Automatic Assessment of Leanness of Construction Contract Provisions: A Proof-of-Concept

Ramesh Balaji[1], Sivakumar K.S[2], Murali Jagannathan[2] and Venkata Santosh Kumar Delhi[3]

[1]Tata Consultancy Services, India
[2]Indian Institute of Technology Madras, India
[3]Indian Institute of Technology Bombay, India
ramesh.balaji@tcs.com, ce22s018@smail.iitm.ac.in, muralij@civil.iitm.ac.in, venkatad@iitb.ac.in

Abstract

Construction projects significantly contribute to a nation's economic development. However, the sector is synonymous with delays and disputes for various reasons, often due to non-productive work practices. Researchers and practitioners recommend applying lean construction principles to mitigate non-value addition activities and improve productivity and performance. However, existing contract forms may contain provisions that are counter-productive, thereby making lean implementation a challenge. Therefore, when planning to go lean, it becomes important to assess the extent to which a contract provision aids or hinders lean implementation, in other words, 'leanness' assessment. A manual analysis is possible but time-consuming and prone to subjective decision-making. Artificial Intelligence (AI)-backed Language Model (LM)-based tools can be potentially used to quickly and efficiently classify a contract clause based on lean implementation-friendliness. Therefore, a dataset containing 734 contract clauses is manually classified into 14 labels based on the literature review, and a part of this data is used to train Bidirectional Encoder Representations from Transformers (BERT)-LM. With an F1 score of 77%, the study shows that LM-based solutions can be potentially employed for construction contract leanness assessment. The study, which is an initial attempt towards developing a reliable leanness prediction model in the future, also noted that the Bert-base-cased LM performs better than its 'large' counterpart under both the 'cased' and 'uncased' conditions.

Keywords –

Contracts; Lean; Language Models; Finetuning; Artificial Intelligence

1 Introduction

Lean construction principles can potentially help the construction industry enable timely project completion, thereby preventing expensive cost overruns and associated disputes. Lean construction principles also help make construction more sustainable by reducing process and material waste [1]. Having said that, construction projects are stakeholder-intensive, and without their buy-in, lean implementation may not yield results [2]. Stakeholder acceptance of such initiatives is not easy, especially for an industry less friendly to innovativeness than sectors like manufacturing and automobiles [3]. Nevertheless, there should be a start, and academicians, practitioners, and researchers are important in triggering the start.

Over the last few decades, there has been a sustained effort by the research community to experiment with lean implementation in construction projects and disseminate the findings to the world at large. Construction firms, at least the leading ones from most developed and developing nations, have either implemented or shown interest in implementing lean construction practices [4]. However, there are still a large number of firms that are yet to realize the importance of lean implementation [5]. This difference in reaction times of various firms within the construction sector has triggered a separate research sub-domain studying the motivation for lean implementation in construction [6]. At the outset, it appears that some firms implement lean through a top-down approach where the firm implements lean as a response to some diktat or directive that insists on lean implementation, and some others embrace lean through a bottom-up approach, leaving the implementation exercise a largely self-driven activity [7], [8]. While there is no single answer to the question of the "better" way to implement lean, it is clear that the role of a "trigger" is inevitable, and it is here that the role of stakeholder practices comes into the picture.

In the construction industry, the demand for construction services is created by the developers and investors in infrastructure development belonging to the public or private sectors. When demand comes with the requirement to implement lean construction practices while designing and executing projects, the supply is more or less assured. The suppliers, being construction contracting and sub-contracting firms, automatically adapt to deliver lean construction practices when they are asked to [9]. However, few researchers have pointed out that when lean is implemented as a reaction to a contractual or a policy requirement, it turns out to be superficial, merely to satisfy bare minimum requirements [6]. Nevertheless, the authors believe that when employers demand implementing lean practices through their contracts, it can at least serve as an initial trigger for firms that may not be self-motivated to embrace change. With this premise, this study attempts to develop a proof-of-concept tool to automatically assess whether a given contractual provision promotes lean implementation in construction projects or does not. While this assessment can be manually performed, given the verbose contractual documents often running into hundreds of pages, it becomes time-consuming to assess document-intensive construction contracts [10] for their lean-friendliness or 'leanness.' Here, using artificial intelligence (AI) and machine learning (ML) can potentially be of immense help to researchers and practitioners to analyze contract documents quickly and efficiently. Building a classification model using the Language Model (LM) - Bidirectional Encoder Representations from Transformers (BERT) [11], the study recorded an F1 score of 77%, showing that AI-based solutions can be potentially employed for construction contract leanness assessment.

2 Background and Literature Review

This study attempts to answer the research question, "Can LMs be used to assess the leanness of a contract clause?" Accordingly, the literature is reviewed for LM and lean construction studies.

2.1 Language Models (LM)

The LM (or its larger counterpart, Large LM or LLM), a text model pre-trained on a large corpus, typically from general domains, is at the core of text analytics. For example, the Generative Pre-trained Transformer or GPT is an LLM on which the "ChatGPT" application is created [12]. Essentially, ChatGPT is a "question-answering" platform. However, LLMs can be useful in developing applications for tasks such as text summarization, topic modeling, and text classification, among other things [13]. As most of the base LMs and LLMs are pre-trained on a large corpus of publicly available data (like Wikipedia), they may have limitations when used in highly specialized or domain-specific application development. For instance, in the instant case, where the objective is to classify a given contract clause based on its lean-friendliness, using a base LM for application development may not yield satisfactory results as the model's training data may not have a sufficient concentration of lean-related information. In such cases, finetuning is one way to improve the model's output accuracy.

2.2 Finetuning

Finetuning is a supervised training process wherein base LMs, or LLMs, are trained with a dataset containing sample question-answer pairs or classified or labeled paragraphs [14]. Through this process, the base LMs generally trained on generic datasets get trained to answer questions or classify as per user requirements, as the case may be, thereby improving the output quality by making it more specific to the domain requirements. During the process of finetuning, the model interprets the pattern in the input data such that the pre-trained machine learning model (in this case, Bert) adapts to a new specific task (in this case, leanness assessment). While it is possible to train models from scratch, full training is computationally intensive, and in such cases, fine-tuning proves helpful. While research has shown considerable improvement, the process of finetuning is as good as the quality and quantity of the training data [14].

2.3 Choice of Base Model

The output accuracy (the extent to which the model helps assess the lean-friendliness of a contract clause) depends on the model size (the training data size and the number of parameters) and the application being developed. While some models like GPT are not open-source beyond a limit, many are open-source models (BERT, FLANT5, etc.). Among the open-source models, depending on the transformer architecture, there are encoder-only models, encoder and decoder models, and decoder-only models. Given the constraints of the scope of the study, and without getting into the technicalities, it is observed by researchers that encoder-only models like BERT (Bidirectional Encoder Representations from Transformers), an open-source Language Model (LM) can perform well for applications aimed at text classification, especially in the context of construction contracts [10], [14]. Based on dataset size and parameters, BERT models have the "base" and "large" and "cased" and "uncased" models. In this study, the 'BERT-base-cased" model is chosen for finetuning. The review undertaken to arrive at the finetuning data is explained next.

2.4 Lean construction principles

Worldwide, there is a push for embracing sustainable construction techniques with the United Nations, Sustainable Development Goal (SDGs) 9 (resilient infrastructure and fostering innovation), specifically target 9.4, pushing for increased resource use efficiency. Here, lean construction principles take center stage in bringing sustainable practices into construction by minimising waste and increasing productivity.

Fundamentally, lean implementation boils down to seven principles that advocate eliminating or reducing non-value-adding activities, in other words, 'waste.' Firstly, lean implementation involves stakeholders, leading to a collaborative decision-making process [15]. When decision-making is collaborative, it is more likely that the parties are committed to the decision. Secondly, lean implementation promotes open communication among stakeholders, thereby helping in the early resolution of conflicts [16]. Thirdly, in construction projects that are often known for an adversarial environment [17], a lean and a "no blame game" culture go hand-in-hand, improving the trust among the stakeholders [15], [18]. Fourthly, while long-term plans are definitely relevant, lean advocates focus on short-term goals as they are within the reach of stakeholder control [16]. However, the proponents of lean construction also advocate that while retaining a greater focus on short-term goals, it was also important to get into details in the form of weekly plans and six-month or 8-month lookahead schedules [16]. The fifth and sixth lean principles refer to identifying constraints through "pull planning" rather than the traditional "push" approach [16]. "Pull planning" refers to the process where the frontline engineers, the process owners, or "last planners" are encouraged to commit to what is achievable, given the resource constraints, rather than being blindly pushed by the top management to achieve unrealistic targets. If the commitment by the last planners is not aligned with the project requirements, the top management must ease the constraints so that the last planners can commit more. Through this, the last planners take ownership, improving productivity [16] and eliminating waste. Finally, lean implementation is about continuous improvement, a process through which parties identify risks and evolve mitigation plans for future projects [16], [19]. To summarise, any contract clause that promotes collaboration, timely decision-making, dispute-prevention, and supports waste reduction can be considered 'lean.'

A recent article reviews the studies presented at the annual conferences conducted by the International Group for Lean Construction (IGLC) for the synergies between lean construction and AI and observes that the LLM-based question-answering application – "ChatGPT" – can potentially empower lean researchers and practitioners [20]. The study also further summarises IGLC articles that directly or indirectly discuss the potential benefits of AI in lean construction, and it is clear that a contract document's lean-friendliness assessment is not explored [20]. Articles with keywords "Construction," "contract management," "classification," "AI," and "label" mostly dealt with classifying the provisions of a contract document based on risk management [14], requirements identification [21], and scope and obligations identification [22], [23]. However, AI-based contract content classification to assess the 'leanness' of the contents is not evidenced. To assess LM's potential for leanness assessment, the study's objective is to develop an automated classification model that classifies a contract clause into a "Lean" or "Not Lean." The rationale for the classification labels is explained in Table 1.

Table 1. Labels for contract clause classification (number in the parentheses indicates count under each label)

Clause/Provision	Ref.	Label
Clauses on Liquidated Damages drafted with clarity and certainty	[24]	Lean - Prevents Delay (11)
Clauses that provide fair cost and time compensation in case of delays caused by the Employer	[25]	Lean - Prevents Disputes (61)
A clause that is drafted with clear timelines for the fulfillment of certain obligations and mentions the implication of non-compliance	[26]	Lean - Prevents Waiting (58)
A clause that discourages a contractual party from reworking/material wastes by focusing on skills and training	[27]	Lean - Prevents Rework, Material Wastes (54)
Clauses that enable early completion bonus	[28]	Lean - Promotes Early Completion (18)
Clauses intended to check and approve the Contractor's submissions and activities but fail to specify the intent/liability of such approvals. Will the approver be liable, or is the check only limited to the review of conformance of the work/submission to specifications/contract requirements? Without such clarification, there will likely be a "blame game."	[29]	Not Lean – Liability undefined (24)

Clauses that contain provisions or terms that may have multiple meanings or are in contradiction with other provisions of the contract. Such provisions result in conflicts and non-collaborative behavior, often leading to delays and disputes.	[30]	Not Lean – Misuse (ambiguous) (33)
Clauses that protect a party from being held responsible for its shortcomings.	[31]	Not Lean – Misuse (No Waiver) (74)
Clauses that provide one party with absolute powers can be potentially misused, leading to non-collaborative behavior	[32]	Not Lean – Misuse (one-sided) (122)
Clauses, which are a kind of "disclaimers", in which one party expects the other to bear risks that may not be reasonable and/or foreseeable even after due diligence. In such cases, the affected party tends to approach arbitration or judiciary for relief, resulting in delays and the development of adversarial relationships.	[33]	Not Lean – Misuse (unfairness) (44)
Clauses that prevent the non-breaching party from seeking compensation for losses incurred due to the delays or breaches by the breaching party. While such clauses are common, they can often lead to disputes when the breaching party excessively relies on such "no damage" provisions to protect itself. This can lead to adversarial and non-collaborative behavior, preventing stakeholder involvement and delaying decision-making.	[34]	Not Lean – No Damages Provision (38)
Clauses with no clear timelines for action, and therefore there is a tendency for delayed decision-making, inducing "waiting."	[26]	Not lean – No Timelines (84)
Clauses that do not explain the implication of not complying with the instructions/orders/contractual promises. In such cases, there is no certainty on how the other party will react to the inaction of the non-complying party. This can lead to disagreements, non-collaborative behavior, and breaking the stakeholder involvement (incompleteness)	[35]	Not Lean – Non-compliance Unaddressed (91)
Clauses, when acted upon, can lead to unnecessary "waiting" at project sites.	[36]	Not Lean – Waiting (21)

3 Methodology

The study employs contract document content analysis using an LM-based classification technique. A three-step methodology is adopted to develop a proof-of-concept model to assess the leanness of a given construction contract provision.

3.1 Step 1: Developing Training Dataset

The initial idea was to approach using a standard supervised classification method in which a training dataset is prepared to develop a classification model annotated with labels derived from the literature.

3.2 Data Pre-processing, Classification Training, and Testing using LM

In this step, as a prerequisite for data preprocessing, the developed file (in the .csv format) is ingested as a Pandas dataframe through the algorithm in the Python programming language. After setting up the environment with key libraries (Datasets, Transformer, Accelerate, sklearn metrics, Pandas, Torch), the data is pre-processed to enable its use in the LM, which, in this case, BERT.

To enable training the language model, the input data will be split in an 80:20 ratio, with 80% of the data used for training and the rest for testing. Since there are more than two labels (14, in this case), the stratification technique is used for sampling the data.

Stratification ensures dividing the labels into homogenous subgroups, called strata, and then applying simple random sampling within each subgroup. As a result, the test set is representative of the population since the percentage of each stratum is preserved. In this context, the stratification is performed on the “label” column with 14 groups. The key idea is to ensure that the train and test dataset has all 14 groups represented in complete. After formatting the current dictionary into a tokenizer-based dataset, the “Bert-base-cased” model is downloaded through the Auto model function and prepared for the training process. Regarding training arguments, 18 epochs are set up, meaning all the training records will run 18 training cycles. In each epoch, the size of the batch will be 16.

3.3 Step 3: Model Evaluation

Lastly, since the evaluation process is also run simultaneously, the evaluation batch of 64 records will be used. In this experiment, "Accuracy" and "F1 score" are the primary metrics that will be evaluated. Considering that the input data is imbalanced, the F1 score eliminates any anomalies in calculating model accuracy.

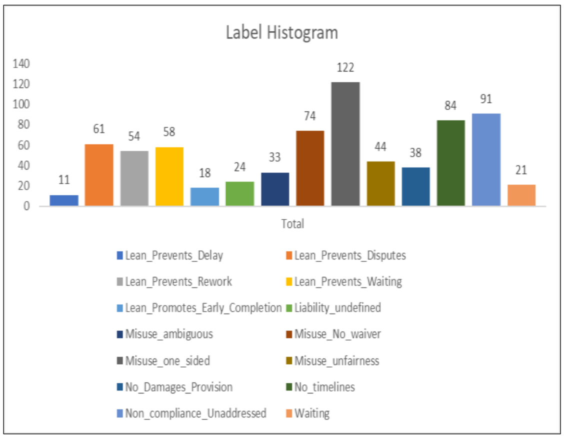

Figure 1. Label Histogram

4 Results

4.1 Step-1 – Developing a Training Dataset

As discussed earlier, 14 labels are considered to classify a contractual provision under lean/not lean. The initial list of clauses for training consisted of 307 clauses sourced from the General Conditions of Contract (GCC) of public sector contract documents from India. However, with the number of instances being low, it was decided to leverage the power of ChatGPT to generate multiple instances of 'Not Lean' provisions through paraphrasing. This helped create paraphrased clauses. After validating the meaning through a manual reading of the paraphrased text, such clauses were added to the original list. The final list consisted of 531 clauses labeled as 'Not Lean' and 202 'Lean' clauses, totaling 733 classified clauses with label count as indicated in the last column of Table 1 in parenthesis and in Figure 1.

4.2 Steps 2 and 3 – Classification and Testing Results

In the training process with 80 to 20 splits, it is observed that the accuracy and F1 score is a maximum of 77%. On increasing the training size to 90% and then to 95%, it is noted that the F1 score improved to 78% and 85%. The results of trying with the Bert-base-uncased, Bert-large-cased, and uncased models are shown in Table 2. In terms of the epoch standpoint, considering the mechanics of double descent, there was no improvement even with 50 epochs. In the above technique, all the weights of the original model are used. However, another technique called a Low-Rank Adoption [37] is used by which the original weights of the Bert model remain untouched, and a new set of weights is created based on the rank of the matrix, which is a user parameter. A snapshot of the finetuning results is shown in Figure 2.

Epoch	Training Loss	Validation Loss	Accuracy	F1 Score
13	No log	1.141195	0.768707	0.768707
14	0.623200	1.204195	0.775510	0.775510
15	0.623200	1.236950	0.775510	0.775510
16	0.623200	1.239883	0.775510	0.775510
17	0.623200	1.249316	0.775510	0.775510
18	0.623200	1.262342	0.775510	0.775510

Figure 2. A Snapshot of the Finetuning Result

Table 2. Results from different Bert Models

Model Name	F1 Score (in percentage)
Bert-base-cased	77
Bert-base-uncased	71
Bert-large-cased	68
Bert-large-uncased	65
Bert-base-LoRA	45

4.3 Discussion

In this study, two different categories of Bert Models are used, namely, the Bert-base model and the Bert-large model. Bert-base has a total of 12 attention heads and 110 million parameters. Meanwhile, Bert-large has 16 attention heads with 340 million parameters. Although from the size standpoint, Bert-large models are 3 times the size of the Bert-base models, the performance of the Bert-base model is superior, indicating that model size parameters do not always matter and that smaller models like Bert-base are less prone to overfitting and more capable of generalizing to new data, making them dependable and robust in real-world settings. Nevertheless, larger models still outperform smaller ones in specific use cases. However, this study indicates that smaller models are often more useful for retraining with recent data or fine-tuning for specific tasks.

Regarding the choice between the cased and the uncased models, the results indicate that the cased model's performance outweighs its uncased counterpart (Table 2) in both large and small Bert models. Cased models have separate vocabulary entries for differently-cased words. For instance, the words "the" and "The" have distinct uses in English. "Contractor" and "contractor" will typically have different meanings in construction contracts. While "Contractor" refers to the specific organization defined in the contract's definitions clause, "contractor" can refer to the word with the dictionary meaning. The cased models, sensitive to such differences, have performed better than the uncased models.

Overall, recalling the research question, "Can LMs be used to assess the leanness of a contract clause?" the results inform the potential of language models to understand and assess the 'leanness' of a given contract clause. However, only the publicly available standard form contracts are used for analysis. The model needs further improvement by including more illustrative contract provisions from various contract documents worldwide. Illustrative provisions from internationally used contract forms like the International Federation of Consulting Engineers (FIDIC) can help generalise the model usage. However, in most cases, contract documents are considered confidential and may not be available to the researchers for analysis. While confidentiality is important, in the absence of relevant data, the power of AI techniques is severely underutilized. Therefore, it will be helpful if the industry worldwide works on a common platform to share anonymized contract provisions so academicians and researchers can help develop AI-based contract risk assessment tools. It is here that the role of industry-academia bodies such as the International Group for Lean Construction (IGLC), Lean Construction Institute (LCI), and Institute for Lean Construction Excellence (ILCE) (Indian lean body) becomes crucial as a bridge to connect industry, academia, and researchers.

Adequately drafted contract documents can be crucial in bringing out lean adoption. However, to enable the catalyzing role of the contract, it is important that the contract documents are drafted in a manner that can promote lean principles in projects. It is here that this study, when fully ready, comes in handy to practitioners to assess the 'leanness' of their construction contracts. In the absence of such an assessment and if the contract provisions do not support lean implementation, attempts to bring a positive change in the project turn futile. In terms of its contribution to theory, the study exposes the power of AI to understand the underlying implicit features in contract provisions, a distinctive feature of AI that can be potentially used to assess many such underlying features in a contract document. Specifically, the differences in the performances of Bert-base and the large models, under both the cased and uncased conditions, are analyzed in the context of assessing a contract document.

5 Limitations and Future Scope

The inference window for this proof-of-concept model is available at the link: https://huggingface.co/RameshBal/LeanContractModel/blob/main/README.md. However, a major limitation of this model lies in the limited training dataset size, which comprises clauses only from Indian public sector contracts, which diminishes model reliability. Therefore, notwithstanding the reasonable F1 score, the model is not industry-ready at this stage. Future studies can consider contract forms from different jurisdictions to enrich the training data, making the model application-friendly to test the leanness of various contract forms. The model development is in a preliminary stage, and with additional data and specific expert validation, this proof-of-concept can be developed to an application scale. Nevertheless, the study helps understand the adaptability of models to real-world situations in construction management tasks. Secondly, only the BERT LM is evaluated in this study, whereas there are other LMs and LLMs whose robustness for similar studies has not been explored. Accordingly, future studies can focus on improving the dataset with additional clauses. Secondly, researchers can attempt to use various LMs and LLMs and evaluate their performance; and lastly, develop lean domain-specific language models for the exclusive use of AI-based lean studies.

6 Future Work

Considering limited data sources, the number of clause illustrations per label is improved by reducing the label count yet retaining the essence. Roberta-Large, with LoRA, is being explored to develop the classification model. Initial trends show a promising improvement in the F1 score. However, the study will be reported after a detailed analysis of results, the role of model architecture, and model validation by industry experts.

7 Conclusion

The study's objective was to develop a proof-of-concept AI-based tool to assess the leanness of contractual provisions in construction. A supervised algorithm-based approach was adopted, and a BERT-base LLM was finetuned with contract provisions labeled as 'lean' or 'not lean.' The resulting model could predict the leanness of a given contract clause with an F1 score of 77%. However, at this stage, the model is just a proof-of-concept to demonstrate the robustness of AI applications to understand the implicit meaning of contract provisions and can potentially be developed into an industry-ready assessment tool. Nevertheless, this study is a step closer to realizing the potential of data in making lean implementation a reality.

References

[1] Jamil, A. H. A. and Fathi, M. S. The Integration of Lean Construction and Sustainable Construction: A Stakeholder Perspective in Analyzing Sustainable Lean Construction Strategies in Malaysia. *Procedia Comput Sci*, 100:634–643, 2016.

[2] Simon, S. M. and Varghese, K. Assessment of organizational culture in construction – A case study approach. In *Proceedings of the 26th Annual Conference of the International Group for Lean Construction: Evolving Lean Construction Towards Mature Production Management Across Cultures and Frontiers, The International Group for Lean Construction,* pages 348–357, Chennai, India, 2018.

[3] Nesensohn, C., Bryde D., Ochieng E., Fearon D. and Hackett V. Assessing lean construction maturity. In *Proceedings of the 22nd Annual Conference of the International Group for Lean Construction: Understanding and Improving Project Based Production, International Group for Lean Construction,* pages 1157–1168, Oslo, Norway, 2014.

[4] Roy, D. and Jagannathan, M. Exploring the Reach of Lean Philosophy in Indian Construction Industry. In *Proceedings of the fourth biennial conference of the Indian Lean Community - Indian Lean Construction Conference,* pages 203–212, Ahmedabad, India, 2021.

[5] Ranadewa, K. A. T. O., Sandanayake, Y. G. and Siriwardena M. Enabling lean through human capacity building: an investigation of small and medium contractors. *Built Environment Project and Asset Management*, 11(4):594–610, 2021.

[6] Bygballe, L. E., Endresen, M. and Fålun, S. The role of formal and informal mechanisms in implementing lean principles in construction projects. *Engineering, Construction and Architectural Management*, 25(10):1322–1338, 2018.

[7] Devkar, G. Delhi, V.S.K. Enablers and inhibitors of lean construction in Indian construction projects. *Proceedings of the second biennial conference of the Indian Lean Community - Indian Lean Construction Conference,* pages. 179–185, Chennai, India, 2017.

[8] Narayanan, S. R. Adopting lean, cycle time got reduced from 15 days to 7 days. *Construction World*, pages 48–48, 2021.

[9] PMI&KPMG, Revamping Project Management. *Project Management Institute*, New Delhi, India, 2019.

[10] Eken, G. Using natural language processing for automated construction contract review during risk assessment at the bidding stage. *Doctoral Thesis*, Middle East Technical University, 2022.

[11] Devlin, J., Chang, M.-W., Lee, K. and Toutanova K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv Preprint*, 2018.

[12] Brockman, G. Sutskever, I. and OpenAI, Introducing OpenAI. On-line: https://openai.com/blog/introducing-openai, Accessed 10/12/2023.

[13] Ghimire, P. Kim, K. and Acharya M. Generative AI in the Construction Industry: Opportunities & Challenges. *arXiv Preprint*, 2023.

[14] S. Moon, S. Chi, and S. B. Im, "Automated detection of contractual risk clauses from construction specifications using bidirectional encoder representations from transformers (BERT)," Autom Constr, vol. 142, Oct. 2022, doi: 10.1016/j.autcon.2022.104465.

[15] Lichtig, W. A. Sutter Health: Developing a Contracting Model to Support Lean Project Delivery. *Lean Construction Journal*, 2(1):105–112, 2005.

[16] Forbes, L. H. and Ahmed S. M., *Modern Construction: Lean Delivery and Integrated Practices*. CRC Press, New York, 2011.

[17] Tazelaar, F. and Snijders, C. Dispute resolution and litigation in the construction industry. Evidence on conflicts and conflict resolution in The Netherlands and Germany. *Journal of Purchasing and Supply Management*, 16(4):221–229, 2010

[18] Aidibi, H. I. Studying the effect of BIM on Construction Conflicts and Disputes using agent-based modeling. *Master Thesis*, American University of Beirut, Lebanon, 2016.

[19] LCI. Work Structuring. *LCI White Paper*, Lean Construction Institute, pages 1–15, 1999.

[20] Hatoum, M. B. and Nassereddine, H. Unleashing the Power of ChatGPT for Lean Construction: An Early Outlook. In *Proceedings of the 31st Annual Conference of the International Group for Lean Construction (IGLC31), International Group for Lean Construction*, pages 208–219, Lille, France, 2023.

[21] Hassan, F. U. and Le, T. Automated Requirements Identification from Construction Contract Documents Using Natural Language Processing. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 12(2):1-14, 2020.

[22] Yang, J., Chen, Y., Yao, H. and Zhang, B. Machine Learning–Driven Model to Analyze Particular Conditions of Contracts: A Multifunctional and Risk Perspective. *Journal of Management in*

Engineering, 38(5):1-16, 2022.

[23] Chalkidis, I. and Androutsopoulos, I. A Deep Learning Approach to Contract Element Extraction. *JURIX*, 2017:155–164, 2017.

[24] Sweet, J. Liquidated Damages in California. California Law Review, 60(1):84–145, 1972.

[25] Osama Jannadia, M., Assaf, S., Bubshait, A. A. and Naji A. Contractual methods for dispute avoidance and resolution (DAR). *International Journal of Project Management*, 18:41–49, 2000.

[26] Jaeger, A.-V. and Hök, G.-S. *FIDIC - A Guide for Practitioners*, 1st ed. Springer, Berlin, Heidelberg, 2010.

[27] Mojahed, S. and Aghazadeh, F. Major factors influencing productivity of water and wastewater treatment plant construction: Evidence from the deep south USA. *International Journal of Project Management*, 26(2):195–202, 2008.

[28] Bubshait, A. A. Incentive/disincentive contracts and its effects on industrial projects. *International Journal of Project Management*, 21:63–70, 2003.

[29] Abu Dief, M. and Metwally, A. Construction Claims Mitigation in Design and Build Contracts. *PM World Journal*, IX:2330–4480, 2020.

[30] Anish, P. R., Sainani, A., Ramrakhiyani, N., Pawar, S, Palshikar, G. K. and Ghaisas, S. Towards Disambiguating Contracts for their Successful Execution-A Case from Finance Domain. In *Proceedings of the First Workshop on Financial Technology and Natural Language Processing*, pages 8-13, Macao, China, 2019.

[31] Padhy, J., Jagannathan, M. and Delhi, V. S. K. Application of Natural Language Processing to Automatically Identify Exculpatory Clauses in Construction Contracts. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 13(4):1–9, 2021.

[32] Agrawal, A. K., Jagannathan, M. and Delhi, V. S. K. Control Focus in Standard Forms: An Assessment through Text Mining and NLP. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 13(1):1–11, 2021.

[33] Thomas, H. R. Differing Site Conditions Indications and Disclaimers. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 4(3):86–89, 2012.

[34] Ramnath International Construction Ltd. v. Union of India, Appeal (civil) 3167-3168 of 2005, Court Judgement, *Supreme Court of India,* 2006.

[35] Badenfelt, U. Fixing the contract after the contract is fixed: A study of incomplete contracts in IT and construction projects. *International Journal of Project Management*, 29(5):568–576, 2011.

[36] Koskela, L., Bølviken, T. and Rooke, J. Which are the wastes of construction? *21st Annual Conference of the International Group for Lean Construction*, pages 905–914, 2013.

[37] Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., Chen, W. LoRA: Low-Rank Adaptation of Large Language Models. *arXiv Preprint*, 2021.