIM simultaneously is quite difficult. Akinade et al. [15] argued that interfacing the voice with BIM will widen the adoption of BIM for improved productivity and fast delivery of projects, as integration of Voice Assistance with BIM would provide a more natural interface for construction workers to interact with BIM on site.

Regrettably, BIM originally is not accessible in real time, as traditional BIM is a standalone system not readily accessible to diverse construction stakeholders, hence, not widely adopted [36]. In contrast, cloud computing is a key enabling technology to facilitate easy access and collaboration for BIM [37]. Also, the government's strategic plan for BIM Level3 will not materialise without the adoption of cloud computing across construction industries. Consequently, interfacing BIM with conversational technology will improve interaction, while cloud computing technology will enhance BIM accessibility [38].

Thus, the need to develop a conversational BIM application, which will enable construction workers to have unhindered interaction with BIM software using speech inputs and responses requires a cloud technology platform. Maximising the opportunities from technologies such as cloud services is dependent on prudent decisions which requires considerations of strategies, facilities and requirements of organisations (Costa, 2013). There are numerous cloud computing services from different providers due to the increasing demand for the technologies (Bello, 2012). Consequently, there has been numerous attempts to select appropriate cloud services; [39,40,41,42,43,44] amongst others. Most of these existing studies on selecting cloud services are for general applications whereas selecting cloud services is better with a particular/specific use case in focus [45]. However, there is no known study that selects cloud service to implement Conversational-BIM application and also focusing on the need of the construction workers, hence this study. This study's objectives are to develop a framework that establishes the relevance and timeliness of Conversational-BIM in construction, formulate its technical requirements, and map the technical requirements to appropriate cloud services for efficient delivery and improved productivity.

The rest of paper is as follows; in Section 2 existing use of cloud computing in construction is discussed. This is followed by discuss on the case study, that is Conversational BIM (Conversational-BIM). Section 4 discusses the methods employed to establish criteria for selecting cloud services to implement Conversational-BIM. Next to this is full discussion of the result, then motivations as well as challenges for the use of Conversational-BIM is discussed. Section 7 discusses the significance of the study while Section 8 concludes the paper.

2. Cloud computing in construction

2.1. Cloud computing

According to National Institute of Standards and Technology (NIST) "Cloud computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (for example, networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [46]. Generally, cloud services are popularly offered as three services, Infrastructure-as-a-service (IaaS), Platform-as-a-service (PaaS) and Software-as-a- service (SaaS). These services could be deployed at the public, private, hybrid or community level, and they are of different forms; some are available on all platforms, whereas some require third-party applications to run effectively. Also, some are simple to set up and use, and some allow for collaboration within a group of users exhibiting a groupware feature. Some cloud services are suitable for small business or enterprise use, while some are for personal use. Lastly, synchronisation is another form, which allows for fast access to cloud storage. Consequently, cloud services offer different control rights to users, depending on the technical ability of users. A highly tech-savvy user may desire more control of the cloud resource, while a novice may opt for lesser control of the service. Cloud services have different price variants. Some have free start then followed by subscription payment, while some start with a subscription offers only. In all, the decision makers' interest [47] is a strong factor in selecting a cloud service for adoption, and selecting the best cloud service could be influenced by decision makers' experience and knowledge [48].

2.2. Existing applications of cloud computing in construction

In Bello et al. [32], cloud computing has been helpful in the preconstruction, construction, and post constructions stages, specifically for managing energy, waste, health and safety, supply chain, and project communication for built assets. Azambuja et al. [49] solved the accumulating large inventories problem resulting in material wastage on construction sites using cloud technologies. Also, Redmond et al. [50] employed cloud technology to alleviate the limited access problem to existing construction information that usually results in resource wastage. Cloud technology was employed to solve the inaccurate components delivery problem due to the lack of coordination among parties in precast construction [51].

Getuli et al. [52] employed cloud technology to effectively monitor construction activities with location information for improved safety on site. Park et al. [53] also employed cloud technology to detect unsafe conditions on construction sites and prevent potential hazards to site workers. Tang et al. [54] used cloud technology to solve the problem of irregular and untimely site inspection. Furthermore, Guo et al. [55] evolved a safety system using cloud technology to observe workers during metro construction, while Li et al. [56] used cloud technology in underground construction for timely and accurate recognition of safety risks during preconstruction.

Cloud computing has been used to manage energy in different stages of construction [57,58]. For instance, Khajenasiri et al. [59] employed cloud technology to intelligently control building energy in smart cities, while Rawai et al. [60] used cloud computing to reduce both energy consumption and CO_2 emissions during construction, Cho et al. [61] employed the technology to manage energy systems for a sustainable decision support system. Wang et al. [62] reported the cloud technology application to realise the Building Management operations of green buildings. Balaras et al. [63] utilised cloud technology to develop a Virtual Energy Laboratory for simulation designs of energy-efficient buildings. Furthermore, Curry et al. [64] employed cloud technology to provide a unified interface to manage building data from diverse integrated sources, and Naboni et al. [65] employed cloud technologies for parametric simulation of a building's energy performance.

Cloud computing has also been employed to solve the problem of a gap in the supply chain that causes delays in project delivery as a result of an uncoordinated traditional material supply chain [66]. Fathi et al. [67] employed cloud technology for accurate information transfer to parties in the construction supply chain process, while Azambuja and Gong [68] used cloud technologies to evolve cost-efficient management of supply chain data. Grilo and Jardim- Gonclaves [69], used cloud technology to improve interoperability among stakeholders in the procurement process. Ko et al. [70] and Sahin et al. [71] employed cloud technologies to provide an affordable tracking system for material movement on construction sites. Hemanth et al. [72] also employed cloud technology to solve the misperception of information in the precast industry.

Cloud technology has been employed to solve the low construction quality problem as a result of poor communication and coordination among stakeholders [73]. Ferrada et al. [74] used cloud technologies to formalise knowledge transfer among local construction companies. Petri et al. [45] used cloud technologies to coordinate multi-site construction activities involving varied organizations and individuals. Alaka et al. [19] employed cloud technologies to analyse data for predicting the failure of construction businesses. Ahn et al. [75] employed cloud technology to integrate information from construction sites together with office work to aid decision making. Petri et al. [76] employed cloud architecture to improve data access during construction, and Beach et al. [77] employed cloud technologies to store and manage building data for improved security. Polter and Sherer [78] used cloud technologies for SMEs to provide affordable data transfer systems, while Núñez et al. [79] employed the technologies for SMEs to manage lessons from previous projects. Jiao et al. [80] employed cloud technologies management to provide a cost-effective life-cycle data management system for the AEC/FM sector.

These various applications of cloud technologies revealed that the technology had been used to solve a number of problems/issues in the construction industry (Ajayi et al., 2016; [81]). No doubt, cloud computing adoption has grossly impacted the efficiency of construction companies as the industry is beginning to feel the relevance of cloud computing, which holds considerable benefits for the industry, including the use of voice-based devices on construction sites. The technology reduces the use of papers for documentation in project delivery and reduces energy even to discard waste papers [82]. Cloud adoption has minimised the energy consumed by individual in-house servers for operations and cooling. Also, cloud computing reduces the commuting of construction workers and reduces carbon emission and carbon footprint [83]. Thus, cloud computing adoption reduces operational and maintenance costs resulting in increased ROI for the construction industry.

2.3. Generative artificial intelligence in the construction industry

No doubt the current wave of generative AI adoption is hitting the construction industry, as its use is being found in the various stages of construction. In 2022, Hayman [84] proposed the ChatGPT to simplify the art of gathering information varieties of topics in architecture and design not limited to building materials, construction methods, or design trends. Rane et al. [85] also opined that the construction industry like manufacturing, finance, retail and transportation could benefit from the use of generative AI for project planning, design enhancement and risk mitigation. Thus, [86] demonstrated the use of GPT in construction optimize material selection in the design phase of construction. Furthermore, Priesto [87] employed ChatGPT to generate a construction schedule that resulted in positive interaction experience thus indicating the potential of generative AI tool to automate repetitive tasks in construction industry. Additionally, You et al. [88] also proposed a sequence planning system for construction tasks leveraging on the advanced reasoning capabilities of the ChatGPT. This was corroborated by Parm [89] who demonstrated the use of Generative AI to ease the process of designing project planning.

Meanwhile, Beach et al. [90] had earlier advanced GPT models leveraging in their NLP capabilities to discern textual relevant information for digitized reasoning can be valuable in automated regulatory compliance during construction activities. Despite the diverse features requires for efficient resource allocation in project management [91,18] suggested that Generative AI can provide necessary parameters for project impact analysis in project quality management. Furthermore, Zheng and Fischer [92] agreed that GPT models is capable of scrutinizing historic data and integrating it with new information on the current state of the project for a comprehensive project risk assessment. Meanwhile, Xia et al. [93] had proposed the use of AI to overcome the limitation in analysing extensive datasets that could miss concealed defects resulting in safety issues in assessing structures.

Akinosho et al. in 2020 gave an insight into how deep learning techniques could benefit the AEC industry in image processing, computer vision and natural language processing. [94] gave insight into how Computer Vision being a branch of AI can benefit the construction industry for better prediction accuracy for onsite health and safety analytics. [95] further demonstrated the CGPT to provide safety education and training for unrecognized hazards on construction sites that can result in unexpected safety incidents construction professionals to improve hazard recognition levels.

To improve building usability, [92] propound the GPT analysing historical data, weather, occupancy and sensor data on equipment to detect waste, predict future usage to optimize energy management and customize resource recommendation for building users. In addition, Saka et al. [7] demonstrated the ChatGPT prompt as a Facility Chatbot to collect and sort occupant requests to improve facility management. No doubt, demolition process is characterised with structural dismantling, debris removal and hazardous material management [96] thus requiring a comprehensive risk assessment as against the traditional risk assessment which may be subjective and time consuming [97]. Thus, the GPT leveraging on its advanced NLP and ML capabilities could provide a more accurate risk assessment to identify and mitigate potential dangers in construction demolition.

3. Integrating BIM with conversational AI (Conversational-BIM)

Conversational AI enables humans to interact freely with computers in the most natural forms, this was earlier demonstrated by ELIZA in 1966 (Gentsch 2019). This process involves the use of voice commands to interface with computer systems as advances in natural language processing has enabled computer systems to identify valuable information from human speeches [98]. Conversational-BIM (Conversational-BIM) enables interaction with the building systems represented in BIM files with voice commands. It leverages artificial intelligence, natural language processing, and deep learning technologies to evolve an automated interaction system using voice and text between humans and BIM files in a human-like conversational flow [99]. This technology allows construction workers the opportunity to interact with the construction database with voice commands and text options; and support workers to simultaneously manoeuvre between getting design information, procedure implementation, and equipment handling. Thus, a worker holding tools with his hands can query the BIM database with voice commands and also receive responses as voice and text outputs. This technology thus has the potential to save time and improve productivity in construction. Voice assistance technology has become widespread with the diffusions from technological giants like Amazon Alexa, Google Assistant, Microsoft Cortana, and Apple Siri. The evolution of construction workers interaction from traditional to the BIM era then to the Conversational- BIM era is illustrated in Fig 1. In the traditional era, construction workers gather around to discuss construction documents produced from computers starting from around 1957 (Cherkaoui, 2017).

BIM crept into the construction industries in the late 1990s [100] and attained about 75 % increase in usage between 2007 and 2009 (Kihong and Mojtaba, 2011). Meanwhile, with BIM evolution, various stakeholders could interact with construction data (BIM platform) using a keyboard and mouse. Conversational interfaces came in around 2014 (Klopfenstein et al., 2017), now culminating into the Conversational-BIM to enable voice interaction with BIM on construction sites while possibly holding tools with hands.

3.1. Selecting cloud service for conversational-BIM

There are several cloud computing providers due to the increase in demand for cloud technology services [101]. There are numerous criteria for evaluating cloud services providers. Bello and Reich [102] discussed some criteria that could be used in evaluating a cloud provider. However, these criteria could be incompatible, i.e., keeping down operational cost while attaining high performance and service security [103]. Though a cloud user can evaluate a cloud provider based on user requirements ([104,105,106,107]& [108]). However, this selection may not be made intuitively [109] as a number of decision frameworks ([110] & [111]) and selection criteria [112,113,114,115,116,117] are available for consideration.

Attempts in selecting cloud services have been classified as decision problems, which contain conflicting criteria. A number of approaches exist to select appropriate cloud services. Menzel et al. [43] employed an ANP approach, while Dastjerdi et al. [39] used a logic-based method to select an IaaS service. Godse and Mulik [109] employed an AHP-based method to select a SaaS. Zheng et al. [118] proposed a cloud service architecture and core algorithms to select a cloud service. Limam and Boutaba [119] employed trust worthiness-based approach to select a cloud service. Also, Saripalli and Pingalli [110] ranked cloud service alternatives and adoption with simple additive weights. Martens et al. [120] suggested community platforms approach, and similarly, Jung et al. [121] proposed a recommendation platform to select a cloud service. Sundareswaran et al. [44] employed a greedy algorithm-based approach, while Yang et al. [122] described the dynamical adjustment methods to select a cloud service. Also, Quinton et al. [123] presented an automatic selection approach while Lee and Seo [124] employed a hybrid MCDM model, using a balanced scorecard (BSC), fuzzy Delphi method (FDM), and fuzzy analytical Hierarchy Process (FAHP) to select IaaS for IT managers. Also, Ji et al. [40] considered the multi-criteria decision-making analysis (MCDM/MCDA), and Liu and Wang [42] employed a fuzzy algorithm to resolve uncertainties around information for MCDM/MCDA. Fuzzy numbers are used to represent linguistic values depicting the weights of the criteria.

Finally, intuitionistic fuzzy set [125] was employed in Liu et al., [41]; Liu, [126] and Liu and Li, [127]. Nevertheless, all the above studies are geared towards selecting cloud services for general applications. However, Patil et al. [128] have opined that selecting a reliable cloud service is dependent on the use case, thus, provided a comparative study of cloud platforms to develop a chatbot system. Abdel-Basset et al. [129] further in 2018 proposed an improved framework to select cloud services for an e-learning platform. These studies though addressed specific use cases, focused on the requirements of system developers, whereas our study employs decisions of Conversational-BIM software end-users to select appropriate cloud services for Conversational-BIM implementation. Thus, this study attempts to select cloud services for the Conversational-BIM employing/using the needs/requirements of the construction workers who are Conversational-BIM target users. This study establishes a structural framework for selecting cloud services for implementing Conversational-BIM in the construction industry using Design Thinking Methodology.

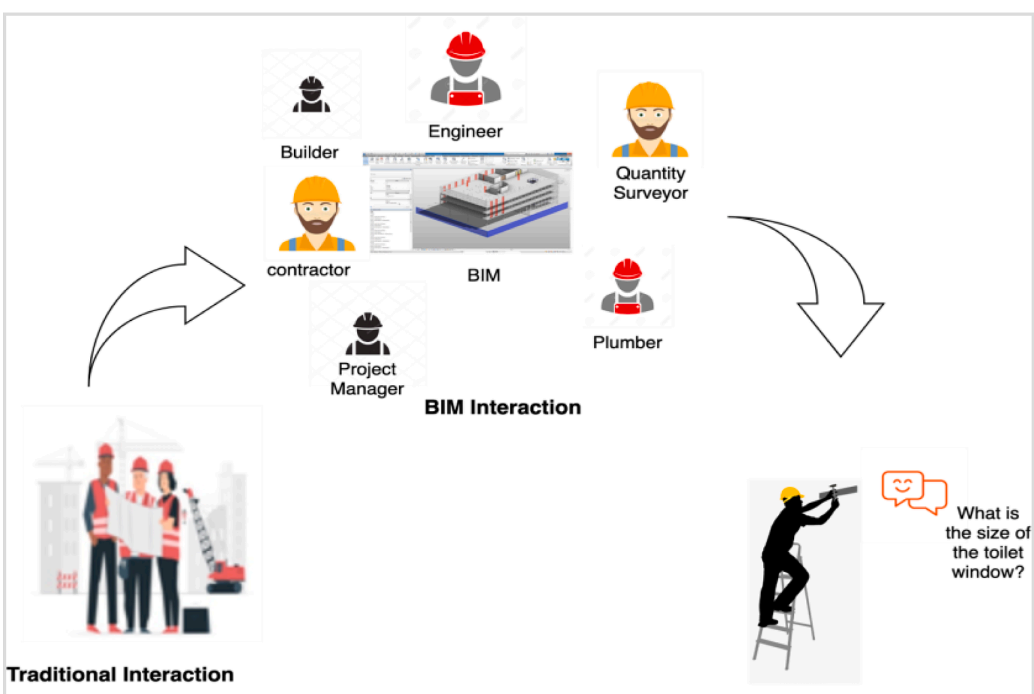

Fig. 1. Evolution of Interactions on Construction Sites.

4. Research methodology

The study involved focus group discussion among practitioners in the construction industry. The output of the discussion was analysed thematically to obtain the user requirements for conversational BIM implementation in the construction industries. The users' requirements were translated into the necessary technical specifications which was matched with appropriate cloud services. The discussion also gave the motivations and challenges for the adoption of BIM Voice Assistant in the Built Industry. The roadmap for the study is as depicted in Fig 2.

4.1. Establishing criteria for the selection of cloud services and providers

In gaining an in-depth understanding of industry experts' experience [130], a descriptive research approach was employed in this study to obtain first-hand information relating to real-life experiences of practitioners [131]. This study employs design thinking methodology which involves conducting focus group discussion with domain experts within the construction industry. This is to facilitate the opportunity to interrelate with competent participants to gain their common understanding of the subject matter. This approach contrasts the biased understanding of a single individual or researcher, or marketer [132]. The approach, therefore, assists in getting comprehensive information from industry practitioners [133] on the criteria to select cloud services for Conversational- BIM. Creswell in 2013 opined that an in-depth interview with individual participants or interview with multiple participants (focus group discussions) could be used to carry out data collection. Hence, this study employed focus group discussions to support inter-subjective opinions among participants to arrive at a common understanding, as it avails participants to build on one another's opinion in the course of the discussion [134]. According to [135] purposeful sampling was employed to determine relevant participants whose understanding is key for the study. Selection criteria for participants were based on job role, years of experience, interest in Conversational-BIM, eagerness, and convenience to participate in the study. The established network of researchers within the industry was used in reaching out to the participants. A similar sampling technique was found in [20,136–140]. As such, participants were selected based on critical sampling to ensure all professions involved in using Conversational-BIM are considered. The professionals selected for the focus group discussion are Engineers, Builders, MEP Professionals, and Project Managers.

In qualitative research, Polkinghorne [141] had recommended 5 to 25 participants; a total of 24 participants were involved in this study. The participants (depicted in Table 1) were selected from the UK construction firms and had 6 to 20 years of experience. The participants have been involved in several projects within the last five years and are committed to using Conversational-BIM software. Two members of the research team moderated each of the focus group discussions. Table 1 shows the number of participants in each discussion group.

Table 1
Participants in the Focus Group Discussion.

Focus group	Categories of participants	No of experts	Years of experience
1.	Civil and Structural Engineers ○ Site based Engineers	5	7 –10
2.	Builders	6	6–13
3.	MEP Professionals ○ 3 Mechanical Engineers ○ 4 Electrical Engineers ○ 2 Plumbing Engineers	9	7–12
4.	Construction Project Managers	4	9–20
Total		24	

The discussion started with a demonstration of a Conversational software. The participants were then asked to state the requirements for implementing a conversational software in the construction industries. To spun the discussion, some set of questions were provided for the participants. The discussion basically is to state the users' requirements or expectations from Conversational-BIM to be implemented in the construction industry. The discussion lasted between 50 and 70 min. The discussion was recorded for ease of transcription and analysis with the consent of the discussants

4.2. Thematic analysis

Qualitative data analysis involves a systematic procedure that enables a researcher to move from a narrow unit of analysis to broader units [135]. The analytical process emanates from the identification of significant statements to broader units of units. In order to accomplish this, the voice data were transcribed into written statements and read over many times to bring out remarkable statements and crucial themes that explain how participants would be able to present their specifications which will be transformed to technical requirements to determine appropriate cloud services to implement Conversational-BIM. To achieve this, a content-driven thematic analysis [142] was employed to explore and identify both implicit and explicit recommendations coming from the data. This process, otherwise called "horizonalisation" [130], was followed by expanding clusters of meaning to highlight the basic criteria for selecting cloud services for Conversational-BIM. Table 2

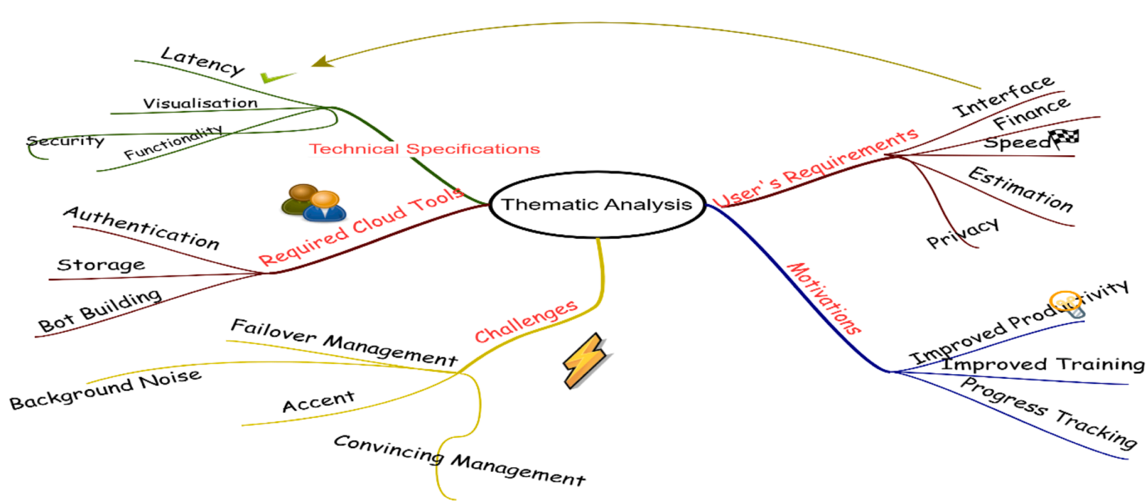

Fig. 2. Mind map of the study.

Table 2
User s specifications for conversational BIM.

Concerns Raised/User's Specifications	Focus Group			
	1	2	3	4
Quick Response Time	✓	✓	✓	✓
Low latency				
Fast Response				
Bill of Quantities Export	✓		✓	✓
Analysis on Bill of quantities				
Quantity Take off				
Easy Navigation		✓		✓
Easy Manoeuvre				
Handle				
Pilot				
Ease of Use	✓	✓	✓	
Easy to operate.				
Easy to manipulate.				
Not too technical				
Intuitive User Interface	✓		✓	✓
built-in interface				
Spontaneous interface				
Graphical interface				
Friendly interface				
Easy Model Manipulation	✓	✓	✓	✓
Zoom and Pan	✓	✓	✓	✓
Consistency with current branding	✓		✓	
Data Locality	✓	✓	✓	
Data in vicinity				
Data within surrounding area				
Data Centre must reside in UK				
User must log in with email and password				
Data Privacy Data Isolation	✓	✓		✓
Data Secrecy Data Separation				
Data Security Data safety Data Reliability				
Data protection				
Price	✓	✓	✓	✓
Budget		✓	✓	✓
Try-out Trial period	✓		✓	✓
Cooling off period Experimentation Testing				
Pay as You Go		✓		

summarises the user requirements identified through the focus group discussion.

4.3. Grouping users specifications for conversational-BIM

A total of five clusters of user's requirements for Conversational-BIM were identified from the discussion. These are (i) Interface (ii) Privacy (iii) Finance (iv) and Estimation (v) Speed. The outcome from the focus group discussion is expected to provide a guide into the user requirements to be translated into technical requirements to implement Conversational-BIM. The user's specifications that are concerned with the interface and interaction with the software are grouped as *interface*. This category involves the views, handling, and navigating of the software to ensure ease of use of the Conversational-BIM system. The users are also concerned about the safety and integrity of the system, this is categorised under the *privacy* requirements. This module is also concerned about protecting the data, as users are concerned about the location of the data centre housing the data. The discussion also revealed that the financial implication of the Conversational-BIM system as a requirement, thus bringing in *finance* as user's specification. Since the burden of the financial implication of Conversational-BIM will be passed to the project. Thus, the users emphasized a cheaper option like Pay-As-You-Go that will not involve a significant take-off cost. Also, users are interested in a trial period that will enable a smooth take off to allow for smooth experimentation and try-out of the Conversational-BIM system. The focus group discussion revealed that users expect some auto computations for recurring operations, for example, components selection, list of components, Bill of Quantities Export components, Quantity Take-off and so on. This is categorised as *estimation* requirement for the Conversational-BIM system. The user's specification also discussed the responsiveness of the system, which refers to the *speed* of operation (latency). That the latency of the Conversational-BIM system is required to be minimal so as to reduce delay in the system's operation. In all, five areas are identified in the discussion as the germane factors that influenced the choice of tools to implement Conversational-BIM.

5. Framework for selecting cloud services for conversational-BIM

This section discusses the actionable insights from the thematic analysis of the discussion. Here, the study translates the user's specifications obtained in Section 4.1 into technical requirements and further identified the cloud services required to implement Conversational-BIM based on the user's specification as depicted in Fig 3. The section also presented the selection of a cloud service provider for Conversational-BIM and finally the architecture of Conversational-BIM using the selected Amazon Web Services.

5.1. Technical requirements identified from users' specifications

The requirements from the users are categorised as the target dimensions. The various specifications obtained from the users are hereby translated into technical requirements for the CovBIM system. The technical requirements are further implemented with cloud services as shown in Fig 3. Adapting Repschlaeger et al. [143], interface need is mapped into interaction dimension, the financial consideration is regarded as the cost of operation, the estimation need is classified as the functionality of the system, the need for a fast and responsive system is categorised technically as the latency, and the privacy requirement is translated as security dimension.

5.1.1. Interaction

The discussants want the Conversational-BIM system to be able to accept both the speech [1] and queries as this is the growing trend [144] and the traditional text. This implies that the system is able to accept speech or text as input and also give out responses as text or speech. As the user talks to the system, the recognised spoken words are displayed on the screen. The voice response from the system is also displayed on the screen. The interaction needs to have a clear and easy to operate interface as the aesthetics of the interface is equally important as the content. The interface must not be clumsy, unappealing or difficult to use. Conversational-BIM should be intuitive [2], presenting users with clear choices and not faced with guesses that may require spending more time to figure out the exact message being passed. Also, the character of the personality in Conversational-BIM should be easy to perceive. Such that the personality should be interesting and memorable to aid the interaction. The conversation needs to reflect some sort of empathy to create a natural scenario. "*It could warn a plumber that the scaffolding is not properly coupled, hence standing on it may be dangerous*". Conversational-BIM interface should reflect the evolving use of languages by digital technologies like emojis, GIFs in an appropriate manner. Since users interact with construction models, these models are of different sizes and formats. Hence, Conversational-BIM is required to recognise construction models and convert models to usable formats for easy manipulation, consequently justifying the need for a model conversion module. The technical specifications for the interface requirements are visualisation, speech processing and model conversion modules.

5.1.2. Functionality

The construction workers desire some functionality from the system, expects that the system is able to automate some routine tasks, i.e., components selections. Conversational-BIM is expected to prove its worth by displaying the true value of the technology and making construction work easier in some ways. Conversational-BIM is desired to meet the expectation of construction workers by computing the

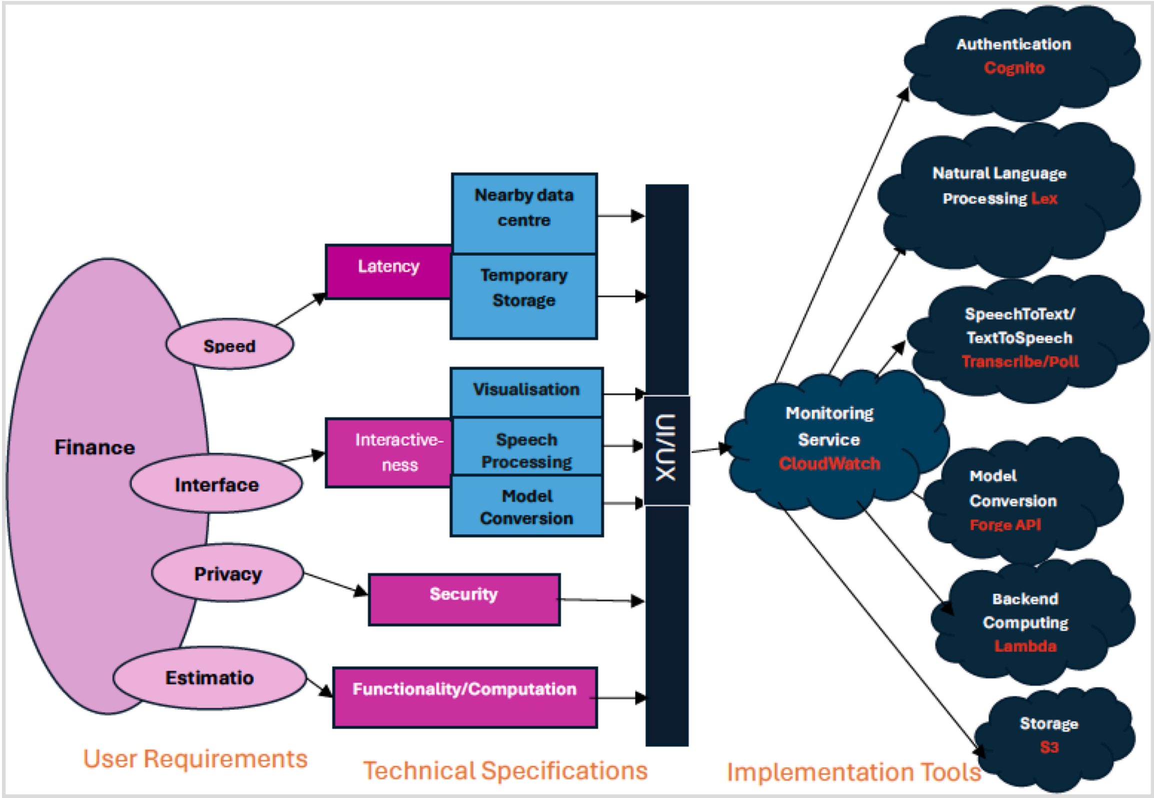

Fig. 3. Translating User Specifications into Conversational-BIM Technical Tools.

regularly and repeatedly engaging operations. The focus group discussion revealed that construction workers expect some sort of automation for recurring tasks on construction site. These can be components selection, list of components, suggesting the next task from the sequence of operations, quantity take-off, bill of quantities export, and analysis on the bill of quantities/Quantities. Conversational-BIM should be able to display some level of intelligence even outside the essential queries. Even for queries outside the construction, the Conversational-BIM system should have a fall-back response that will not frustrate the user but rather engage them in a meaningful manner. Conversational-BIM should be able to provide/offer a way forward, especially when the request from the user is not understood and could not find an appropriate answer.

5.1.3. Latency

Response time is a recognized component to measure the usability of IT systems [145]. This is in consonance with Mishra et al. [146], where latency was considered in the choice of cloud configurations for smart home applications. A lengthy response time may cause lower satisfaction and poor productivity among system users, which may eventually lead to discontinuing the use of the system [147]. This requirement, however, reflects the need for the site workers that will use the system on the construction site, as a highly responsive system will improve the efficiency of site workers. However, very rapid responses could also lead to higher error rates [145]. Recent advances in hardware speed and communication bandwidth have really improved response time and system performance for IT systems. However, the speed of conversational cloud service may require more than these. For example, the location of the server, the type of storage mechanism and efficiency of the back-end processing service will determine the overall response of the system. To overcome the latency problem may require the need for temporary storage to hold the model in use instead of contacting the server for every operation. Also, this might necessitate choosing a nearby data centre. Speed of operation is critical for site workers in order to achieve the schedule for a given period.

5.1.4. Security

Security is concerned with authorised access and privacy of the system. Privacy concerns were raised as important in the use of the Conversational-BIM system during the discussion, and this is in tandem with [148,149] and [150]. As personal voice being recorded also requires protection since personal data as voice is no different to other types of data. Although, voice-enabled technologies are expected to wait for an activation word to prompt the system to listen and respond. Since microphones are always on, if an activation error occurs, personal/private conversation could be recorded and exposed to the cloud. Moreover, as voice data is also prone to a number of cyberattack [151]. Studies have shown that exposing an individual’s voiceprint is posed to security risks such as spoofing attacks [152] and reputation attacks [153]. Also, the use of voice technology is improving/increasing; the ability to mimic voice for nefarious purposes or fraud like “replay attack” is on the increase. However, effort is on to alleviate some of the privacy and security concern over speech data processing as demonstrated in (Han et al., 2020).

Authentication is concerned with the process of gaining access to the system. There are a number of ways to identify/verify users of the platform. It could be with PIN, OTP, Password or biometric features. Biometric authentication involves using body parts (fingerprints, voice or iris) to authenticate a user. These body parts are not identical, even for identical twins. However, the construction workers chose to use organisation emails and passwords to authenticate users. This is understandable as an onsite worker may not find it easy to swipe a finger or adjust the iris in order to be authenticated to use a system. Rather an organisational email may require no extra effort to be entered into the Conversational-BIM system for authentication even while working on site. Though being a password authentication system, it requires a password to be strong and, if possible, not repeated for other platforms.

Storing construction data in the cloud implies that the regulation of the physical location housing the server prevails over the stored data. Since personal speech reflects biological and behavioural characteristics, thus speech can be classified as sensitive data as reflected in the GDPR policy [154]. Nautsch et al. [155] has argued that there is increasing privacy concern over processing speech data. The physical location of the server housing the speech data dictate the regulation that will apply to the data. Thus, the discussion opined the need to choose a provider that can store the Conversational-BIM data in a location only approved by the construction company.

5.2. Required implementation tools for conversational-BIM

5.2.1. Authentication module

Authentication is to establish, create, manage and use identities through a secured delivery model. It is an access and authentication platform. It enables the construction company to control access to Conversational-BIM resources, which are on a centralised access authentication policies and single sign on. Authentication service includes transparent and authentication methods for identity assurance. Authentication service in Conversational-BIM uses a username-password matching identification system. Authentication policies describe the level of access, which part of the Conversational-BIM can be accessed by the different category of users. A secure and scalable authentication platform for user identity is required. The authentication service satisfies the requirements of the users for data security, as data is only available for authorised users after due verification.

5.2.2. Storage/Database module

The need to store outside the user's device and still achieve low latency necessitates a storage medium. Storage service could be for block, file or object storage. The service is available for various use cases ranging from data lakes, websites, backup and restore, archive, enterprise applications, IoT devices, big data analytics to mobile applications. The storage service enables Conversational-BIM data to be stored on a storage platform outside the device of the user. The agility of Conversational-BIM demands scalable storage as its performance can be affected by static storage facilities. The storage provides adequate data durability as it creates and stores copies across multiple systems. This satisfies the user's requirement for a low latency service, as this storage enables data to be retrieved quickly thus achieving fast response.

5.2.3. Backend computing module

Back-end computing is required to process the entire application in order to give the desired output. This module is the application layer at the back that applies business logic to the data, culminating in implementing the entire Conversational-BIM. Back-end service consumes other necessary services in order to actualise the entire system. The Backend computing service allows for codes to be run virtually on any application without provisioning or managing servers. Codes can be uploaded into the service or written in the service code editor. Codes can be automatically triggered from other cloud services or can be called directly from any web or mobile app using only the required resources. Execution time can be optimised by choosing the right memory size of functions as functions can be kept initialised in the computing service. The Backend computing service will enable users to perform regular and on the fly computations, i.e., list of components, components selection, exporting Bill of Quantities, estimating Quantity Take off, and determining the next task to perform.

5.2.4. Bot building platform module

Bot building platforms are employed to build and deploy interactive conversational robots, otherwise called chatbots. Bot platforms allow users to determine behaviours and program reaction. Bot platforms also enable intelligent maintenance and updates. Bot service embeds voice and text to build a conversational interface for applications. It leverages the functionalities of automatic speech recognition (ASR) and the natural language functionalities to create a Speech-Language Understanding System for conversational interactions. This cloud service takes in the input, understand the intent and realize/accomplish/satisfy the intent by invoking appropriate response. Bot service can easily deploy a chatbot on mobile devices, web apps and chat services. The service orchestrates the dialogue by prompting for the appropriate slot to build multi-turn conversations. The service simplifies complex conversations by dynamically transferring control from one intent to another based on the user input. The service accepts queries and delivers response in voice and text as required by the users.

5.2.5. Speech-to-Text module

Users of Conversational-BIM interact with the system using the conversation which produces audio files. The Speech-to-Text service is to convert the audio inputs from Conversational- BIM users to text files to enable the system analyse and process them further. The service is required as it is not possible for the Conversational-BIM system to process audio files. This service employs automatic speech recognition (ASR), a deep learning process, to convert speech to text accurately. The service is suitable for audio input from microphones, audio files, video files either as live audio streams or batch audio content. It affixes punctuation and formatting to enable the output to closely match the quality of the manual transcription. The service could return a timestamp for each word to improve the search and analysis process. It also accepts a corpus of data to enable users to build and train customised language models.

5.2.6. Text-to-Speech module

This Text-to-Speech service converts strings, words and sentences in text files to audio files to enable a human user to comprehend the sound. This service is required by Conversational-BIM to convert the text files into synthetic human speech to be played as audio to the Conversational-BIM user. This cloud service converts text into human speech to create speech- enabled applications. The service uses deep learning technologies to produce natural sounding human voices in several languages. The cloud service supports both a Newscaster reading style for narration use cases as well as a Conversational speaking style, for two-way communication. The cloud service can build and train a customised voice model.

5.2.7. Interaction module

The user specifications include an intuitive user interface for easy navigation and also easy manipulation of the construction model. This is into two parts, interaction with the construction model and interaction with the system interface. These requirements are met with a separate implementation. A UI/UX application was developed to achieve the intuitive user interface, while the Autodesk Forge API (Autodesk Forge, [156]) service was used to manipulate the construction model, as demonstrated in Zhang et al. [157].

5.2.8. Monitoring module

This is an analytics platform to monitor used services usage, price, troubleshooting)-no of times called, price implications. This platform is a monitoring and observability service that provides data and actionable insights for applications running in the cloud, thus giving a unified view of its operational health to respond to resource utilisation and performance optimisation changes. The cloud service detects anomalous behaviour, set alarms, display logs, troubleshoot issues in applications running in the cloud environment.

5.3. Selecting cloud services provider for conversational-BIM

This section describes four big players in the cloud service world for conversational service; that include Amazon Web Services (AWS), Microsoft Azure, Google Cloud Services and IBM Cloud Services. The four players were compared using the five identified users' specification in the study. Table 3 presented some of the features of these conversational services according to the providers while Table 4 summarises experiences of some users of the services. On a very high-level comparison, all the four providers are all fast with good accuracy and acceptable prices, AWS offers an unlimited free one-year trial period that allows more time for experimentation with the Conversational-BIM software, while others offered limited free usage on a monthly basis. The interaction describes the easiness of setting up the service, the type of input acceptable to the service, and the platform is the conversational service can work on. The four providers under consideration accepts both voice and text input. The AWS works with mobile service texting, while Google Cloud and IBM Cloud uses website interface, Facebook Messenger in addition to Google Assistant and SMS, and Nance uses the Microsoft Azure User account.

All the providers provide a visual interface for easy navigation, though AWS interfaces are a bit less intuitive (Matteo, 2021). Going by the recommendations of Repschlaeger et al. [143], that price transparency, price granularity and location of data are high-level priorities for consideration when selecting a cloud provider. Consequently, AWS with more data centre, presented an added advantage over the coverage of the service, as this gives flexibility to users in terms of choosing location to store the Conversational-BIM data for improved latency. This also, allows for easy compliance with the government regulations and policies of storing data within local territory. AWS has been chosen for Conversational- BIM software implementation as it provides a mix of the required functionalities.

5.4. AWS cloud services for conversational-BIM

The identified cloud services necessary for Conversational-BIM were implemented on AWS. Hence Amazon Cognito, Amazon Polly, Amazon S3, Amazon Transcribe, Amazon Lex, Amazon Lamda and Amazon Cloud Watch were employed to implement the Conversational-BIM system.

Conversational BIM uses Amazon Cognito for users' login management, including authentication and authorization. It allows Conversational-BIM to provision user identity management and easily integrates with BIM 360. Furthermore, once a user gets authenticated, it releases a token that allows access management to the various resources available on conversational BIM. Different roles are created for users on the Conversational-BIM app and Cognito is used to map users to different resources based on their defined roles.

Amazon Polly provides Text-to-Speech service by using advanced deep learning to synthesize natural sounding human speech. The Conversational BIM uses Polly to convert user's query fulfilment text to lifelike speech and employ Polly's Neural Text-to-Speech (NTTS) voices to deliver conversational style readout to the user. This is also called the AWS speech synthesizer/TTS service.

Amazon Transcribe provides quick, accurate and automated speech to text functionality using a deep learning process called automatic speech recognition (ASR). The Conversational BIM app. Employs Transcribe to convert users' query to text that can be passed to Amazon Lex for further processing. Hence, the audio input captured from users are first sent to Transcribe to obtain the corresponding text transcript.

Amazon S3 is an extremely reliable and persistent cloud storage system that allows object storage with scalability and security. Conversational BIM uses S3 to store application assets and resources. In addition, data extracted by Amazon Lambda during query fulfilment is temporarily stored on Amazon S3 before serving it to the user. Thus, bringing the data nearer to reduce latency and improve the speed of the operations.

Amazon Lex is a service for building conversational interfaces. It provides the advanced deep learning functionalities of automatic speech recognition (ASR) for converting speech to text and natural language understanding (NLU) to recognize the intent of the text. The Conversational BIM application uses Amazon Lex to extract intent and slots from a user query. It parses the user query to understand the intent behind the query and then extract actionable intent to enable query fulfilment. Lex can be referred to as the Amazon Bot/conversational interfaces building platform.

Amazon Lambda enables the execution of code without provisioning or managing servers. Expert functions and business logic implementations for query fulfilment in conversational BIM all reside and run on Lambda. It allows modular development of functions that are then attached to each Lex intent. Lambda is also called the AWS Serverless computing platform.

AWS object storage platform. Route S3 is a highly available and scalable Domain Name System (DNS) web service. It enables reliable routing of users' request to valid and appropriate endpoints resources on the conversational BIM application.

Conversational BIM application uses AWS CloudWatch for monitoring and building operational health overview of the various AWS services that Conversational BIM uses. It allows detection of anomaly behaviour and detailed troubleshooting of operational issues. Overall, CloudWatch enables Conversational BIM to easily track the performance of all the AWS services and allows step-tracing when issues develop.

5.5. Implementation of conversational-BIM on AWS

The Amazon Cognito is implemented in the Conversational-BIM frontend module for users' identity management, the implementation architecture is illustrated in Fig 4. An authenticated user issues a verbal query into the Conversational-BIM system through the Dashboard module. The received verbal query (speech) is sent to the Amazon Transcribe service for conversion to texts. The text file is passed onto the Amazon Lex service to analyse and interpret the query's intent and then draws out an actionable intent to fulfil the query. The actionable intent is passed onto the Amazon Lambda service to effectuate the intent. The BIM model is stored in readily accessible storage (Amazon S3) to the Lambda service for its computations, and the fulfilled intent is returned to the Amazon Polly service through Amazon Lex. The Amazon Polly service then converts the texts from Lex to speech and returns an audio output to the query issuer through the frontend dashboard. This process is illustrated in Fig 5. For example, a query to compute the GFA of a

Table 3
Some features of selected cloud service providers.

Cloud provider	Languages supported	Mode of operation	Custom vocabulary support	Multi speaker identification	Openness	Data center location
Google	Over 120	Real time and batch	Yes	Yes	Closed-source	US, Asia, Europe Australia
Amazon	31	Real-time	Yes	Yes	Closed-source	US, UK, Europe, Ireland, Japan, China, Singapore, Australia, Brazil
IBM	7	Real-Time	Yes	Yes	Closed -source	US, Europe
Azure	43	Real-Time	Yes	Yes	Closed -source	USA (Uses Microsoft Azure data center)

Table 4
Comparing the selected conversational service providers.

		Google cloud	Amazon web service	Microsoft azure	IBM cloud
Cost		• Limited free usage per month (chatbotbusinessframework.com) • Pay per use	Free one year Pay per use	•Limited free usage per month (chatbotbusinessframework.com) •Pay per use	Limited free usage/month (chatbotbusinessframework.com) Pay per use
Speed		Good speed	Good speed	Good speed	Good speed
Security/Privacy		US, Asia, Europe Australia	US, UK, Europe, Ireland, Japan, China, Singapore, Australia, Brazil	US	US, Europe
Computation strength		Very good Machine applications and AI capabilities (Scott, 2020)	Well spread infrastructure (Scott, 2020)	Vast Enterprise application (Scott, 2020)	Strong for Social Business (Scott, 2020)
Interaction	Ease of use	Easy to set up (g2.com)	A bit less intuitive user interface (Matteo, 2021)	Easy to set up [45]	Not easy to set up. High quality interaction [45]
	How can users engage	voice and text (Ahern, 2021)	voice and text (Ahern, 2021)	voice and text	voice and text (Ahern, 2021)
	Platform	Websites, Facebook Messenger Account, SMS, google Assistant (Ahern, 2021)	SMS (Ahern, 2021)	Microsoft Azure Account	Websites, Facebook Messenger Account, SMS (Ahern, 2021)

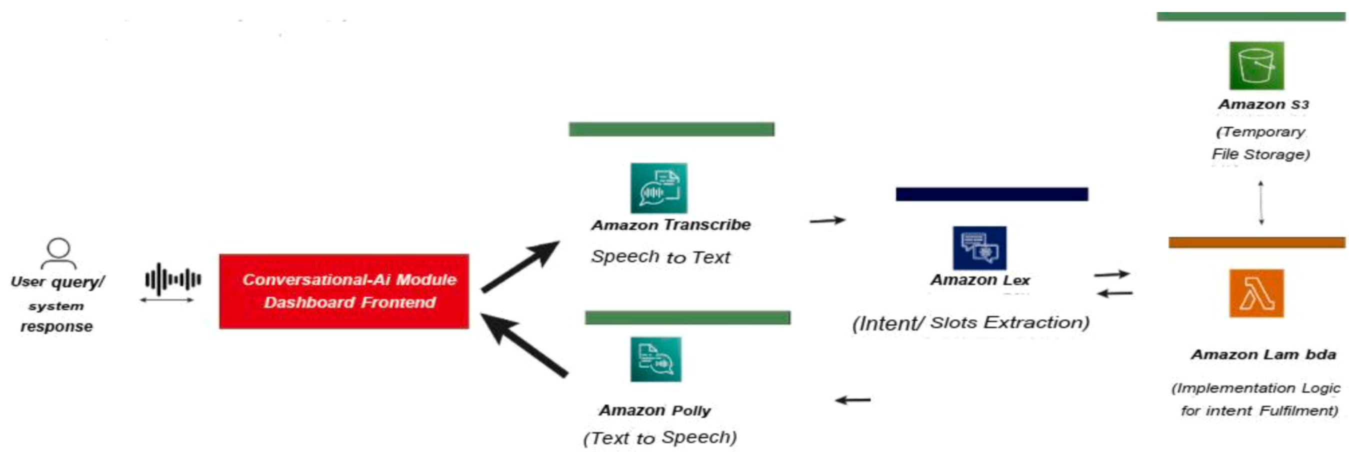

Fig. 4. Architecture of Conversational-BIM Using Amazon Web Services.

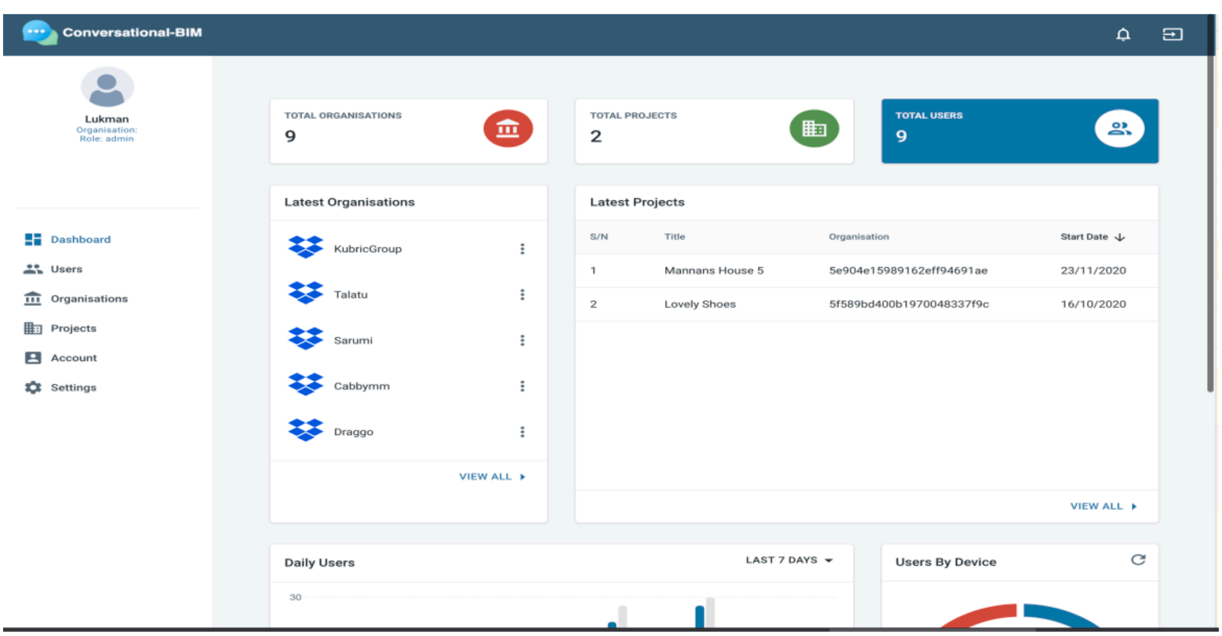

Fig. 5. Backend of the Conversational-BIM System showing some BIM Projects.

model issued through the frontend dashboard is converted to text by the Amazon Transcribe service. Amazon Lex receives the text, extracts and passes the intent to recognise the user's needs (GFA model to Lambda). The Lambda service then pulls the BIM model from Amazon S3 and computes the GFA. The computed GFA is returned as a text via Amazon Lex to Amazon Polly. Amazon Polly converts the text to an audio equivalent for onward transmission to the query issuer via the dashboard module. Figs. 5, 6 and 7, show the screenshots of the backend and frontend of the Conversational-BIM system. The backend (Fig 6) shows a project page with three BIM models uploaded. The backend is where the project information and related BIM files are setup. Fig 6 is platform that allows users to query the BIM model through voice and text conversation. Fig 7 shows an example of conversation between a user and the system.

6. Motivations and challenges for conversational-BIM in the construction industry

The focus group discussion came up with issues that can induce the adoption of Conversational-BIM as well as the challenges that may arise with the adoption of the technology in AEC industries. This section discusses the motivations and challenges of adopting Conversational-BIM in the construction industry as elucidated from the study.

6.1. Motivations for conversational-BIM in the construction industry

According to the stakeholders that participated in the study, the following are the incentives that can accelerate the adoption of BIM ChatBot in the Construction Industries**.**

6.1.1. Improved compliance with health and safety guidelines

Since Conversational-BIM eliminates the need to memorise commands or navigate through several menus for interaction, prompt safety guidelines can be obtained for real-time usage of site workers. Construction workers could get updates or regulations guiding the use of some equipment in a timely and concise manner during use. Conversational-BIM could provide handy information that can be comprehended easily instead of having to read pages of documents. Thus, making safety guidelines accessible to workers for immediate compliance.

6.1.2. Improved productivity

Construction workers spend a huge time doing repetitive tasks and answering queries about these tasks [158,159]. Meanwhile, it is not easy for construction workers to get data while on construction sites. Therefore, using project information stored in the Conversational-BIM database, repetitive queries about equipment, design and implementation can be easily answered by Conversational- BIM. Thus, with Conversational-BIM providing real-time responses to these queries, construction workers can do more meaningful activities and improve productivity

6.1.3. Tracking real-time activity progress

Conversational-BIM is capable of accessing the efficiency of a worker to give the performance on the assigned schedule. Feedback from individuals can be used to monitor the progress of construction worker [160]. Conversational-BIM can leverage its analytics ability to give the progress of a project. Conversational-BIM can monitor available resources and give notifications about the current status. This feature will help to replenish depleted resources without having to wait till exhaustion which can delay project. A construction worker can ask Conversational-BIM about the status of any equipment to verify that everything is up and running.

6.1.4. Improved training

Conversational-BIM has the potential to aid on-site training of construction workers. Conversational-BIM, as an expert knowledge base in construction can take, for instance, site workers through the training on the use of equipment. Conversational training is easy and accessible on construction sites. Site workers may not find it easy to make time for extra learning [161]. Conversational-BIM on hands-on training can assist a team to create BIM models where a human instructor may not be

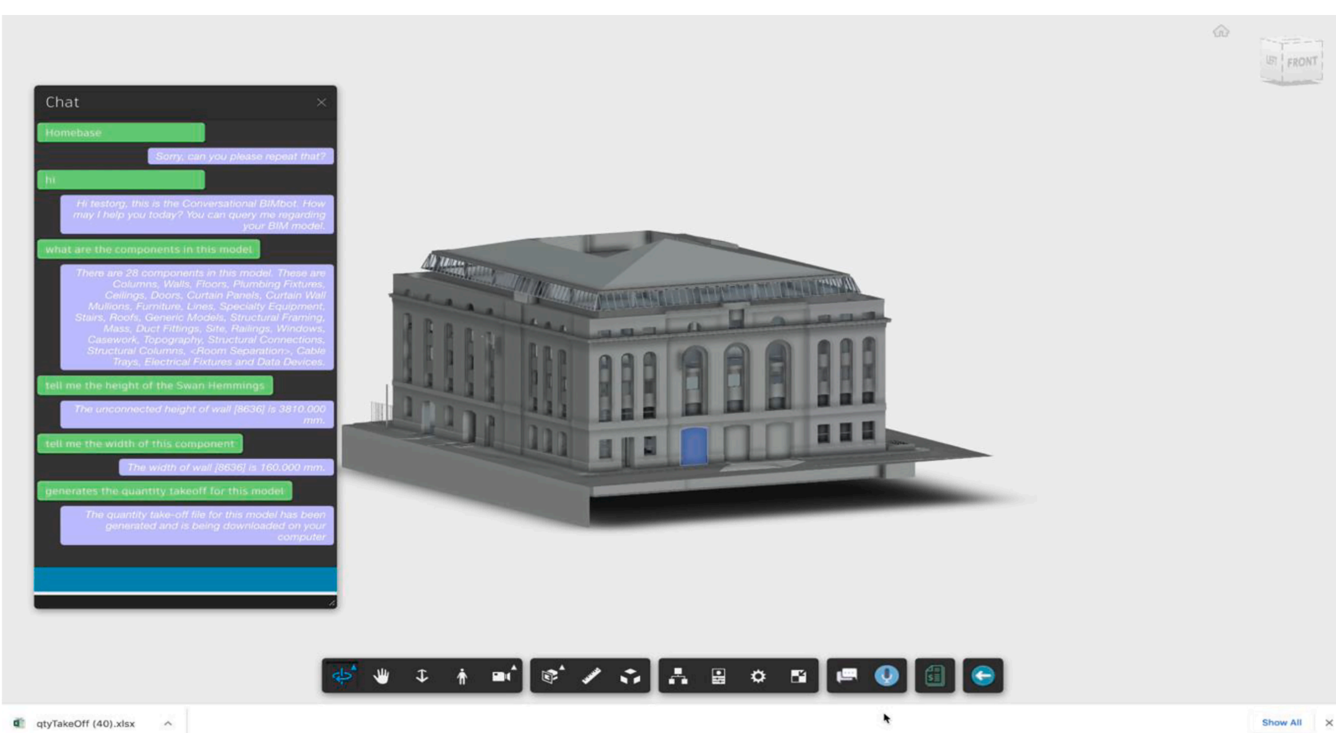

Fig. 6. Conversational-BIM System's Frontend showing Conversation between a User and the System.

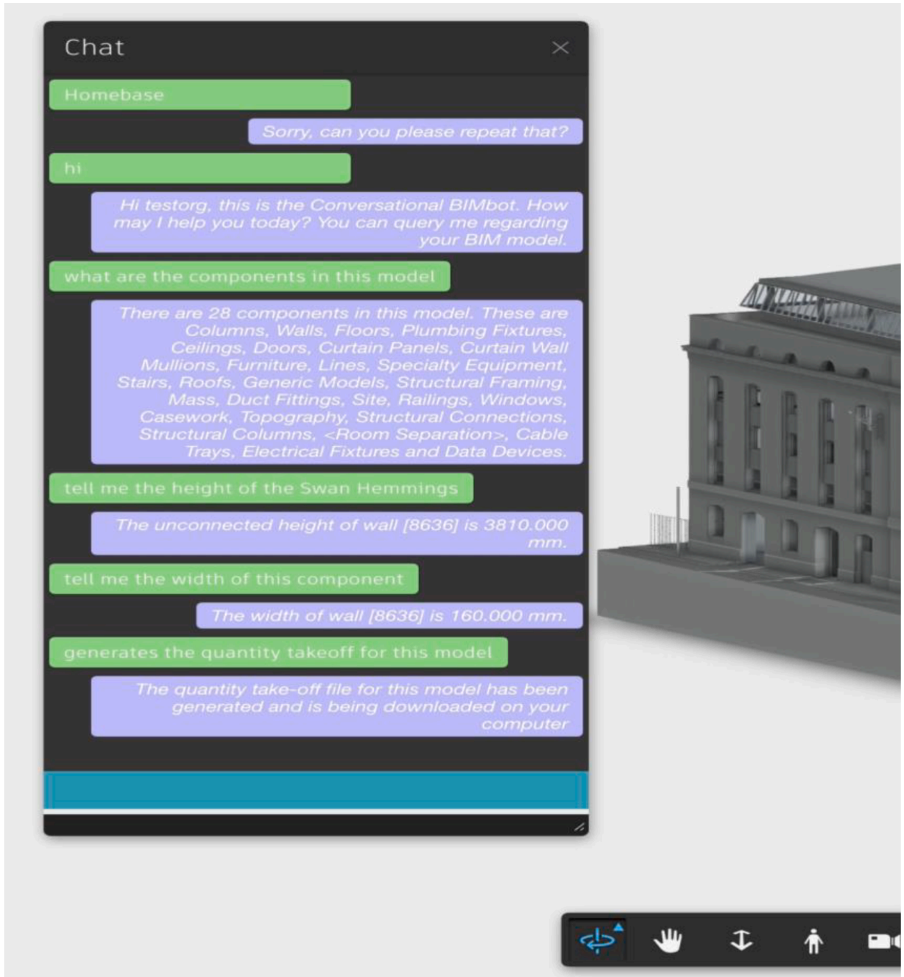

Fig. 7. Screenshot of Voice Conversation Querying BIM Model.

readily available for clarifications and assistance

6.1.5. *Improved collaboration for easy tracing of problems*

Since Conversational-BIM could automate routine tasks in construction process, also to improve collaboration, it can be used to schedule meetings for stakeholders by scanning through team members calendars and proposing a convenient time that suites everyone's schedule. Conversational-BIM can also track equipment inventory, equipment status updates, delivery timing schedules, and RFI (Request for Information – open, updated, close) status. Conversational-BIM can browse through databases for patterns to help in automated reports generation. These reports can give a clue to some persistent problems. Conversational-BIM can give updates both on the project and on the equipment in an on-the-fly manner.

6.2. *Challenges of conversational-BIM in construction*

The discussion identified some of the exceptions that must be taken into consideration for effective use of Conversional BIM in the AEC sector as presented in this section.

6.2.1. *Language*

The ability of the conversational service to accept voice input, recognise a language, process the intent and produce an audio output is very crucial/fundamental to maximise/optimise the Conversational-BIM system. Since Conversational-BIM accepts natural language input, the choice of language accepted by the conversational service is of importance. Conversational-BIM accepts the English language for now. Though most of the available conversational service accepts varieties of languages, some are still in the developmental stages. Nevertheless, the choice of language to interact with the system is increasing. Understanding the semantics of a sentence is paramount to the success of voice-based technologies. Since conversation service allows developers to define custom vocabularies [162], the received audio input is matched with sample utterances from configured intents. This ability has made intent identification relatively easy and, thus, reducing misinterpretation of the voice commands.

6.2.2. *Accents*

A wide range of accents occurs in every language, as same words can be pronounced differently, with the syllables and phonetics varying, thus making it harder for the software to recognise. Languages are spoken differently by different tribes, such that variation in accents can pose a challenge, for example, the ability to understand American or Scottish English. Conversational systems require a clear and discernible voice as a simple mispronunciation could trick the software. Modern conversational systems are able to accommodate a varied number of accents, though could also be challenged when voice inputs deflect too much from the average. Construction workers using the software will need to speak clearly and enunciate each word. A simple cold can affect the output of a human voice. Kambeyanda et al. (1997) once argued that using conversational software may require the user to maintain constant pitch, volume and inflexion, keeping the vocal tract musculature in a fixed position and avoid throat-clearing before starting a conversation.

6.2.3. Background noise

Background noise is a common feature at construction sites as varied works are going on simultaneously. Background noise blurs the sound and could create confusion and inhibit the efficient processing of the input sound. The conversational software should be able to filter noise from the actual user's input. Nevertheless, most available conversational services employ sophisticated algorithms to filter out unwanted sound from the user's input.

6.2.4. Convincing the managerial team

It is true that there are many different highlighted benefits of Conversational-BIM to the construction industry, getting to convince the managerial team for its implementation may not be an easy task. Efforts to integrate new technologies or digital change are usually met with internal resistance, especially from superiors Hess et al. (2017). Though, observed that firms still face notable challenges in digital transformation even if internal leadership are well disposed to the transformation processes (Warner and Wager, 2019).

6.2.5. Failover management

A proper contingency plan is required to be in place as Conversational-BIM, like any digital technology, can sometimes malfunction as a result of bugs. However, this may be minimised through feedback from construction workers on their experience and utilizing such for improving the system.

7. Implications of the study

This study has implication for both academic and practice. The study developed robust selection criteria for the implementation of cloud services in the development of Conversational-BIM solutions based on contributions from the stakeholder in the construction industry. This is no doubt an addition to the academic literature in the field of Conversational AI application development. The study has also provided IT developers with guidelines for implementing chatbots for construction industries as it presents the relevant considerations for the development of conversational AI applications in the industry.

This result of the study reflects the comprehensive nature of the study, as it encompasses the different categories of workers in the construction industry thus reflecting the different requirements of each category of construction workers. The cost is very important to the managerial category as this will affect the price of the project. Whereas the speed of operation is quite germane to site workers as this will improve their efficiency. The functionality requirement analysis is essential to site workers as well. The security requirement is important to all categories of construction workers. Also, the visualisation requirements reflect the needs of all categories of construction workers. Thus, the study presented a comprehensive requirement for the different categories of construction workers to implement the Conversational-BIM system.

8. Conclusion

The construction industry is embracing the voice-based Conversational-BIM to improve its productivity as seen in other profession; healthcare, aviation, tourism, etc. The success of the Conversational-BIM applications in the construction industry is hinged on selecting appropriate tools for its implementation by carefully considering the peculiarities of the industry. There are numerous incompatible criteria to evaluate cloud service adoption to implement Conversational-BIM. This study has interacted with construction stakeholders to get their expectations for cloud services to implement Conversational-BIM, as against the existing selection criteria based on the views of system developers. The study found out that speed, security, functionality, visualisation and cost are important specifications for construction stakeholders and are thus employed for cloud service selection to implement Conversational-BIM. The comprehensive study brought to bear, the different requirements of diverse categories of construction workers. The four leading cloud service providers for conversational service were compared, a careful selection results in the choice of AWS. The study went further to develop an architecture for Conversational-BIM using AWS cloud services. Further study will evaluate the efficiency of the Conversational-BIM application to different categories of workers in the construction industry.

CRediT authorship contribution statement

Sururah A. Bello: Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Lukumon O. Oyedele:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Lukman A. Akanbi:** Writing – review & editing, Resources, Project administration, Methodology, Formal analysis. **Abdul-Lateef Bello:** Writing – review & editing, Visualization, Validation, Resources, Methodology, Formal analysis, Data curation.

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.

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Data availability

Data will be made available on request.

References

[1] Interaction Design Foundation, 2018. Voice user interfaces [WWW Document].
[2] C. Pearl, Designing Voice User Interfaces, O'Reilly Media, 2016.
[3] S. Ruan, J.O. Wobbrock, K. Liou, A. Ng, J.A. Landay, Comparing speech and keyboard text entry for short messages in two languages on touchscreen phones, in: Proc. theACM Interactive 1, Wearable Ubiquitous Technol, Mobile, 2018, pp. 1–23.
[4] K. Lee, C. Nass, Social-psychological origins of feelings of presence: creating social presence with machine generated voices, MediaPsychology 7 (2005) 31–45, https://doi.org/10.1207/S1532785XMEP0701_2.
[5] H. Feng, K. Fawaz, K. Shin, Continuous authentication for voice assistants, in: ACM 23rd Annual International Conference on Mobile Computing and Networking, 2017, pp. 343–355.
[6] Department Statista Research, 2019. Number of digital voice assistants in use worldwide from 2019 to 2023. [WWW Document].
[7] A.B. Saka, L.O. Oyedele, L.A. Akanbi, S.A. Ganiyu, D.V.M. Chan, S.A. Bello, Conversational artificial intelligence in the AEC industry: a review of present status, challenges and opportunities, Adv. Eng. Inf. 55 (2023) 101869.
[8] M.H. Wen, A conversational user interface for supporting individual and group decision-making in stock investment activities, in: 4th IEEE International Conference on Applied System Innovation 2018, ICASI, 2018, pp. 216–219.
[9] A. Pradana, G.O. Sing, Y.J. Kumar, SamBot - Intelligent conversational bot for interactive marketing with consumer-centric approach, Int. J. Comput. Inf. Syst. Ind. Manag. Appl 9 (2017) 265–275.
[10] F. Ali Amer Jid Almahri, D. Bell, M. Arzoky, Personas design for conversational systems in education, Informatics 6 (2019) 46.
[11] E.V. Comendador, B.M.B. Francisco, J.S. Medenilla, S.M.T. Nacion, T.B.E. Serac, Pharmabot: a pediatric generic medicine consultant Chatbot, J. Autom. Control Eng. 3 (2015) 137–140.
[12] L. Laranjo, A.G. Dunn, H.L. Tong, A.B. Kocaballi, J. Chen, R. Bashir, D. Surian, B. Gallego, F. Magrabi, A.Y.S. Lau, E. Coiera, Conversational agents in healthcare: a systematic review, J. Am. Med. Inf. Assoc. 25 (2018) 1248–1258.
[13] S.A. Ganiyu, L.O. Oyedele, O. Akinade, H. Owolabi, L. Akanbi, A. Gbadamosi, BIM competencies for delivering waste-efficient building projects in a circular economy, Dev. Built Environ. 4 (2020) 100036.

[14] B. Kumar, J. Cheng, L. McGibbney, Cloud computing and its implications for construction IT, in: W. Tizani (Ed.), 13th International Conference on Computing and Building Engineering/17th International European Group Workshop on Intelligent Computing in Engineering, Nottingham University Press, 2010, pp. 315–320.
[15] O.O. Akinade, L.O. Oyedele, K. Omoteso, S.O. Ajayi, M. Bilal, H.A. Owolabi, Alaka, L. Ayris, J.H. Looney, BIM-based deconstruction tool: towards essential functionalities, Int. J. Sustain. Built Environ. (2017).
[16] J.M. Davila Delgado, L.O. Oyedele, BIM data model requirements for asset monitoring and the circular economy, J. Eng. Design and Technology 18 (5) (2020) 1269–1285.
[17] J.M. Davila Delgado, L.O. Oyedele, Digital Twins for the built environment: learning from conceptual and process models in manufacturing, Adv. Eng. Inf. 49 (2021) 101332.
[18] S.O. Abioye, L.O. Oyedele, L. Akanbi, A. Ajayi, J.M. Davila Delgado, M. Bilal, O. O. Akinade, A. Ahmed, Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges, J. Build. Eng. (2021) 44.
[19] H. Alaka, L. Oyedele, H. Owolabi, M. Bilal, S.O. Ajayi, O. Akinade, A framework for big data analytics approach to failure prediction of construction firms, IEEE Trans. Eng. Manag. 66 (4) (2019) 689–698, https://doi.org/10.1109/TEM.2018.2856376.
[20] M. Bilal, L.O. Oyedele, J. Qadir, K. Munir, S.O. Ajayi, O.O. Akinade, H. A. Owolabi, H.A. Alaka, M. Pasha, Big Data in the construction industry: a review of present status, opportunities, and future trends, Adv. Eng. Inf. 30 (2016) 500–521, https://doi.org/10.1016/j.aei.2016.07.001.
[21] M. Bilal, L.O. Oyedele, H. Kusimo, H.A. Owolabi, L.A. Akanbi, A.O. Ajayi, O. O. Akinade, J.M. Davila Delgado, Investigating profitability performance of construction projects using big data: a project analytics approach, J. Build. Eng. 26 (1) (2019) 100850.
[22] A. Gbadamosi, L. Oyedele, A. Mahammadu, H. Kusimo, O. Oladimeji, The Role of the Internet of Things in Delivering Smart Construction. Paper presented at: ; Jun 17–21; International council for Rese, CIB World Building Congress, Hong Kong SAR, 2019.
[23] M. Bilal, L.O. Oyedele, Guidelines for applied machine learning in the construction industry: a case of forecasting profit margins, Adv. Eng. Inf. 43 (2020) 101013.
[24] X.J. Luo, L.O. Oyedele, A.O. Ajayi, O.O. Akinade, Comparative Study of Machine Learning-Based Multi-Objective Prediction Framework for Multiple Building Energy Loads, 61, Sustainable Cities and Society, 2020 102283.
[25] L.A. Akanbi, A.O. Oyedele, L.O. Oyedele, R.O. Salami, Deep learning model for demolition waste prediction in a circular economy, J. Clean. Prod. 274 (2020) 122843.
[26] T.D. Akinosho, L.O. Oyedele, B. Muhammad, A.O. Ajayi, M.D. Davila Delgado, O. O. Akinade, Deep learning in the construction industry: a review of present status and future innovations, J. Build. Eng. 32 (2020) 101827.
[27] J.M. Davila Delgado, L.O. Oyedele, Deep learning with small datasets: using autoencoders to address limited datasets in construction management, Appl. Soft Comput. 110 (2021) 107587.
[28] J.M. Davila Delgado, L. Oyedele, T. Beach, P. Demian, Augmented and virtual reality in construction: drivers and limitations for industry adoption, J. Constr. Eng. Manag. 146 (2020) 04020079.
[29] J.M. Davila Delgado, L.O. Oyedele, P. Demian, T. Beach, A research agenda for augmented and virtual reality in architecture, engineering and construction, Adv. Eng. Inf. 45 (2020) 101122.
[30] J.M. Davila Delgado, L.O. Oyedele, A. Ajayi, L. Akanbi, O. Akinade, B. Muhammad, H…A. Owolabi, Robotics and automated systems in construction: understanding industryspecific challenges for adoption, J. Build. Eng. 26 (2019) 100868.
[31] J.M. Davila Delgado, L.O. Oyedele, Robotics in construction: a critical review of the reinforcement learning and imitation learning paradigms, Adv. Eng. Inf. 54 (2022) 101787.
[32] S.A. Bello, L.O. Oyedele, O.O. Akinade, M. Bilal, J.M.D. Delgado, L.A. Akanbi, A. O. Ajayi, H.A. Owolabi, Cloud computing in construction industry: use cases, benefits and challenges, Autom. Constr. (2021) 122.
[33] C. Kamm, User interfaces for voice applications, Colloq. Pap. 92 (1995) 10031–10037, https://doi.org/10.1073/pnas.92.22.10031.
[34] Z. Adamu, K.O. Ayinla, Bridging the digital divide gap in BIM technology adoption, Eng. Constr. Archit. Manag. 25 (2018) 1398–1416.
[35] N. Azhar, R. Farooqui, S. Ahmed, Cost overrun factors in construction industry of Pakistan. First International Conference on Construction In Developing Countries : Advancing and Integrating Construction Education, Research & Practice, 2008, pp. 499–508. Karachi, Pakistan.
[36] S. Azhar, Building information modeling (BIM): trends, benefits, risks, and challenges for the AEC industry, Leadersh. Manag. Eng. 11 (2011) 241–252.
[37] A. Ghaffarianhoseini, Building Information Modelling (BIM) uptake: clear benefits, understanding its implementation, risks and challenges, Renew. Sustain. Energy Rev. 75 (2017) 1046–1053.
[38] A. Konanahalli, M. Marinelli, L.O. Oyedele, Big data value proposition in UK facilities management: a structural equation modelling approach, Buildings 14 (7) (2024) 2083.
[39] A.V. Dastjerdi, S.G.H. Tabatabaei, R. Buyya, An effective architecture for automated appliance management system applying ontology-based cloud discovery, in: 10th IEEE/ACM International Conference on Cluster, Cloud and Grid Computing, 2010, pp. 104–112.
[40] P. Ji, H.-y. Zhang, J.-q. Wang, Fuzzy decision-making framework for treatment selection based on the combined QUALIFLEX–TODIM method, Int. J. Syst. Sci. 48 (2017) 3072–3086.
[41] P. Liu, J. Liu, S.-M. Chen, Some intuitionistic fuzzy Dombi Bonferroni mean operators and their application to multi-attribute group decision making, J. Oper. Res. Soc. 69 (2018) 1–24.
[42] P. Liu, P. Wang, Some q-rung orthopair fuzzy aggregation operators and their applications to multiple attribute decision making, Int. J. Intell. Syst. 33 (2018) 259–280.
[43] M. Menzel, M. Schönherr, S. Tai, (MC2)2: criteria, requirements and a software prototype for cloud infrastructure decisions, Softw. Pract. Exp. 43 (2013) 1283. –1.
[44] S. Sundareswaran, A. Squicciarini, D. Lin, A brokerage-based approach for cloud service selection, in: 5th International Conference on Cloud Computing, 2012, pp. 558–565.
[45] I. Petri, T. Beach, O. Rana, Y. Rezgui, Coordinating multi-site construction projects using federated clouds, Autom. Constr. 83 (2017) 273–284, https://doi.org/10.1016/j.autcon.2017.08.011.
[46] P. Mell, T. Grance, The NIST Definition of Cloud Computing, National Institute of Standards and Technology, 2011.
[47] S. Wibowo, H. Deng, Consensus-based decision support for multicriteria group decision making, Comput. Ind. Eng. 66 (2013) 625–633.
[48] C.-H. Yeh, H. Deng, S. Wibowo, Y. Xu, Multi criteria group decision support for information systems project selection, Next-Generat. Appl. Intell. (2009) 152–161.
[49] M. Azambuja, T. Schnitzer, M. Sahin, F. Lee, Enabling lean supply with a could computing platform - an exploratory case study, in: Annual Conference of the International Group for Lean Construction, 2013, pp. 815–824. Fortaleza, Brazil.
[50] A. Redmond, A. Hore, R. West, Developing a Cloud integrated life cycle costing analysis model through BIM, in: Proceedings of the International Council for Research and Innovation in Building and Construction (CIB) CIB W078 – W102 Conference: Computer, Knowledge, Building, Sophia Antipolis, France, 2011.
[51] M. Abedi, N.M. Rawai, M.S. Fathi, M.S. Fathi, A.K. Mirasa, Cloud computing as a construction collaboration tool for precast supply chain management, J. Teknol. 70 (2014) 1–7, https://doi.org/10.11113/jt.v70.3569.
[52] V. Getuli, S. Ventura, P. Capone, A. Ciribini, A BIM-based construction supply chain framework for monitoring progress and coordination of site activities, Procedia Eng. 164 (2016) 542–549, https://doi.org/10.1016/j.proeng.2016.11.656.
[53] J. Park, K. Kim, Y.K. Cho, Framework of automated construction-safety monitoring using cloud-enabled BIM and BLE mobile tracking sensors, J. Constr. Eng. Manag. 143 (2016), https://doi.org/10.1061/(ASCE)CO.1943-7862.0001223. Article 05016019.
[54] N. Tang, H. Hu, F. Xu, F. Zhu, Personalized safety instruction system for construction site based on internet technology, Saf. Sci. 116 (2019) 161–169, https://doi.org/10.1016/j.ssci.2019.03.001.
[55] S. Guo, H. Luo, L. Yong, A big data-based workers behavior observation in China metro construction, Procedia Eng. 123 (2015) 190–197, https://doi.org/10.1016/j.proeng.2015.10.077.
[56] M. Li, H. Yu, P. Liu, An automated safety risk recognition mechanism for underground construction at the pre-construction stage based on BIM, Autom. Constr. 91 (2018) 284–292, https://doi.org/10.1016/j.autcon.2018.03.013.
[57] X.J. Luo, L.O. Oyedele, A.O. Ajayi, O.O. Akinade, J.M. Davila Delgado, H. A. Owolabi, A. Ahmed, Genetic algorithm-determined deep feedforward neural network architecture for predicting electricity consumption in real buildings, Energy AI 2 (2020) 102283.
[58] B.A. Salami, S.I. Abba, A.A. Adewunmi, U.A. Dodo, G.A. Otukogbe, L.O. Oyedele, Building energy loads prediction using bayesian-based metaheuristic optimized-explainable tree-based model, Case Stud. Construct. Mater. 19 (2023) e02676.
[59] I. Khajenasiri, A. Estebsari, M. Verhelst, G. Gielen, A review on internet of things solutions for intelligent energy control in buildings for smart city applications, Energy Procedia 111 (2017) 770–779, https://doi.org/10.1016/j.egypro.2017.03.239.
[60] N. Rawai, M. Fathi, M. Abedi, S. Rambat, Cloud computing for green construction management, in: International Conference on Intelligent System Design and Engineering Applications, Hong Kong, 2013, pp. 432–435, https://doi.org/10.1109/ISDEA.2012.107.
[61] Y.K. Cho, H. Li, J. Park, K. Zheng, A framework for cloud-based energy evaluation and management for sustainable decision support in the built environments, Procedia Eng. 118 (2015) 442–448, https://doi.org/10.1016/j.proeng.2015.08.445.
[62] M. Wang, S. Qiu, H. Dong, Y. Wang, Design an IoT-based building Management Cloud Platform for Green Buildings, Chinese Automation Congress, Juhan, China, 2017, pp. 5663–5667, https://doi.org/10.1109/CAC.2017.8243793.
[63] C. Balaras, S. Kontoyiannidis, E. Dascalaki, K. Droutsa, Intelligent services for building information modelling- assesing variable input weather for building simulations, Open Constr. Build. Technol. J. 7 (2013) 138–145.
[64] E. Curry, J. O'Donnell, E. Corry, S. Hasan, M. Keane, S. O'Riain, Linking building data in the cloud: integrating cross-domain building data using linked data Adv, Eng. Inform 27 (2) (2013) 206–219, https://doi.org/10.1016/j.aei.2012.10.003.
[65] E. Naboni, Y. Zhang, A. Maccarini, E. Hirsh, D. Lezzi, Extending the use of parametric simulation in practice through a cloud based online service, in: IBPSA-Italy Conference BSA, 2013, pp. 105–112. Bozen, Italy.
[66] X.J. Luo, L.O. Oyedele, Integrated life-cycle optimisation and supply-side management for building retrofitting, Renew. Sustain. Energy Rev. 154 (2022) 111827.

[67] M. Fathi, M. Abedi, N. Rawai, The potential of cloud computing technology for construction collaboration, Appl. Mech. Mater. 174 (2012) 1931–1934.
[68] M. Azambuja, J. Gong, Visualizing construction supply chains with Google cloud computing tools. Developing the Frontier of Sustainable Design, Engineering, and Construction, 2013, pp. 671–678. Texas, USA.
[69] A. Grilo, R. Jardim-Goncalves, Cloud-marketplaces: distributed e-procurement for the AEC sector, Adv. Eng. Inf. 27 (2013) 160–172, https://doi.org/10.1016/j.aei.2012.10.004.
[70] H. Ko, M. Azambuja, H. Lee, Cloud-based materials tracking system prototype integrated with radio frequency identification tagging technology, Autom. Constr. 63 (2016) 144–154, https://doi.org/10.1016/j.autcon.2015.12.011.
[71] M. Sahin, H. Ko, H.F. Lee, M. Azambuja, A simulation case study on supply chain management of a construction firm adopting cloud computing and RFID, Int. J. Ind. Syst. Eng. 27 (2017) 233–254, https://doi.org/10.1504/IJISE.2017.086269.
[72] G. Hemanth, C. Sidhartha, S. Jain, P. Saihanish, V. Rohit, AHP analysis for using cloud computing in supply chain management in the construction industry, in: International Conference for Convergence in Technology (I2CT), Mumbai India, 2017, pp. 1228–1233.
[73] S.A. Bello, L. Oyedele, O.K. Olaitan, K.A. Olonade, A.M. Olajumoke, A. Ajayi, L. Akanbi, O. Akinade, M.L. Sanni, A. Bello, A deep learning approach to concrete water-cement ratio prediction, Result. Mater. 15 (2022) 100300.
[74] X. Ferrada, D. Núñez, A. Neyem, A. Sepúlveda, M. Serpell, A lessons-learned system for construction project management: a preliminary application, Procedia-Social Behav. Sci. 226 (2016) 302–309, https://doi.org/10.1016/j.sbspro.2016.06.192.
[75] J.-S. Ahn, C.-H. Park, D.-M. Lee, Y.-N. Cha, S.-Y. Chin, Development plan of individual unit PMIS using smartphone, in: International Symposium on Automation and Robotics in Construction, 2013, pp. 1110–1118. Waterloo.
[76] I. Petri, O. Rana, T. Beach, Y. Rezgui, A. Sutton, Clouds4Coordination: managing project collaboration in federated clouds, in: IEEE/ACM 8th International Conference on Utility and Cloud Computing, 2015, pp. 494–499, https://doi.org/10.1109/UCC.2015.88. Limassol, Cyprus.
[77] T.H. Beach, O.F. Rana, Y. Rezgui, M. Parashar, Cloud computing for the architecture, engineering & construction sector: requirements, prototype & experience, J. Cloud Comput. Adv. Syst. Appl. 2 (2013), https://doi.org/10.1186/2192-113X-2-8. Article 8.
[78] M. Polter, R. Scherer, Towards an adaptive civil engineering computation framework, Procedia Eng. 196 (2017) 45–51, https://doi.org/10.1016/j.proeng.2017.07.171.
[79] D. Núñez, X. Ferrada, A. Neyem, A. Serpell, M. Sepúlveda, A user-centered mobile cloud computing platform for improving knowledge management in small-to-medium enterprises in the chilean construction industry, Appl. Sci. 8 (2018) 516, https://doi.org/10.3390/app8040516. -.
[80] Y. Jiao, Y. Wang, S. Zhang, Y. Li, L. Yang, B. Yuan, A cloud approach to unified lifecycle data management in architecture, engineering, construction and facilities management: integrating BIMs and SNS, Adv. Eng. Inf. 27 (2013) 173–188, https://doi.org/10.1016/j.aei.2012.11.006.
[81] H. Alaka, L. Oyedele, M. Bilal, O. Akinade, H. Owolabi, S.O. Ajayi, Bankruptcy prediction of construction businesses: towards a big data analytics approach, in: IEEE First International Conference on Big Data Computing Service and Applications, 2015, pp. 347–352, https://doi.org/10.1109/BigDataService.2015.30. Redwood City, CA, USA.
[82] A. Ajayi, L. Oyedele, J.M. Davila Delgado, L. Akanbi, M. Bilal, O. Akinade, O. Olawale, Big data platform for health and safety accident prediction, World J. Sci. Technol. Sustain. Dev. 16 (1) (2019) 2–21, https://doi.org/10.1108/WJSTSD-05-2018-0042.
[83] L. Akanbi, L. Oyedele, J.M. Delgado, M. Bilal, O. Akinade, A. Ajayi, N. Mohammed-Yakub, Reusability analytics tool for end-of-life assessment of building materials in a circular economy World Journal of Science, Technol. Sustain. Dev. 16 (1) (2019) 40–55, https://doi.org/10.1108/WJSTSD-05-2018-0041.
[84] Hayman, P. (2022) Chat GPT is revolutionizing the world of architecture and design wooduchoose https://www.wooduchoose.com/blog/ai-and-architecture/.
[85] Rane, N.L. (2023). Multidisciplinary collaboration: key players in successful implementation of ChatGPT and similar generative artificial intelligence in manufacturing, finance, retail, transportation, and construction industry. https://doi.org/10.31219/osf.io/npm3d.
[86] A. Saka, R. Taiwo, N. Saka, B.A. Salami, S. Ajayi, K. Akande, H. Kazemi, GPT models in construction industry: opportunities, limitations, and a use case validation, Dev. Built Environ. 17 (2024) 100300, https://doi.org/10.1016/j.dibe.2023.100300. ISSN 2666-1659.
[87] S.A. Prieto, E.T. Mengiste, B. García de Soto, Investigating the use of ChatGPT for the scheduling of construction projects, Buildings 13 (4) (2023), https://doi.org/10.3390/buildings13040857.
[88] You, H., Ye, Y., Zhou, T., Zhu,Q. and Du, J. (2023) Robot-enabled construction assembly with Automated sequence planning based on ChatGPT: roboGPT arXiv preprint 10.48550/arXiv.2304.11018.
[89] Parm A.G. (2023) How ChatGPT can help in project management https://parm.com/en/chatgpt-in-project-management/.
[90] T.H. Beach, J.L. Hippolyte, Y. Rezgui, Towards the adoption of automated regulatory compliance checking in the built environment, Autom. Constr. 118 (2020) 103285.
[91] H. Kusimo, L. Oyedele, O. Akinade, A. Oyedele, S. Abioye, A. Agboola, N. Mohammed-Yakub, Optimisation of resource management in construction projects: a big data approach, World J. Sci. Technol. Sustain. Dev. 16 (2) (2019) 82–93.
[92] J. Zheng, M. Fischer, Dynamic prompt-based virtual assistant framework for BIM information search, Autom. Constr. 155 (2023) 105067.
[93] Y. Xia, X. Lei, P. Wang, L. Sun, Artificial intelligence based structural assessment for regional short-and medium-span concrete beam bridges with inspection information, Remote Sens. (Basel) 13 (18) (2021) 3687.
[94] S. Arshad, O. Akinade, S. Bello, M. Bilal, Computer vision and IoT research landscape for health and safety management on construction sites, J. Build. Eng. 76 (2023) 107049, https://doi.org/10.1016/j.jobe.2023.107049. ISSN 2352-7102.
[95] S.J. Uddin, A. Albert, A. Ovid, A. Alsharef, Leveraging ChatGPT to aid construction hazard recognition and support safety education and training, Sustainability. 15 (9) (2023) 7121.
[96] L.A. Akanbi, L.O. Oyedele, O.O. Akinade, A.O. Ajayi, M.D. Delgado, M. Bilal, S. A. Bello, Salvaging building materials in a circular economy: a BIM-based whole-life performance estimator, Resour. Conservat. Recycl., 129 (2018) 175–186.
[97] M. Alipour-Bashary, M. Ravanshadnia, H. Abbasianjahromi, E. Asnaashari, Building demolition risk assessment by applying a hybrid fuzzy FTA and fuzzy CRITIC-TOPSIS framework, Int. J. Build. Pathol. Adaptat. 40 (1) (2022) 134–159.
[98] Dona Kambeyanda, M., Lois Singer, D.S.P.A., Cronk, S., 1997. Potential problems associated with use of speech recognition products. Assist. Technol. 9, 95–101. https://doi.org/10.1080/10400435.1997.10132301.
[99] M. Bilal, L.O. Oyedele, Big data with deep learning for benchmarking profitability performance in project tendering, Expert Syst. Appl. 147 (2020) 113194.
[100] A. Konanahalli, M. Marinelli, L.O. Oyedele, Drivers and challenges associated with the implementation of big data within UK facilities management sector: an exploratory factor analysis approach, IEEE Trans. Eng. Manag. 69 (4) (2022) 916–929.
[101] M.F. Tutunea, SMEs' perception on cloud computing solutions, Procedia Econ. Financ. 15 (2014) 514–521, https://doi.org/10.1016/S2212-5671(14)00498-5.
[102] S.A. Bello, C. Reich, Cloud utility price models, in: F. Desprez, D. Ferguson, E. Hadar, F. Leymann, M. Jarke, M. Helfert E.S. (Eds.), CLOSER 2013 - Proceedings of the 3rd International Conference on Cloud Computing and Services Science, SciTePress, Aachen Germany, 2013, pp. 317–320, https://doi.org/10.5220/0004350503170320.
[103] M.-G. Avram, Advantages and challenges of adopting cloud computing from an enterprise perspective, Procedia Technol 12 (2014) 529–534.
[104] A. Benlian, T. Hess, P. Buxmann, Drivers of SaaS-adoption – an empirical study of different application types, Bus. Inf. Syst. Eng. 1 (2009) 357–369.
[105] M. Janssen, A. Joha, Challenges for adopting cloud-based software as a service (saas) in the public sector, in: 19th European Conference on Information Systems (ECIS). Helsinki, Finland, 2011.
[106] C. Low, Y. Chen, M. Wu, Understanding the determinants of cloud computing adoption, Ind. Manag. Data Syst. 111 (2011) 1006–1023.
[107] E. Luoma, T. Nyberg, Four scenarios for adoption of cloud computing in China, in: 19th European Conference on Information Systems (ECIS), 2011. Helsinki, Finland.
[108] M. Xin, N. Levina, Software-as-a service model: elaborating client-side adoption factors, in: International Conference on Information Systems (ICIS), 2008, p. 8. Paris.
[109] M. Godse, S. Mulik, An approach for selecting software-as-a-service (SaaS) product, in: IEEE International Conference on Cloud Computing, 2009, pp. 155–158.
[110] P. Saripalli, G. Pingali, MADMAC: multiple attribute decision methodology for adoption of clouds, in: IEEE International Conference on Cloud Computing, 2011, pp. 316–323.
[111] Y.-C. Lee, H. Tang, V. Sugumaran, A deployment model for cloud computing using the analytic hierarchy process and BCOR analysis, in: 18th Americas Conference on Information Systems (AMCIS), 2012. Seattle, WA.
[112] S. Bello, A proposed criteria for evaluating cloud-based systems, Int. J. Comput. Innov. Res. 13 (2014) 4282–4290, https://doi.org/10.24297/ijct.v13i3.2759.
[113] P. Geczy, N. Izumi, K. Hasida, Cloudsourcing: managing cloud adoption, Glob. J. Bus. Res. 6 (2012) 57–70.
[114] J. Hetzenecker, S. Kammerer, M. Amberg, V. Zeiler, Anforderungen Cloud Computing Anbieter, Multikonferenz Wirtschaftsinformatik (MKWI), Braunschweig, 2012.
[115] S. Kaisler, W.H. Money, S.J. Cohen, A decision framework for cloud computing, in: 45th Hawaii International Conference on System Science (HICSS), 2012, pp. 1553–1562. Maui.
[116] P. Koehler, A. Anandasivam, D. Ma, C. Weinhardt, Customer heterogeneity and tariff biases in cloud computing, in: International Conference on Information Systems (ICIS), 2010. St. Louis.
[117] B. Martens, F. Teuteberg, M. Gräuler, Design and implementation of a community platform for the evaluation and selection of cloud computing services: a market analysis, in: 19th European Conference on Information Systems, ECIS 2011, 2011.
[118] Z. Zheng, X. Wu, Y. Zhang, M.R. Lyu, J. Wang, QoS ranking prediction for cloud services, Inst. Electr. Electron. Eng. Trans. PARALLEL Distrib. Syst. 24 (2013) 1213–1222, https://doi.org/10.1109/TPDS.2012.285.
[119] N. Limam, R. Boutaba, Assessing software service quality and trustworthiness at selection time, IEEE Trans. Softw. Eng. 36 (2010) 559–574.
[120] B. Martens, F. Teuteberg, M. Gräuler, Design and implementation of a community platform for the evaluation and selection of cloud computing services: a market analysis, in: 19th European Conference on Information Systems, ECIS 2011, 2011.
[121] G. Jung, T. Mukherjee, S. Kunde, H. Kim, N. Sharma, F. Goetz, CloudAdvisor: a recommendation-as-a-service platform for cloud configuration and pricing, IEEE Ninth World Congr. Serv. (2013) 456–463.

[122] J. Yang, W. Lin, W. Dou, An adaptive service selection method for cross-cloud service composition, Concurr. Comput. Pract. Exp. 25 (2013) 2435–2454.
[123] C. Quinton, D. Romero, L. Duchien, Automated selection and configuration of cloud environments using software product lines principles, in: 7th IEEE International Conference on Cloud Computing, 2014, pp. 144–151.
[124] S. Lee, K. Seo, A hybrid multi-criteria decision-making model for a cloud service selection problem using BSC, fuzzy delphi method and fuzzy AHP, Wirel. Pers. Commun. 86 (2016) 57–75, https://doi.org/10.1007/s11277-015-2976-z.
[125] K.T. Atanassov, Intuitionistic fuzzy sets, Fuzzy. Sets. Syst. 20 (1986) 87–96.
[126] P. Liu, Multiple attribute group decision making method based on interval-valued intuitionistic fuzzy power heronian aggregation operators, Comput. Ind. Eng. 108 (2017) 199–212.
[127] P. Liu, H. Li, Interval-valued intuitionistic fuzzy power Bonferroni aggregation operators and their application to group decision making, Cogn. Comput. 9 (2017) 494–512.
[128] A. Patil, K. Marimuthu, R.A. Nagaraja, R. Niranchana, Comparative study of cloud platforms to develop a Chatbot, Int. J. Eng. Technol. 6 (2017) 57–61, https://doi.org/10.14419/ijet.v6i3.7628.
[129] M. Abdel-Basset, M. Mohamed, V. Chang, NMCDA: a framework for evaluating cloud computing services, Futur. Gener. Comput. Syst. 86 (2018).
[130] C. Moustakas, Phenomenological Research Methods, Sage Publications, Thousand Oak, 1994.
[131] M. Van Manen, Researching Lived Experience: Human Science for an Action Sensitive Pedagogy, Althouse, London, Ontario, 1990.
[132] M. Crotty, The Foundations of Social Research: Meaning and Perspective in the Research Process, Sage Publications, London, 1998.
[133] M.A. Jasper, Issues in phenomenology for researchers of nursing, J. Adv. Nurs. (1994) 309–314, 191994.
[134] S. Kvale, InterViews: An Introduction to Qualitative Research Interviewing, Sage, CA, USA, 1996.
[135] J.W. Creswell, Qualitative Inquiry and Research Design: Choosing Among Five Approaches, 3rd ed., Sage, Thousand Oaks, 2013.
[136] S.O. Ajayi, L.O. Oyedele, O.O. Akinade, M. Bilal, H.A. Alaka, H.A. Owolabi, Optimising material procurement for construction waste minimization: an exploration of success factors, Sustain. Mater. Technol. 11 (2017) 38–46.
[137] S.O. Ajayi, L.O. Oyedele, O.O. Akinade, M. Bilal, H.A. Owolabi, H.A. Alaka, Ineffectiveness of construction waste management strategies: knowledge gap analysis, in: M. Okeil (Ed.), Smart, Sustainable and Healthy City. First International Conference of the CIB Middle East and North Africa Research Network (CIB-MENA 2014), 2014, pp. 261–280 (2014)pp. 261–280.
[138] S.O. Ajayi, L.O. Oyedele, K.O. Kadiri, O.O. Akinade, M. Bilal, H. Owolabi, H. A. Alaka, Competency-based measures for designing out construction waste: task and contextual attributes, Eng. Construct. Architect. Manag. 23 (4) (2016) 464–490.
[139] A. Akintoye, C. Taylor, E. Fitzgerald, Risk analysis and management of private finance initiative projects, Eng. Constr. Arch. Manag. 5 (1998) 9–21.
[140] L.O. Oyedele, M. Regan, J.V. Meding, A. Ahmed, O.J. Ebohon, A. Elnokaly, Reducing waste to landfill in the UK: identifying impediments and critical solutions World, J. Sci. Technol. Sustain. Dev. 10 (2013) 131–142.
[141] D.E. Polkinghorne, Phenomenological research methods, in: R.S. Valle, S. Hallin (Eds.), Existential-Phenomenological Perspectives in Psychology, Springer, Boston, MA, 1989.
[142] V. Braun, V. Clarke, Using thematic analysis in psychology, Qual. Res. Psychol. 3 (2006) 77–101.
[143] J. Repschlaeger, S. Wind, Z. R, K. Turowski, Decision model for selecting a cloud provider: a study of service model decision priorities, in: Americas Conference on Information Systems, AMCIS, Chicago, Illinois, USA, 2013.
[144] E. Corbett, A. Weber, What can I say?: addressing user experience challenges of a mobile voice user interface for accessibility, in: 18th International Conference on Human-Computer Interaction with Mobile Devices and Services, 2016, pp. 72–82, https://doi.org/10.1145/2935334.2935386.
[145] B. Shneiderman, Designing the User Interface: Strategies for Effective Human-Computer Interaction, 3rd ed., Addison-Wesley, Reading, MA, 1998.
[146] A. Mishra, T. Reichherzer, E. Kalaimannan, N. Wilde, R. Ramirez, Trade-offs involved in the choice of cloud service configurations when building secure, scalable, and efficient Internet-of-Things networks, Int. J. Distrib. Sens. Netw. (2020).
[147] J.A. Hoxmeier, C. DiCesare, System response time and user satisfaction: an experimental study of browser-based applications, in: AMCIS 2000 Proceedings, 2000, p. 347.
[148] Cho, G., Choi, J., Kim, H., Hyun, S., Ryoo, J., 2019. Threat Modeling and Analysis of Voice Assistant Applications., in: Kang B., J.J. (Ed.), Information Security Applications.
[149] Y. Wang, W. Cai, T. Gu, W. Shao, Y. Li, Y. Yu, Secure your voice: an oral airflow-based continuous Liveness detection for voice assistants, Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. (2019), https://doi.org/10.1145/3369811, 3, 4, Artic. 157 28 pages.
[150] S. Liao, C. Wilson, L. Cheng, H. Hu, H. Deng, Measuring the effectiveness of privacy policies for voice assistant applications, in: Annual Computer Security Applications Conference (ACSAC '20)., in: Association for Computing Machinery Annual Computer Security Applications Conference (ACSAC '20), 2020, pp. 856–869, https://doi.org/10.1145/3427228.3427250. New York, NY, USA.
[151] Q. Yan, K. Liu, Q. Zhou, H. Guo, N. Zhang, Surfingattack: interactive hidden attack on voice assistants using ultrasonic guided wave, in: Network and Distributed Systems Security (NDSS) Symposium, 2020.
[152] Z. Wu, N. Evans, T. Kinnunen, J. Yamagishi, F. Alegre, H. Li, Spoofing and countermeasures for speaker verification: a survey, Speech. Commun. 66 (2015) 130–153.
[153] S. Suwajanakorn, S.M. Seitz, I. Kemelmacher-Shlizerman, Synthesizing obama: learning lip sync from audio, ACM Trans. Graph. 36 (2017) 1–13.
[154] European Parliament and Council, 2016. Regulation (EU) 2016/679 of the European Parliament and the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data and repealing directives 85/46/EC (General Data.
[155] Nautsch, A., Jasserand, C., Kindt, E., Todisco, M., Trancoso, I., Evans, N., 2019. The GDPR & speech data: reflections of legal and technology communities, first steps towards a common understanding. arXiv preprint arXiv:1907.03458.
[156] Autodesk Forge API https://forge.autodesk.com. Accessed March 2021.
[157] D. Zhang, J. Zhang, J. Guo, H. Xiong, A semantic and social approach for real-time green building rating in BIM-based design, Sustainability. 11 (14) (2019) 3973, https://doi.org/10.3390/su11143973.
[158] L.O. Oyedele, Sustaining architects' and engineers' motivation in design firms: an investigation of critical success factors, Eng. Construct. Architect. Manag. 17 (2) (2010) 180–196.
[159] L.O. Oyedele, Analysis of architects' demotivating factors in design firms, Int. J. Project Manag. 31 (3) (2013) 342–354 (2013).
[160] L.O. Oyedele, K.W. Tham, B.E. Jaiyeoba, M.O. Fadeyi, Model for predicting architect's performance in building delivery process, J. Eng. Des. Technol. 1 (2) (2003) 168–186.
[161] L.O. Oyedele, K.W. Tham, Clients' assessment of architects' performance in building delivery process: evidence from Nigeria, Build. Environ. 42 (5) (2007) 2090–2099.
[162] Developer.amazon.com., 2018. Alexa skills kit - build for voice with Amazon.