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Abstract
The UK construction sector has increasingly encountered cost management inefficiencies in overruns, errors, rework and variations. This study demonstrated how Generative AI (GAI), an emerging trend in digital construction, can foster large language models (LLMs) from the industry's historical data to predict costs. The process of developing the GAI system architecture applied the V-model and agile methodological approach and BIM templates. As used in the UK construction sector, the BIM templates considered data from building cost information service (BCIS) and task information delivery plan (TIDP) to develop the architecture. The system architecture designed in this study aligned with the RICS New Rules of Measurement 1 (NRM1) for early cost advice and text-to-task models. The implication of the GAI system architecture for digital cost management presented in this study elicited the integration of GAI with the BIM processes, offering substantial benefits to the construction industry. This includes streamlined

workflows, reduced errors, and improved decision-making. The implications of the system architecture offer opportunities for increased BIM uptake in the UK and the sector globally.

Keywords
Construction cost, Generative AI, V-model.

1 Introduction

Following the re-evaluation of the disposition of cost management strategies by Omotayo et al.(2020), digital cost management is essential in the construction sector because it is fraught with productivity issues emanating from cost overruns, rework, variations, project delays, conflicts and disputes (Omotayo et al., 2022; Shoar, 2023). According to Nast & Koch (2023) 5D BIM is assumed to surmount the challenges of conventional cost management transpiring on building projects. Integrating digital technologies into traditional cost management practices in the dynamic construction industry has become a pivotal factor in enhancing productivity and efficiency. An example of these technologies is Building Information Modelling (BIM), which has presented a transformative approach to facilitating the uptake of digital construction from conception to completion (Magill et al., 2022). Nonetheless, new thinking in the construction industry and the emergence of Construction 4.0, coupled with discussions on Construction 5.0, necessitates a fluid approach to the sector. This study presents the process of designing a generative AI (GAI) system architecture to enshrine the development of an AI and data-driven digital construction cost management platform using existing BIM structures.

This study designed and proposed a generative AI system architecture for explicating the methodological guidelines and challenges of designing advanced algorithms and machine learning (ML) techniques to automate and optimise construction cost management processes using the UK BIM templates (BIM-GAIcost). This system architecture design process was demonstrated using the agile methodology approach known as V-Model.

2 Literature Review

The challenges confronting construction organisations presented are multi-dimensional. With systematic reviews of authors such as Nast & Koch (2023); Noviani et al.(2022); and Vigneault et al. (2020) on 5D BIM in the context of construction cost management, these challenges persist. Some of these are synonymous with training, and technical know-how of construction digitalisation. These challenges are prevalent in project planning, value chain management, digital information workflow, and integration of new cost management systems. Nagy et al. (2021) highlighted the all-inclusive influence of digitalisation on construction, emphasising the need for a rounded perspective on construction digital transformation. An insightful overview of the benefits and challenges associated with BIM adoption in UK residential projects, pointing out the significant shift towards managing digital information across the project lifecycle, was provided by Georgiadou (2019). This further justifies seamlessly integrating new technologies such as artificial intelligence. Generative artificial intelligence (GAI) is a new approach applied in design, carbon capture and sustainability in the built environment. Conversely, the intricacies behind developing this new technology for the construction sector demand a theoretical framework.

The GAI system architecture must address these limitations by leveraging advanced AI algorithms and machine learning (ML) tools and techniques to automate and optimise construction cost management processes. Amalgamating GAI closely with 5D BIM will simplify real-time data analysis, predictive modelling, and scenario simulation. Thus, enabling construction cost management stakeholders to make informed decisions, reduce costs, and improve project outcomes. The adoption of 5D BIM and related digital technologies introduces a set of organisational-level challenges that necessitate innovative solutions. This investigation constructed the architecture of a GAI system to bolster productivity in digital construction cost management through BIM, addressing both the challenges and solutions inherent in Construction 4.0.

2.1 Digital Construction Cost Management: 5D BIM and limitations

Building Information Modelling (BIM) has revolutionised the construction sector, offering a sophisticated multi-dimensional methodology for infrastructure design, construction, and management. The progression from 3D to 5D BIM encapsulates an evolution from geometric representations to integrating cost data, enhancing both complexity and utility within the model. The geometric dimension (3D) facilitates the visualisation of the infrastructure, aiding in design validation and decision-making processes (Nast & Koch, 2023). Incorporation of the temporal element (4D) allows for the simulation of construction sequences, thus optimising processes and enhancing safety (Noviani et al., 2022). The quintessential focus, integrating cost data (5D), enables real-time cost estimation and monitoring, significantly contributing to accurate cost management (Vigneault et al., 2020). Despite the acknowledged benefits, the adoption of 5D BIM presents challenges, notably in its deployment within the UK construction sector. Studies have indicated a requisite for a paradigm shift in design, construction practices, and operations to leverage 5D BIM advantages fully. Effective implementation of 5D BIM necessitates a structured approach, from establishing clear objectives and comprehensive data collection to continuous model updating and stakeholder collaboration.

2.2 Application of Generative AI in the construction sector

GAI has marked a significant shift in the construction sector, introducing novel methodologies to address longstanding challenges. This technology, harnessing algorithms to synthesise new data from existing datasets, has been applied across various construction stages, from initial design to execution and subsequent monitoring. In the sphere of generative design, GAI has been instrumental. It utilises algorithms to sift through myriad design options, refining these based on specific criteria such as material utilisation, financial outlay, and environmental considerations. Alsakka et al. (2023) elucidated a strategy that merges generative design principles with genetic algorithms aimed at crafting reinforced concrete structures that are both cost-effective and environmentally benign. Such approaches significantly augment construction process efficiency, aligning with broader sustainability and environmental stewardship objectives. GAI is crucial in education and knowledge transfer within the construction domain. Ali et al. (2023) coordinated a workshop event on "*Dreaming with AI,"* designed to inform students of GAI and ML algorithms. The event highlighted the criticality of preparing upcoming construction professionals to navigate GAI technologies adeptly. The concept of Digital Twins, creating virtual counterparts of tangible entities, has also seen advancements through GAI integration. GAI's application extends to the complex area of construction scheduling. The construction sector's intricate variable interplay necessitates GAI models that exhibit resilience and adaptability.

GAI harbours the potential to redefine the construction industry. It provides mechanisms and strategies for surmounting traditional construction hurdles, from design optimisation to advanced learning methods and Digital Twins development. As the sector progresses, GAI's assimilation and proficient application will undoubtedly be instrumental in delineating its future direction. Apart from the recent study conducted by Omotayo et al. (2024) on sentiment surrounding GAI ethics and acceptance, there is no documented application or architecture of GAI in construction cost management. This research intends to bridge the gap.

2.3 Technical approach to applying GAI in BIM

Big data is essential for GAI development. One of the first steps after data capture and storage is pre-training, with multiple pre-training options. The pace-setting technology of pre-trained transformers, which are generative, has produced generative pre-trained transformers (GPT), text-to-text transfer transformers (T5) and bidirectional encoder representations from transformers (BERT). Consequently, pre-training of data can also apply decision tree options such as random forest, XGBoost and convoluted neural network (CNN). This has created new paradigms in natural language processing (NLP) applications and a trend for exploratory action research with significant implications for BIM and cost management. Pre-training large datasets supports generating and interpreting complex texts, an indispensable capability for 5D BIM applications (Raffel et al., 2019). The process of fine-tuning these models for 5D BIM-centric tasks, including the interpretation of project specifications and cost estimations, exemplifies the application of transfer learning, where the pre-existing knowledge of the model is adapted to cater to specific BIM tasks. Additionally, other ML training options such as Recurrent neural networks (RNNs), gated recurrent units (GRUs) and long short-term memories (LSTMs) are specialist NN architectures for sequential data processing. RNNs are significantly applied in temporal dynamic performance. RNN can capture and store information from successive processing to impact outputs. The aforementioned ML pre-training alternatives are often inundated with waning gradient issues (Goodfellow et al., 2016). LSTMs were introduced to mitigate these issues through a more complex architecture incorporating forget, input, and output gates. GRUs simplify this architecture by merging the forget and input gates into a single "update gate," thus offering comparable performance with a more streamlined architecture.

Custom sequence-to-sequence models, leveraging encoder-decoder architectures, have shown proficiency in translating informal project descriptions into formal 5D BIM (Sutskever et al., 2014). ML models such as these often adopt structures in the form of RNNs, LSTMs, or GRUs. These pre-training options are necessary to process sequential data, which is sacrosanct for contextualisation and advancement of information. Vaswani et al. (2017) proposed attention mechanisms and transformers to improve the ML model's capacity to concentrate on pertinent segments of the text. This enhances the understanding of context in BIM applications, which is crucial for accurately interpreting project specifics and requirements. Effective AI model training for BIM requires clean and structured datasets. Data pre-processing techniques such as text normalisation, tokenisation, and augmentation are employed to enlarge the dataset, ensuring that AI models are trained on data that mirrors real-world BIM scenarios and thus enhancing their precision and reliability (Bird et al., 2023). For a successful user interface (UI) and experience (UX), natural language understanding (NLU) and natural language generation (NLG) must be applied to excerpt relevant meanings and produce outputs in human-like text. Hence, text-to-text outputs would depend on the types of NLU and NLG frameworks. NLU techniques extract project requirements from documents, and NLG-generated project reports and can be applied to produce cost estimates (Patil et al., 2024). Dependency parsing, named entity recognition, and sentiment analysis are among the techniques used for NLU, while narrative generation techniques are applied for NLG.

3 Research Methodology

Mishra and Alzoubi (2023); Graessler & Hentze,(2020)' Childs (2019) explored diverse methodologies such as waterfall, agile, hybrid and V-model to address software development. The V-Model serves as a structured approach to software development, including creating GAI platforms.

This model, characterised by its sequential development and corresponding testing stages, ensures thorough verification and validation at each step (Graessler & Hentze, 2020). A comprehensive requirements analysis establishes the generative AI system's functionalities, data needs, and performance criteria. Subsequent phases involve systematically designing the system's architecture and the decomposition into manageable modules, encompassing algorithm selection, neural network configuration, and data handling processes. The implementation phase sees the development of these components, which are then rigorously tested for performance and adherence to specifications through unit, integration, system, and acceptance testing. This methodology Figure 1 guarantees the reliability and efficiency of the GAI platform. It facilitates adaptability in the face of evolving requirements, a critical aspect given the dynamic nature of AI technologies (Lähteenmäki et al., 2023). Applying the V-Model in designing a GAI platform commenced with a review of pre-training options and considerations for user interface (UI) and user experience (UX). The next section reviews the GAI options for construction digital cost management.

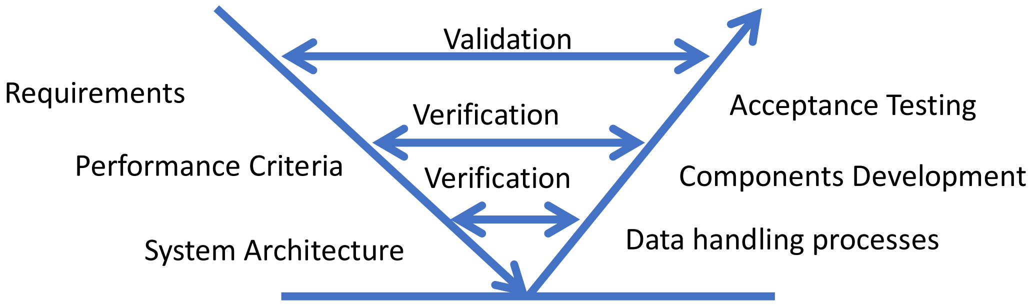

Figure 1. V-Model methodology for creating GAI platforms

The technical approach for GAI for digital cost management through BIM using the V-Model includes *i) requirement analysis, ii) system architecture design, iii) model design iv) implementation v) unit testing, vi) integration testing vii) system testing, viii) acceptance testing, ix)deployment, and x)maintenance and updates.* The development of a GAI platform for digital cost management in the construction sector, employing the V-Model, is delineated through a series of methodical steps, ensuring meticulous planning, development, and exhaustive testing. A comprehensive requirements analysis establishes the platform's objectives and identifies essential data for AI training. Subsequent phases involve the system's architectural design, including hardware specifications and software architecture, and integration with digital tools like BIM software. The AI model's architecture is then crafted, selecting suitable algorithms and designing data processing pipelines. Following module design, the platform undergoes development, focusing on scalability to accommodate the extensive data volumes characteristic of construction projects. Rigorous testing phases, encompassing unit, integration, system, and acceptance testing, ensure each component's functionality and the system's overall efficacy in managing digital costs. Post-development, the platform is prepared for deployment, with provisions for end-user training and ongoing support. Maintenance and regular updates are crucial for adapting to new data and user requirements, underscoring the platform's dynamic nature in enhancing construction cost management efficiency. This study has only applied requirement analysis, system design and architecture design to produce the system architecture.

4 Findings: Initial system architecture

A systematic literature review elucidated the system requirement for BIM-GAIcost system architecture for digital cost management. The findings identified productivity enhancement in the areas of *i) early* *cost advice, ii) cost planning using the New Rules of Measurement 1 (NRM1), iii) Quantification leading to the production of bills of quantities (BOQ) using NRM, 2iv) Lifecycle costing and facilities management using NRM3.* Furthermore, the application of the BIM framework considered the use of employer information requirement (EIR), BIM execution plan (BEP), Task information delivery plan (TIDP) and Master information delivery plan (MIDP) templates. The templates would be embedded within the BIM-GAIcost system as automatically generated spreadsheets. The agenda of the BIM-GAIcost framework is to produce text-to-text outputs through promoting. The first phase of a feasibility study considered incorporating early cost advice with TIDP through Amazon Web Service (AWS) Platform-as-a-Service (PaaS).

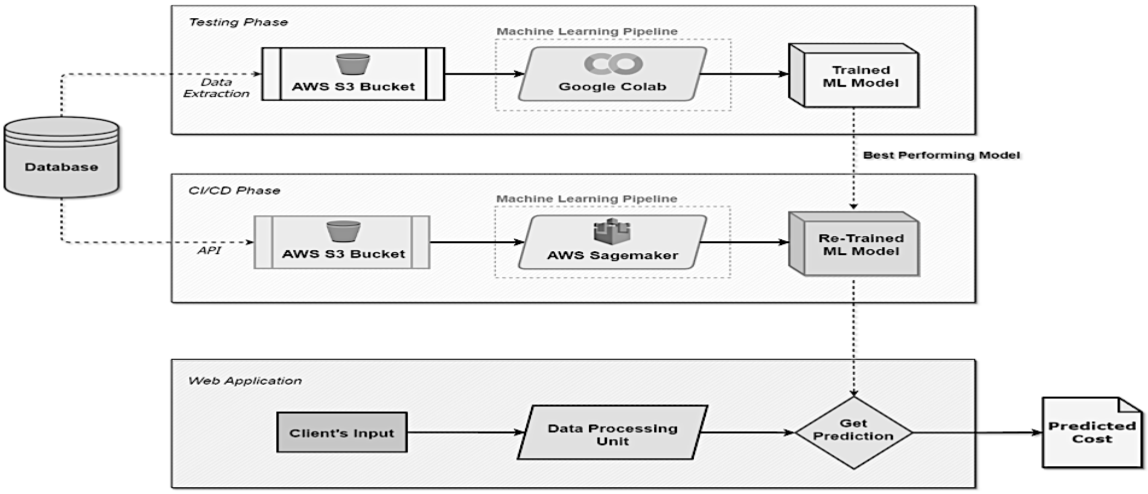

Figure 2. System architecture for costplan.ai

Other options, such as Google Cloud Services and Microsoft Azure, were considered. AWS was chosen because of its accessibility and free educational resources compared to other options. As shown in Figure 2, cost data was extracted from the Building Cost Information Service (BCIS), which included 21,000 samples of UK new build data. Data extraction is possible by developing an application programming interface (API). The data extracted in .xml format was converted to .csv for pre-training in Google Colab. The pre-training applied a quasi-experimentation of the recurrent neural network (RNN), random forest, XGBoost, and convoluted neural network (CNN) to identify the most suitable model. Random forest produced the least error rate in the quasi-experiment. A database was created in an AWS S3 bucket for AWS SageMaker and Amplify integration. Firewall, encryptions, authentication and alert monitoring was made possible through the AWS Amplify.

4.1 Implications: Benefits of BIM-GAIcost for the construction sector

The integration of AI with BIM provides an strategic implication for the construction sector in terms of automating and otpmising the adoption of 5D BIM for effective cost management, cost overrun and accuracy preductions and enhancements, waste reduction and fraud prevent in projects. The significant of the BIM-GAIcost platform is the early cost advice generated from previous client data and benchmarked against fine-tuned LLM algorithms. This will create a continuous improvement process in cost preduction. The ethical implications of using BIM as a data-points for GAI driven cost management was managed through effective firewall systems, creating a client specific-login system, storage in AWS S3 main for clients and privacy protection in terms of the General Data Protection

Regulation (GDPR) 2018 Act in form of plugins, adherance to the UK Responsible AI system and the EU AI which come into effect in August 2024. In protecting the privacy of end-users, a terms and conditions statement will be issued for the users to accept. The terms and conditions will clearly state what client data usage, protections, storage, application and caveats of the accuracy that are generated from platforms. GAI introduces transformative capabilities in digital cost management within the construction industry, heralding a new era of efficiency and accuracy. The application of GAI facilitates the automation of cost estimation processes, enabling the rapid analysis of vast datasets to predict costs with unprecedented precision. This technology significantly reduces the time required for cost estimation, accelerating project timelines and enhancing productivity.

Moreover, GAI supports dynamic cost management, allowing for real-time adjustments in response to changes in project scope, material prices, and labour rates. This adaptability ensures that cost forecasts remain accurate throughout the project lifecycle, mitigating the risk of budget overruns. Additionally, GAI's predictive analytics capabilities offer the potential to identify cost-saving opportunities by analysing patterns and trends within historical data, thereby informing strategic decision-making. Integrating GAI into digital cost management systems promotes transparency and stakeholder collaboration. GAI facilitates informed decision-making by providing access to real-time cost data, fostering a culture of accountability and trust.

4.2. Implications: Challenges of Generative AI for the construction industry

With the emergence of AI and the power of GAI in the construction sector, there has been concerns about job displacement, especially in the developing economies where there is no shortage of labour or professional expertise. This is a misconception that must be addressed culturally in the construction sector. Biases in AI models are significant challenges most GAI and LLM platforms face. Such biases results in hallucinations in the quality of outputs provided. To address this challenge frameworks such as knowledge graphs and fine-tune LLMs are making it more proficient to have accurate outputs. The question of what will happen to BIM with the rise of AI’s intrusion into the ecosystem of digital construction is a significant challenge worth researching. In the BIM-GAIcost project BIM has become data for LLM development. Hence, AI-augmented construction workforce will required additional orientation, training and capacity building to fit into construction industry 5.0. This poses more questions that answers worth researching.

5 Further Research

With reviews on BIM cost management, this research established how V-model methodology enhances the integration of GAI system architecture and BIM templates, aligning with RICS New Rules of Measurement. GAI can reduce cost overruns, errors, and rework in cost estimation by at least 80% through text-to-text prompting. However, AI ethical considerations and end-user acceptance requirements must be overcome. GAI's precision in cost estimations marks a significant leap from conventional methods, reducing errors and the likelihood of financial discrepancies. This accuracy ensures that budget allocations are more reliable, facilitating smoother project execution and financial planning. The system architecture designed for the BIM-GAIcost project efficiently hallmarks GAI to automate and streamline the cost management processes. By rapidly processing complex datasets, GAI minimises the manual effort required, thereby freeing up valuable resources for other critical aspects of project management. This automation speeds up the cost estimation process and enhances the overall project timeline, contributing to timely project delivery. GAI's adaptability to fluctuating market conditions and project requirements introduces a dynamic approach to cost management. It enables continuous monitoring and updating of cost-related data, ensuring project budgets reflect current realities. This flexibility is crucial for managing unforeseen changes and maintaining financial control. GAI provides strategic insights through its advanced analytics capabilities. Historical cost data analysis from sources such as BCIS, Spons, and Laxton price books can bolster the identification of patterns that offer predictive insights that can lead to cost optimisation and informed decision-making. This strategic advantage supports the identification of potential cost overruns and exploring alternative strategies for cost savings. Integrating GAI into digital cost management transforms the construction industry's financial planning and control approach. Furtherance and full-scale implementation of the BIM-GAIcost system architecture will include lifecycle costing, circular economy, carbon capture, circular procurement practices, and error identification in red-amber-green.

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7 References

Ali, S., Ravi, P., Williams, R., DiPaola, D., & Breazeal, C. (2024, March). Constructing dreams using generative AI. In *Proceedings of the AAAI Conference on Artificial Intelligence* 38 (21), pp. 23268-23275.

Alsakka, F., Haddad, A., Ezzedine, F., Salami, G., Dabaghi, M., & Hamzeh, F. (2023). Generative design for more economical and environmentally sustainable reinforced concrete structures. *Journal of Cleaner Production*, *387*, 135829.

Bird, J. J., Ekárt, A., & Faria, D. R. (2023). Chatbot Interaction with Artificial Intelligence: human data augmentation with T5 and language transformer ensemble for text classification. *Journal of Ambient Intelligence and Humanized Computing*, *14*(4), 3129-3144.

Childs, P., R., N., (2019). Mechanical Design Engineering Handbook (Second Edition).

Georgiadou, M. C. (2019). An overview of benefits and challenges of building information modelling (BIM) adoption in UK residential projects. *Construction innovation*, *19*(3), 298-320.

Ghimire, P., Kim, K., & Acharya, M. (2024). Opportunities and Challenges of Generative AI in Construction Industry: Focusing on Adoption of Text-Based Models. *Buildings*, *14*(1), 220.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.

Graessler, I., & Hentze, J. (2020). The new V-Model of VDI 2206 and its validation. *at-Automatisierungstechnik*, *68*(5), 312-324.

Lähteenmäki, J., Ahola, P., Baraian, A., Förger, K., Granlund, T., Hopia, J., Kaikkonen, R., Mikkonen, T., Niemirepo, T., Pajula, J. and Partanen, J. (2023). Agile and Holistic Medical Software Development: Final report of AHMED project.

Magill, L. J., Jafarifar, N., Watson, A., & Omotayo, T. (2022). 4D BIM integrated construction supply chain logistics to optimise on-site production. *International journal of construction management*, *22*(12), 2325-2334.

Mishra, A., & Alzoubi, Y., I., (2023). Structured software development versus agile software development: a comparative analysis. Springer. Int J Syst Eng, 13 (4). https://doi.org/10.1007/s13198-023-01958-5

Nagy, O., Papp, I., & Szabó, R. Z. (2021). Construction 4.0 organisational level challenges and solutions. *Sustainability*, *13*(21), 12321.

Nast, A., & Koch, C. (2023). Practical experiences with 5D building information modeling–A systematic literature review. *ECPPM 2022-eWork and eBusiness in Architecture, Engineering and Construction 2022*, 508-515.

Noviani, S. A., Amin, M., & Hardjomuldjadi, S. H. (2022). The impact of 3D, 4D, and 5D Building Information Modeling for reducing claims to service providers. SINERGI, 26(1), 47-56.

Omotayo, T. S., Awuzie, B., Obi, V. K., Ajayi, S., Obi, L. I., Osobajo, O., & Oke, A. (2022). The system dynamics analysis of cost overrun causations in UK rail projects in a COVID-19 epidemic era. *SAGE open*, *12*(2), 21582440221097923.

Omotayo, T. S., Awuzie, B., Egbelakin, T., Obi, L., Ogunnusi, M., (2020).AHP – Systems Thinking Analyses for Kaizen Costing Implementation in the Construction Industry.MDPI, buildings, 10(230), http://dx.doi.org/10.3390/buildings10120230

Omotayo, T., Deng, J., Hossain, S., Khan, S. and Parmar, M. (2024). Generative AI for BIM-based Digital Construction Cost Management: A Qualitative Sentiment Analysis Approach. *Proceedings of the 14th Annual International Conference on Industrial Engineering and Operations Management* Dubai, United Arab Emirates (UAE), February 12-14.

Patil, A. R., Mane, S. C., Patil, M. A., Gangurde, N. A., Rahate, P. G., & Dhanke, J. A. (2024). Artificial Intelligence and Machine Learning Techniques for Diabetes Healthcare: A Review. *Journal of Chemical Health Risks.* 14(2), 1058-1063

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W. and Liu, P.J. (2020). Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, *21*(140), 1-67.

Rane, N. (2023). ChatGPT and similar Generative Artificial Intelligence (AI) for building and construction industry: Contribution, Opportunities and Challenges of large language Models for Industry 4.0, Industry 5.0, and Society 5.0. *Opportunities and Challenges of Large Language Models for Industry*, *4*.

Shoar, S., Yiu, T.W., Payan, S. and Parchamijalal, M., 2023. Modeling cost overrun in building construction projects using the interpretive structural modeling approach: a developing country perspective. *Engineering, Construction and Architectural Management,* 30(2), pp.365-392.

Sutskever, I., Vinyals, O., and Le, Q. (2014). Sequence to sequence learning with neural networks. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 27, pages 3104–3112. Curran Associates, Inc.

Taiwo, R., Bello, I. T., Abdulai, S. F., Yussif, A. M., Salami, B. A., Saka, A., & Zayed, T. (2024). Generative AI in the Construction Industry: A State-of-the-art Analysis. *arXiv preprint arXiv:2402.09939*.

Vaswani, S., Kveton, B., Wen, Z., Ghavamzadeh, M., Lakshmanan, L. V., & Schmidt, M. (2017). Model-independent online learning for influence maximization. In *International conference on machine learning*, 3530-3539. PMLR.

Vigneault, M. A., Boton, C., Chong, H. Y., & Cooper-Cooke, B. (2020). An innovative framework of 5D BIM solutions for construction cost management: a systematic review. *Archives of Computational Methods in Engineering*, *27*, 1013-1030.