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Automation in Construction Cost Budgeting using Generative Artificial Intelligence

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Abstract

This paper explores the paradigm of continuous improvement in construction cost management, emphasizing the utilization of Generative Artificial Intelligence (Generative AI) as a pivotal factor in driving this advancement. Embracing the lean construction principle and the plan-do-check-act approach, the study emphasizes the need for requirements and techniques in cost management. Building Information Modeling (BIM) is recognized as crucial for budgeting construction costs, but it faces challenges related to automation and technology. In this study we explore the use of Generative AI in generating Bills of Quantities (BOQs) for building cost management in small and medium-sized enterprises (SMEs). The exploration combines transformer-based techniques and Large Language Models (LLM), introducing a novel approach to development of BOQs in construction projects. Robustly Optimized BERT Pre-training approach (RoBERTa), an effective and reliable transformer architecture, categorizes substructure and superstructure components with an impressive 91% accuracy, forming a solid foundation. Fuzzy similarity matching connects sub-element records to project cost tables, incorporating cost data for meticulous computations. Leveraging the advanced text-generation capabilities of GPT-4, a state-of-the-art language model, the study automates the construction of a detailed and comprehensive BOQ. This departure from traditional rule based BOQ development offers enhanced flexibility and contextual knowledge. This approach, combining transformer-based models for precise categorization with LLM (GPT-4) for automated BOQ generation, presents a simplified and efficient solution for cost budgeting in building projects. This innovative method not only promises improved project documentation but also signifies potential revolutionary progress in building cost-management procedures. The findings provide valuable insights for construction professionals, paving the way for a more efficient and advanced approach to cost management in the construction industry.

Keywords
Generative AI, Bill of Quantities, BIM, Construction and Cost Budgeting.

1. Introduction

Ensuring continuous cost improvement in construction is vital for effective cost management. Methods for implementing continuous improvement in cost management involve utilizing decision-making tools to address cost overruns and selecting appropriate procedures for specific project categories (Omotayo et al., 2022). Guidelines and resources are available for the ongoing enhancement of the cost management process in construction. The book "Continuous Cost Improvement in Construction: Theory and Practice" provides ways to implement continuous improvement in cost management within the construction industry. It employs case studies to challenge readers' perspectives on continuous cost improvement tactics throughout the project lifecycle (Omotayo et al., 2022). Moshkalev (2022) suggests techniques and practical tools for managing construction expenses that can be utilized at every stage of a construction project. Wang (2022) examines distinct cost management tactics for various phases of a project to enhance project cost management. Guo (2022) explores cost management issues in the construction process and suggests appropriate solutions and enhancement techniques, such as implementing a dynamic cost control system. Cho (2020) proposes strategies to enhance the efficiency of construction project management by establishing explicit standards for managing the overall project costs.

The cost management techniques in construction enterprises are influenced by several factors, including the experience and competency of quantity surveyors/commercial managers, the support and control provided by management, the effectiveness of project communications, the external economic climate, and the utilization of project management systems (Okereke et al., 2022). Therefore, automating this procedure could effectively enhance the balance of these systems compared to before. Within the cost management process, the tasks involved in construction cost budgeting include quantifying the building works and inputting rates to generate the Bill of Quantities (BOQ).

1.1 Objectives

The objectives of this study are:

- To understand the Generative AI approaches required to automate the cost budgeting processes in the UK construction businesses.
- To produce the indicators for successfully creating a cost budgeting application based on Generative AI with consideration for database information, costs, professional ethics, user experience, and government regulations.

2. Literature Review

2.1 Bill of Quantities

A Bill of Quantities (BOQ) is a comprehensive document detailing the quantities and specifications of all products required for a building contract. It is compiled through the meticulous process of measurement (Juszczyk et al., 2017) and plays a crucial role in cost estimation and building activity planning (Bandi, 2015). Quantity Surveyors create the BOQ, a vital component of tender and contract agreements (Rashid et al., 2016), used by contracting organizations to fulfill their contractual obligations (Odeyinka et al., 2009). The BOQ includes information on work quantity, temporary structures, ancillary works, and environmental practices (Yan et al., 2014). However, concerns exist regarding the BOQ's efficacy in meeting project procurement requirements, with its reliability for ensuring cost certainty varying based on project complexity. Strategies for enhancing BOQ utilization should consider crucial information needs and concerns identified through research.

Expanding BOQ usage in construction involves adopting novel frameworks and procedures to strengthen cost control. An effective strategy employs blockchain technology and encryption methods to ensure data integrity and privacy in managing building costs (Cheng et al., 2023). This includes constructing a cost data model with classified cost information and employing access control models based on encryption technologies to prevent unauthorized access to sensitive blockchain data. Another enhancement involves integrating precise engineering predictions, including suitable contingencies and adjustment variables, to accommodate market volatility (Sayed et al., 2023). A comprehensive approach that integrates statistical and expert techniques can improve construction forecasting systems, leading to accurate cost and volume predictions (Jenkins & Deiters, 2022). These innovations can enhance the precision and effectiveness of cost control in construction projects.

Recent advancements in construction cost budgeting have incorporated applied Building Information Modeling (BIM) to improve the process. However, the use of BIM faces hindrances due to a lack of automation, and its complexities require extensive training, regular upgrades, and ongoing professional development. Similarly, creating the BOQ is a laborious process prone to errors. Therefore, automating the BOQ production process is imperative to prevent errors and facilitate the efficient use of cost planners' and quantity surveyors' time.

2.2 Application of Generative AI in Construction

Generative AI has the potential to revolutionize the bill of quantities (BOQ) creation process by leveraging its ability to generate human-like text and make context-based decisions through user input (Korzynski et al., 2023; Noy & Zhang, 2023). Employing a generative pre-trained transformer model, coupled with extensive training on a vast dataset of business process data, allows for refining the model's capabilities to produce process flows and provide valuable insights and recommendations for enhancing process efficiency (Beheshti et al., 2023). This technology can automate repetitive tasks, increasing process efficiency and improving decision-making in data- and knowledge-intensive systems (Beheshti et al., 2023).

Several studies explore the application of Generative AI techniques in various construction domains. Liu et al.'s study focuses on using generative Pre-trained Transformers (GPT) models for Automated Compliance Checking (ACC) in the Architecture, Engineering, and Construction (AEC) industry, highlighting the potential of GPT models in ACC while addressing limitations that require further advancement (Liu et al., 2023). Another study by Zhang et al. evaluates GPT models in building energy management data mining scenarios, finding that GPT-4 can generate energy load prediction codes and diagnose device faults, although limitations in output stability and familiarity with certain tasks are noted (Zhang et al., 2024).

Korzynski et al. present a comprehensive examination of challenges and prospects in AI prompt engineering, establishing a theoretical framework and introducing the AI PROMPT framework for text-to-text prompt engineering (Korzynski et al., 2023). Clarisó and Jordi Cabot shed light on applying Model-driven Engineering (MDE) to prompt engineering for Generative AI systems, advocating for platform-independent prompts through MDE techniques and introducing the Impromptu domain-specific language for modular prompts (Clarisó & Jordi Cabot, n.d.).

This investigation aims to assess the feasibility of incorporating Generative AI into the construction sector to automate BOQ creation. Beyond feasibility evaluation, the study seeks to offer profound insights and suggestions to enhance the efficiency of future AI cost-budgeting applications in the building field. The project aims to contribute to the foundational knowledge and best practices in AI and construction cost management by examining practical implications and challenges of AI-driven BOQ creation.

3. Methodology

3.1 Data Collection

Initially, data entries relevant to the construction project were extracted from the Revit database, with a specific focus on the substructure and superstructure components of construction. To compute the Bill of Quantities (BOQ) for each designated building project, our consideration is limited to records falling under seven distinct sub-element categories: Concrete Frames, Steel Frames, Lowest Floor Construction, Upper Floor Construction, Specialist Foundations, Standard Foundations, and Concrete Casings for Steel Frame. These categories are derived from the RICS new rules of measurement: order of cost estimating and cost planning for capital building works (NRM1) sub-elements, which are part of the two NRM1 main group-elements: substructure and superstructure (as depicted in Table 1).

Table 1. BOQ categories extracted from NRM1

New Rules of Measurement 1	
Group-element	**Sub-element (Categories)**
Substructure	• Lowest Floor Construction • Specialist Foundations • Standard Foundations
Superstructure	• Concrete Frames • Steel Frames • Upper Floor Construction • Concrete Casings for Steel Frame

3.2 Implementation Framework

To accomplish identified challenges, this study presents a framework in construction for early adoption in research and industry application. The initial stage of this framework, illustrated in Figure 1, involves gathering data from pertinent sources. The dataset comprises records from multiple real projects, each associated with specific categories. This data serves as the training set for the RoBERTa classifier. Once the model is successfully trained, it can identify patterns in the data, enabling the classification of new and undiscovered project records.

Although these records were not seen during the model's training, they pertain to project categories different from the training data. The values in these records are used for aggregation post-classification. This entails grouping record values based on the assigned categories. For instance, all records falling under the "Concrete Frames" category are amalgamated, consolidating their lengths, volumes, and quantities.

These aggregated values are integral to constructing a comprehensive and informative Bill of Quantities (BOQ). The procedure involves generating a detailed report encompassing numerous factors and quantities associated with the classified project records using the combined data. Through this research scenario, the successive phases of data collection, model training, classification, aggregation, and BOQ generation synergistically contribute to advancing scholarly knowledge regarding the utilization of AI in building project cost management.

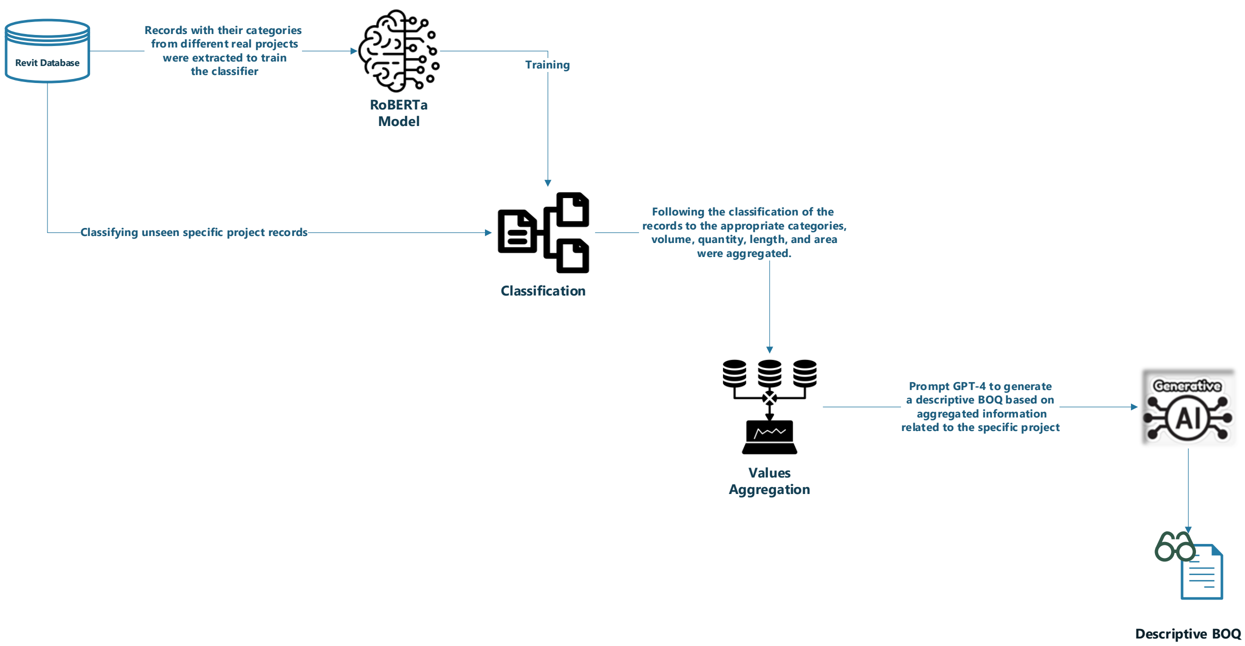

Figure 1. Generative AI Bill of Quantities Generation Framework

3.3 Sub-element Classification

Subsequently, we aimed to identify the most significant dimensions by treating each column in a database as a separate dimension. Thus, the dataset was organized into 10 dimensions. After completing the initial preprocessing tasks, we proceeded to train transformer-based models, namely RoBERTa (Y. Liu et al., 2019) and Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019), for the purpose of categorizing sub-elements in the incoming project input data. Additionally, a Fine-tuned GPT-3.5 (OpenAI, GPT, 2023) model was utilized, developed on the same dataset with the identical objective.

The use of various advanced models like RoBERTa, BERT, and a Fine-tuned GPT-3.5 underscores our commitment to leveraging the latest developments in natural language processing and deep learning for the complex task of sub-element classification in construction project data. The primary goal was to classify these sub-elements based on the ten most crucial dimensions discovered during the feature selection process. RoBERTa, being an advanced transformer architecture, ensures the model's effectiveness in capturing complex patterns and correlations in the data, thereby improving its capability to identify project-unseen data sub-elements effectively. This strategy enhances the model's ability to handle various and intricate project input data by utilizing the chosen dimensions considered essential for precise categorization, thereby improving its resilience and efficacy.

3.4 Value aggregation

The classification assignment was completed successfully, achieving an impressive accuracy rate of 91%, establishing a robust foundation for further analysis. Leveraging this remarkable accuracy, we conducted aggregations of diverse parameters—such as volume, quantity, length, and area—based on the predicted categories. This categorization is crucial as it forms the groundwork for calculating the Bill of Quantities (BOQ) and efficiently managing cost items in project records.

The prominent level of accuracy in categorization not only enhances the reliability of subsequent computations but also underscores the model's proficiency in precisely categorizing and aggregating various project components. This capability facilitates streamlined and efficient cost management operations, highlighting the model's expertise in handling intricate project data with precision.

3.4 Fuzzy similarity matching for sub-element cost analysis

Following the initial classification and aggregation, we employed fuzzy similarity based on Fuzzywuzzy Python package (Python Community, 2020) to identify matches between each aggregated sub-element record and corresponding items in the project cost unit and rate tables. It is essential to acknowledge that these tables may vary based on specific criteria established by each organization. Consequently, this method enables the creation of a comprehensive data set comprising consolidated records of sub-elements. These records encompass critical measurements such as volume, quantity, length, and area and the associated cost rates and units.

This interface facilitates seamless cost calculation operations, offering project managers and stakeholders a robust framework for accurate and efficient financial evaluations within the project's scope. By incorporating both measurements and cost-related information, the dataset contributes to a more thorough understanding of the project's financial landscape.

3.5 Automated bill of quantities generation with Generative AI

After extracting pertinent information from the original records in previous stages, the research process seamlessly progresses to automatically generate a detailed and descriptive Bill of Quantities (BOQ) by analyzing a meticulously prepared text dataset. Traditionally, BOQs are created using rule-based models. However, this study adopts an unconventional approach by harnessing the capabilities of advanced language models, particularly GPT-4 (OpenAI, GPT, 2023). Large Language Models (LLMs) like GPT-4 highlight an impressive ability to generalize, highlighting their effectiveness in adeptly handling textual information across diverse formats.

The incorporation of sophisticated language models introduces a significant shift in BOQ generation, providing a more adaptable and contextually aware approach that enhances the richness of the generated content. This innovative method not only simplifies the process of BOQ generation but also demonstrates the capabilities of advanced language models in revolutionizing and enhancing text-based tasks in the field of cost management in construction.

Prompt engineering plays a crucial role in optimizing the performance of LLMs by precisely formulating instructions given to them. This process involves crafting prompts to enforce regulations, streamline procedures, and ensure desired attributes of the output (White et al., 2023). To conclude the workflow, the extracted information is inputted into the GPT-4 model, which is then instructed to construct a descriptive BOQ using the information provided in the prompt section. The result of this procedure is evident in Table 3, displaying the model's capacity to convert information into a comprehensive and contextually intricate BOQ. This stage illustrates the versatility and effectiveness of GPT-4 in understanding complex construction-related information and presenting it in a structured and instructive manner.

4. Results

In this section, we present the outcomes of the sub-element classification experiments conducted using three state-of-the-art language models: RoBERTa, GPT3.5, and BERT. The evaluation metrics include classification accuracy, training loss, and training details such as epochs (steps). The classification outcomes are displayed in Table 2, and Figures 2 and 3. Table 2 illustrates the classification accuracy achieved by each model. RoBERTa exhibited the highest accuracy at 91%, showcasing its effectiveness in accurately classifying sub-elements.

Table 2. Results of Sub-Element Classification

Classifier	Classification Accuracy	Training Loss	Epochs (Steps)	Train records	Test records
RoBERTa	91	0.05	20	300	50
GPT3.5	89	0.12	751	300	50
BERT	87	0.16	20	300	50

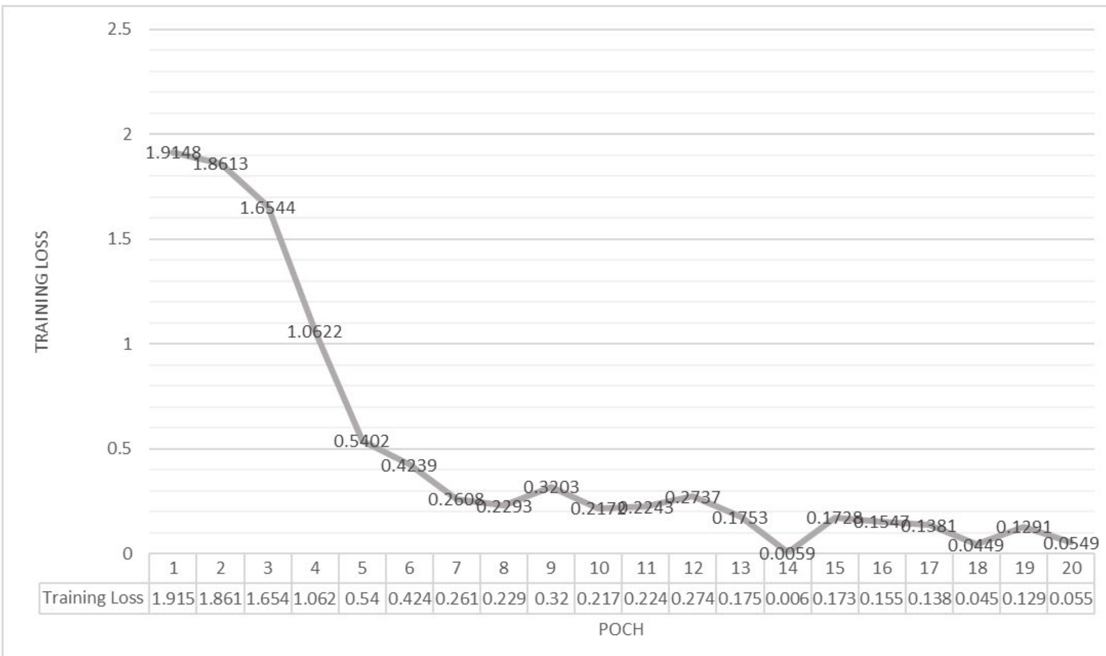

Figure 2. The RoBERTa Training Loss

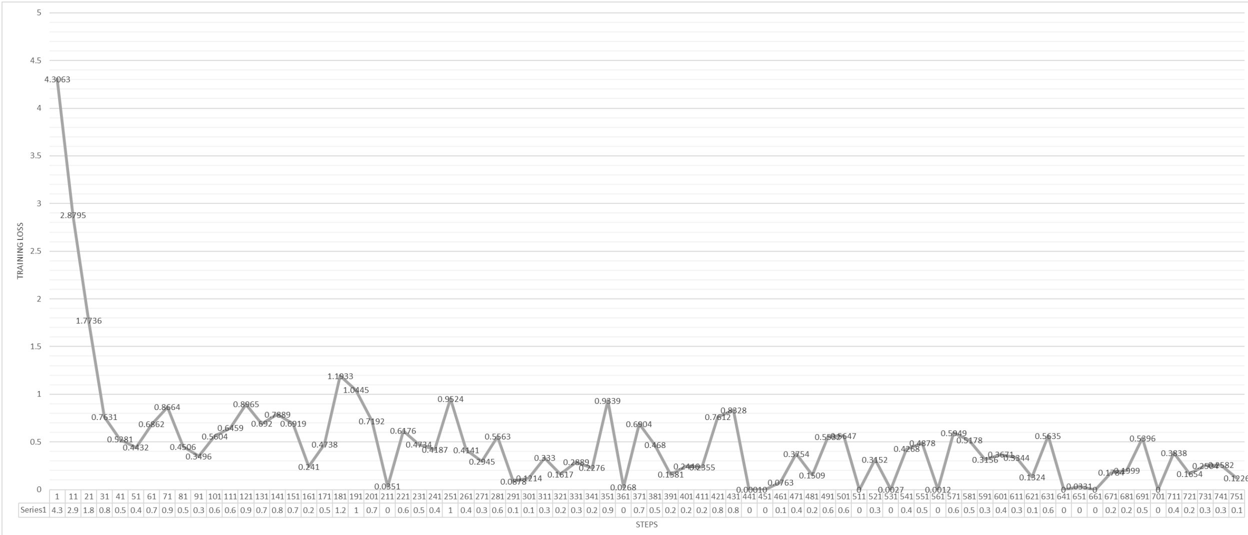

Figure 3. The GPT 3.5 as Classifier Training Loss

Table 3 visually represents the fruitful constructive collaboration of advanced language models and construction cost data, providing a tangible outcome of the generated BOQ. Utilizing GPT-4 not only speeds up creating a BOQ but also introduces a degree of subtlety and flexibility that conventional rule-based models may lack. This impressive outcome highlights the potential for significant positive change when incorporating innovative language models into the construction management process, promoting improved depth in creating essential project documentation. Each sample output provides a detailed breakdown of a specific item in the BOQ, including its description, area, volume, quantity, rate, and the total cost calculation. These outputs serve as informative and transparent documentation for construction projects, aiding in accurate cost estimation and project planning.

Table 3. Sample outputs of generated descriptive BOQ

Sample Output 1	• Superstructure - Floors - Floor - 150mm STEEL DECK COMPOSITE SLAB (COMFLOR 80 DECK AND CONCRETE C30/37) consists of a steel deck and concrete C30/37 with a thickness of 150mm. • The material is ideal for the high load-bearing capacity required for superstructures with an area of 32.867 m2. • This specific type of floor is commonly used in construction due to its durability and strength. • The quantity specified is 1 unit with a rate of 350 per m2. • Given this, the total cost for the '150mm STEEL DECK COMPOSITE SLAB (COMFLOR 80 DECK AND CONCRETE C30/37)' would be the rate multiplied by the area (m2). • Total cost = Rate (per m2) * Area (m2) • Total cost = 350 * 32.867 • Total cost = $11,503.45 • Note: The volume is 4.93 m3 but it's not included in the cost calculation as it's based on area."
Sample Output 2	• The BOQ description provided would look like this: • Description: Lowest floor construction work including polystyrene insulation and 2500mm thick raft slab or raft foundation. • This is part of the substructure work that involves the preparation and construction of floors. • This specifically involves a floor - 2500mm THK. RAFT - 2500mm THK. RAFT • Area: 154.708 m² • Volume: 386.77 m³ • Rate: £197.48 per m³ • Total Cost: The total cost for the substructure work would be calculated by multiplying the volume of the work by the rate.

	• Therefore, the total cost is 386.77 m³ * £197.48/m³ = £76,286.75. • (Note: the actual total cost might vary depending on factors such as location, complexity of the work, and availability of materials and labor.)
Sample Output 3	• Structural Foundations - _ACM-Concrete Pile - 1500 DIA - 1500 DIA - R.C. PILE. • This sub-element pertains to specialist foundations within the Substructure group element. • The volume of the concrete pile is 47.71 m3. • To get the Total Cost, multiply the Volume by the Rate (240). • Total Cost = Volume (47.71) * Rate (240) = £11,450.40

5. Conclusion

Generative AI can create a level playing field for all experience levels of construction costing professionals, business scales, and project types by simplifying the approach to construction project measurement and costing. SMEs and large construction companies have unused big data, essential in producing large language models that would serve the Generative AI for the cost. SMEs would benefit from a low-cost, easier, and quicker approach to quantifying and costing construction costs through Generative AI. To ensure the ongoing success, acceptance, and practical implementation of cost-related projects, it is important to continuously improve productivity across the whole project lifecycle. Generative AI will enable quantity surveyors, cost estimators, construction managers, and contractors to gradually enhance project cost efficiency. This research contributes to exploring the dynamic opportunities and challenges associated with integrating Generative AI into the construction industry. The process of using Generative AI for BOQ productions creates more time for more productive cost planning and management tasks, thereby adding value to the role of the quantity surveyor and cost planning teams. This innovative method not only streamlines the automatic generation of BOQ but also serves as a fundamental component for precise cost estimation and management in construction projects. It signifies a positive trajectory for future enhancements. The feasibility study decisively demonstrates the practicality of employing AI for BOQ and the comprehensive administration of building expenses. The findings from our proposed framework underscore the immense potential inherent in deploying such technologies, highlighting their effectiveness in reshaping established procedures within the construction industry. The findings of this research can direct the construction research community to focus on the practical applications of Generative AI capabilities. Moreover, this study provides an initial groundwork for realizing the capacity and challenges of Generative AI in this industry. Further validation studies implementing the proposed framework and developing real construction applications would be a natural extension of this research.

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Biographies

Pouyan Parsafard is a PhD candidate at Birmingham City University, who specializes in studying the nexus between construction and natural language processing. Because of his comprehensive knowledge of deep learning, machine learning, neural networks, and natural language processing, he has made himself an expert in the industry. Pouyan's strong programming skills in Python and his familiarity with data science-related libraries complement his academic background, enabling him to translate abstract concepts into real-world applications.

Ogerta Elezaj is a Lecturer of Computer Science at the School of Computing and Digital Technology. She was recipient of Alain Bensoussan postdoctoral fellowship from European Research Consortium for Informatics and Mathematics in 2019-2020 and held ERCIM postdoc fellow positions at the Norwegian University of Science and Technology. Her main fields of competence are artificial intelligence, machine learning applications and big data. She has participated in projects funded by EU Horizon 2020, and Erasmus+ programs. Dr. Elezaj has worked for more than eight years at The Office for National Statistics in Albania, in the position of Director of IT and Methodology Department. Dr. Elezaj, during her experience, has worked as a trainer and consultant for different international organizations such as UNDP, UNFPA, and the European Commission.

Damilola Ekundayo is an Associate Professor in Built Environment and the MSc Quantity Surveying Programme Director at BCU. Damilola has substantial professional experience in the construction industry and in the UK higher education sector and varied management experience. Before joining academia, he worked in the construction industry as a chartered quantity surveyor, chartered construction manager and professional project manager both in the UK and abroad on varied projects from building construction to civil engineering work. Besides working for a construction consultancy practice and a property developer at different points in his professional career, he was also recently involved in a multi-million-pound building and redevelopment project successfully completed by one of the UK's largest contractors.

Dr. Edlira Vakaj is a Senior Lecturer of Computer Science in the Computing and Data Science department. She is leading the Natural Language Processing (NLP) AI Lab and conducting research in multidisciplinary projects in close collaboration with the Build Environment. She is acting as the Academic Lead of the 4Net KTP, as supervisor of the King & Moffat KTP, and advising on the Hadley Group KTP. Edlira is the principal investigator of the ACCORD Horizon project and engaged in several European and UK-funded projects of various domains where Semantic Web Technologies are applied such as Renewable Energy (FP7 RENESENG), Industrialised Construction and Industry 4.0 (Innovate UK DfMA, KTPs), Higher Education and Youth (Erasmus + Capacity Building, Learning mobility of individuals, Cooperation for innovation and the exchange of good practices action).

Milan Parmar joined the Property Box in 2018 to ensure our technologies are used efficiently, profitably, and securely. Evaluating and implementing new systems is one of its key roles in our business and improving our existing technology. Milan's background is in Quantity Surveying, with an MSc degree and a wealth of experience in digital construction. He has worked with RIB Software for 7+ years, where he built robust, scalable, data-driven technology solutions for clients worldwide.

Mudasir Ahmad Wani is currently working as a Research Scientist in Natural Language Processing (NLP) at Prince Sultan University, KSA. He has served as a Lecturer and Researcher at the Department of Information Security and Communication Technology (IIK) at the Norwegian University of Science and Technology (NTNU), Norway. He pursued his postdoctoral research at the Norwegian Biometrics Laboratory, NTNU, Norway and He is the recipient of the Alain Bensoussan Fellowship award under the European Research Consortium for Informatics and Mathematics (ERCIM), Sophia Antipolis Cedex, France. He obtained his Ph.D. from Jamia Millia Islamia (A Central University), New Delhi, India in 2019 in Computer Science. He holds a master's in computer applications (MCA) and M.Phil. (Data Mining) from the University of Kashmir (UoK) in 2012 and 2014, respectively. His research focuses on the extraction and analysis of social data, and the application of different statistical, machine/deep learning, and NLP techniques in developing prediction models.