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PAPER

Lean Construction Strategies Supported by Artificial Intelligence Techniques for Construction Project Management—A Review

Lesly Velezmoro-Abanto[1], Rocío Cuba-Lagos[2](✉), Bryan Taico-Valverde[3], Orlando Iparraguirre-Villanueva[4], Michael Cabanillas-Carbonell[5]

[1]Universidad Peruana de Ciencias Aplicadas, Lima, Perú

[2]University of Birmingham, Birmingham, United Kingdom

[3]Escuela Universitaria de Posgrado, Universidad Nacional Federico Villarreal, Lima, Perú

[4]Universidad Tecnológica del Perú, Chimbote, Perú

[5]Facultad de Ingeniería, Universidad Privada del Norte, Lima, Perú

rmc025@alumni.bham.ac.uk

ABSTRACT

This paper analyzes the application of artificial intelligence (AI) techniques in lean construction (LC) and their potential to enhance project management (PM) for improved cost and schedule efficiency. The PRISMA methodology is used to select relevant articles in four steps. Furthermore, a bibliometric analysis of keywords and their occurrences is conducted. The study emphasizes the different methods of utilizing lean tools and AI techniques to attain optimal results in the construction industry. By combining a variety of tools and techniques, it is possible to create an environment that fosters improved project outcomes while minimizing risks and inefficiencies. According to the articles reviewed, the LC methodology and its tools are becoming increasingly relevant in general practice (GP). Machine learning (ML) techniques, particularly artificial neural networks (ANN), have been extensively researched as a tool to enhance construction projects by minimizing delays, fostering collaboration, cutting costs, saving time, and boosting productivity. Combining LC with ML can enhance profitability and align with lean principles, leading to successful outcomes for construction projects.

KEYWORDS

construction project management, lean construction, lean tools, artificial intelligence, machine learning

1 INTRODUCTION

Construction projects are self-contained systems with the goal of completing a building, and their efficient management is crucial for success within the established parameters [1]. Project management (PM) must identify and overcome several challenges in order to achieve higher productivity and greater efficiency on the job site [2]. Construction PM experts and enthusiasts are seeking innovative models that incorporate lean construction (LC) methodology tools and strategies to enhance the

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performance of the sector [3–5]; as well as the utilization of machine learning (ML) techniques [6–8]. LC's philosophy focuses on identifying and eliminating waste and maintaining a steady flow work. and properly managing of resources to avoid delays and additional costs while improving efficiency and productivity [9]. ML, a subfield of artificial intelligence (AI) [10], is capable of analyzing large amounts of data, generating predictive or control models to optimize performance [11], and learning from the information it analyzes. [12], [13]; it also helps the manager to better monitor the project, thereby improving PM in terms of cost, time, and risk [14]. Combining LC and ML improves job performance, even in real time [15]. Productivity indicators in the construction industry have not improved since the 1950s [16]. Therefore, continuous improvement is necessary for performance and production in construction projects. The integration of LC and ML is used to effectively maximize these objectives [17]. Similarly, their combination is used to automate processes and gather information from different sectors, enabling the prediction of when maintenance or quality control is needed [18] [19]. The objective of this paper is to explore the scope of AI techniques in LC methodology and how they can revolutionize PM. By harnessing these advanced technologies, it is possible to achieve remarkable results in terms of cost and time efficiency, ultimately leading to improved project outcomes.

2 REVIEW OF RELATED

The LC methodology aims to enhance the value of construction projects while minimizing project waste. Scholars and academics have extensively researched this issue. For example, in reference [20], lean tools and techniques used in construction project management are analyzed to evaluate their impact on productivity improvement and delay reduction. Similarly, in [21], various lean practices are identified and classified along with their advantages. It also highlights that the last planner system (LPS) and just-in-time (JIT) are the most commonly used tools in the construction industry. It is argued that understanding the challenges of implementing lean methodology is crucial to achieving its benefits. The construction industry faces several obstacles that impede project objectives. In [22], various technological methods and innovative tools aimed at developing construction projects within the initial parameters are analyzed. The methods used to achieve the objective involve planning, ML, and optimization. In [23], the utilization of AI in engineering and construction is examined, revealing a growing interest in its potential to automate processes, mitigate risks, enhance efficiency through digitization, and employ computer vision technology. In [24], the use of AI in software projects, PM, and development estimation are explored. The result is enhanced accuracy and predictability for projects. The paper also explores how AI can enhance decision-making in PM and its advantages over traditional methods. The study concludes that the implementation of AI has significant potential to enhance accuracy, efficiency, risk management, and cost-effectiveness in engineering construction projects. In [25], the potential and limitations of using AI in PM construction are examined. The study shows that, while its application is not yet widespread, AI is used to plan, schedule, and monitor projects. Similarly, in [26], the results demonstrate that ML is highly beneficial for construction PM due to its capacity to enhance planning, measurement, performance, and decision-making. In [27], it is demonstrated that AI has a positive impact on risk management, cost efficiency, and time efficiency. It also enhances productivity by overcoming barriers caused by project variability, uncertainty, and complexity. In [28], methods for construction risk management are compared and evaluated. Suggestions are provided for the implementation of AI at various management levels. The study also examines the most effective and accurate AI tools for addressing the shortcomings of construction risk management. In [29], the author examines the use of AI in LC PM and concludes that combining it with visualization and optimization techniques can enhance waste reduction, process improvement, workflow efficiency, and productivity. In [30], the primary machine learning techniques and algorithms utilized in construction project management are analyzed. It also presents a model that generates digital building models partially by analyzing historical data using the building information modeling (BIM) methodology.

3 METHODOLOGY

The present systematic literature review (SLR) research was conducted using the PRISMA methodology to gather concise information from articles related to the main topic. The objective is to present the analyzed publications in a more comprehensive and accurate manner, aiding interested stakeholders in evidence-based decision-making [31]. The PRISMA statement is a structured guide that helps to organize and clarify research development. It consists of several methodological steps.

- Relevant and significant documents pertaining to the subject under study are identified.
- The articles are analyzed, exclusion and inclusion criteria are applied, and duplicate documents are eliminated.
- An eligibility analysis is conducted.
- Final papers are chosen for thorough review.

3.1 Research questions

Selected articles and papers that examine the LPS methodology and its strategies, supported by ML techniques for enhancing PM in the construction sector, are analyzed. The following research questions (RQ) have been formulated to conduct the systematic literature review:

- RQ1: ¿Qué herramientas y estrategias LC utiliza la GP constructivos?
- RQ2: ¿Cuáles son las técnicas y/o algoritmos de la IA más utilizados en la gestión de proyectos constructivos y cómo se integran con la filosofía LC para mejorar la eficiencia y productividad en la construcción?
- RQ3: ¿Cuáles son los principales beneficios y ventajas de la combinación de las estrategias LC y ML en la gestión de GP, en términos de costos, tiempos y riesgos?

3.2 Search strategy

To conduct the research, a specific search string is developed, and different filters are applied to each of the databases used, including EBSCOhost, IEEE Xplore, ScienceDirect, Scopus, SpringerLink, and Web of Science. The criteria are detailed in Table 1. The search process aims to identify documents relevant to the research topic and then apply the inclusion and exclusion criteria, as detailed in Table 2 according to the PRISMA statement, to determine which documents will be selected and used in the paper, using an SLR matrix.

Table 1. Search string and filters applied to each database

<table>
<tr><th>Data Base</th><th>Equation</th><th>Filters</th></tr>
<tr><td>EBSCO HOST</td><td rowspan="5">(Construction Project Management AND Lean Construction) OR (Construction Project Management AND Lean TOOLS) OR (Construction Project Management AND Artificial Intelligence) OR (Construction Project Management AND Machine Learning) OR (Lean Tools AND Machine Learning) OR (Lean Tools AND Artificial Intelligence)</td><td>Types of sources: Scholarly publications
Thesaurus term subject: Construction Project management, Construction projects, lean Construction, artificial intelligence, Project management, machine Learning, 2018–2023</td></tr>
<tr><td>IEEE Xplores</td><td>Filters Applied: Journals learning (artificial intelligence), optimization, deep learning (artificial intelligence) neurales nets, construction industry, project management. 2018–2023. Open Access.</td></tr>
<tr><td>ScienceDirect</td><td>Refine by: Years: 2018–2023. Article type: Research articles. Piblucation title: Automation in construction, Engineering Applications of Artificial Intelligence, Advanced Engineering Informatics. Subject areas: Engineering. Acces type: Open Access</td></tr>
<tr><td>Scopus</td><td>(LIMIT-TO (OA, “all”)) AND (LIMIT-TO (PUBYEAR, 2023) OR LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018)) AND (LIMIT-TO(DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “re”)) AND (LIMIT-TO (SUBJAREA, “ENGI”)) AND (LIMIT-TO (EXACTKEYWORD, “Project Management”) OR LIMIT-TO (EXACTKEYWORD, “Artificial Intelligence”) OR LIMIT-TO (EXACTKEYWORD, “Lean Construction”) OR LIMIT-TO (EXACTKEYWORD, “Machine Learning”)) AND (LIMIT-TO (LANGUAGE, “English”))</td></tr>
<tr><td>Web of Science</td><td>Refine by: Open Access, Publication Years: 2023 or 2022 or 2021 or 2020 or 2019 or 2018. Citation Topics Meso: 4.61 Artificial Intelligence & Machine Learning or 6.3 Management. Document Types: Review Article or Article</td></tr>
</table>

Table 2. Criterio de inclusión, exclusión y justificación

Inclusion Criteria
Include studies related to the LC methodology and/or its strategies or tools applied to construction PM.
Include studies that apply LC techniques in construction PM.
Include studies published in the last 6 years (2018–2023).
Articles in reliable database.
Exclusion Criteria
Short papers.
Articles older than 6 years.
Studies that are not related to the subject matter.
Articles in Spanish

The PRISMA statement consists of four phases for selecting scientific articles for research (see Figure 1). The initial phase involves identifying 43,654 articles using a search string in selected databases. In the second phase, filters are applied based on inclusion and exclusion criteria, resulting in 376 articles. Next, eligibility is determined by analyzing the titles using specific phrases related to the research objective, resulting in 168 selected and 208 excluded. Finally, relevant articles are selected by carefully reviewing the abstracts related to the topic, resulting in 63 articles that will support the following areas of research:

- The tools and strategies of LC used in PM construction.
- The most commonly used AI techniques in project management and how they integrate with the LC philosophy to enhance efficiency and productivity in the construction industry.
- The main benefits and advantages of integrating LC and modern methods of construction (MMC) strategies in PM include cost reduction, time efficiency, and risk mitigation.

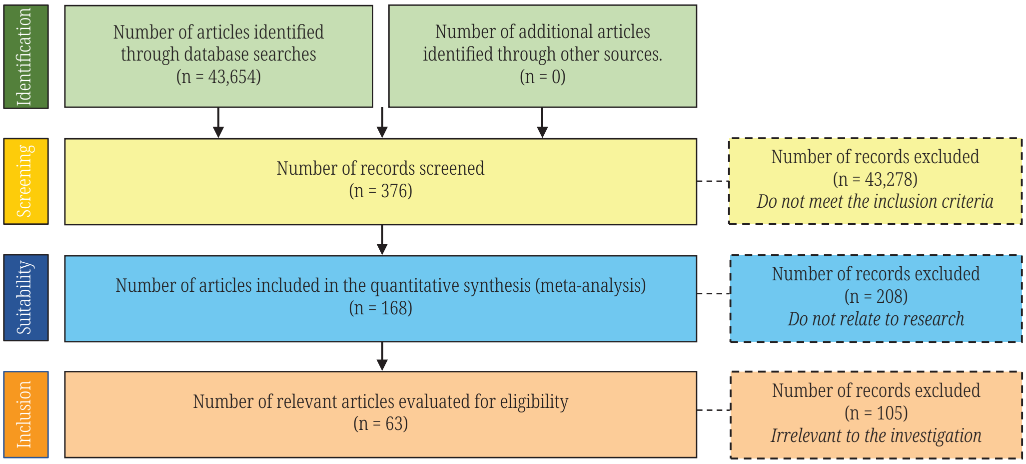

Fig. 1. Scientific flow diagram for the selection of articles following the PRISMA methodology

4 RESULTS AND DISCUSSION

The initial section of the text involves a bibliometric analysis and provides a detailed examination of 63 articles. The second part analyzes LC tools, strategies, the benefits of their application, and ML techniques presented by researchers in their studies, as well as the main advantages of combining LC with ML for construction project management.

4.1 Bibliometric analysis

The VOSviewer program is utilized for conducting bibliometric analysis and visualizing the connections between journals, researchers, or publications based on citation data. The study uncovers the keywords and their occurrences related to LC strategies and AI techniques applied in construction PM. In Figure 2, the bibliometric map shows the connections and relationships between the keywords, which are classified into 24 groups. The most common keywords are LC, IA, ML, BIM, and construction management.

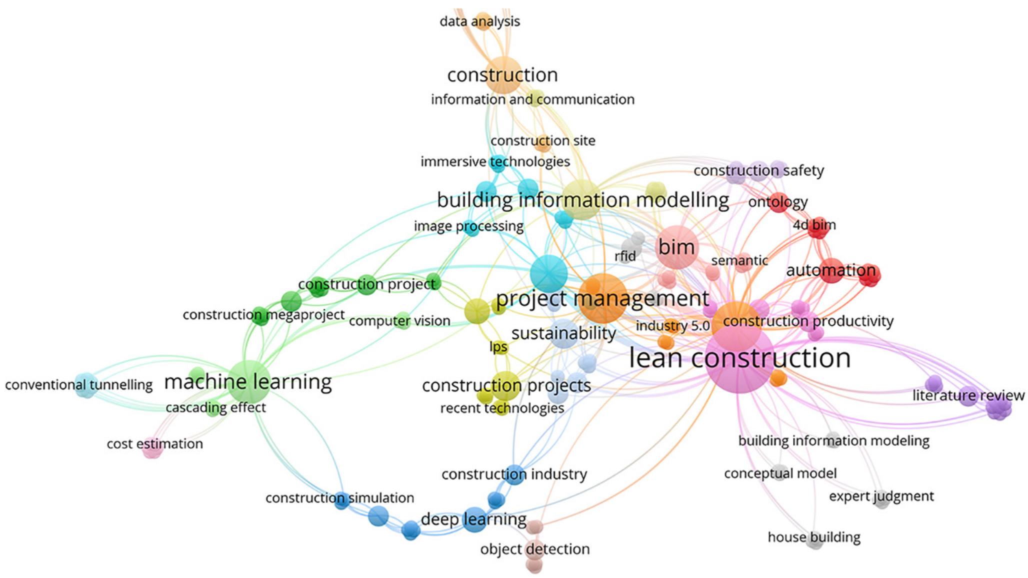

Fig. 2. Bibliometric map of the relationships between keywords

4.2 Manuscript analysis

Five databases were selected for article retrieval: EBSCOhost, IEEE Xplore, ScienceDirect, Scopus, and Web of Science. The initial search yielded 43,654 articles. After applying the PRISMA methodology and the agreed-upon criteria, 63 relevant articles were obtained and included in the research. Scopus has the largest number of articles selected, with 40 documents, representing 63% of the total. It is followed by EBSCOhost with 19%, ScienceDirect with 11%, IEEE Xplore with 3%, and WoS with 2%. This information can be seen in Figure 3, which shows that the number of research studies on the discussed topic has increased since 2018, with a decrease in 2023 due to reaching the halfway point. Scopus had the highest number of articles published between 2018 and 2023, reaching peaks in 2020 and 2022 with seven and ten articles, respectively. The highest number of articles was published between 2021 and 2022, with a total of 13 and 14, respectively.

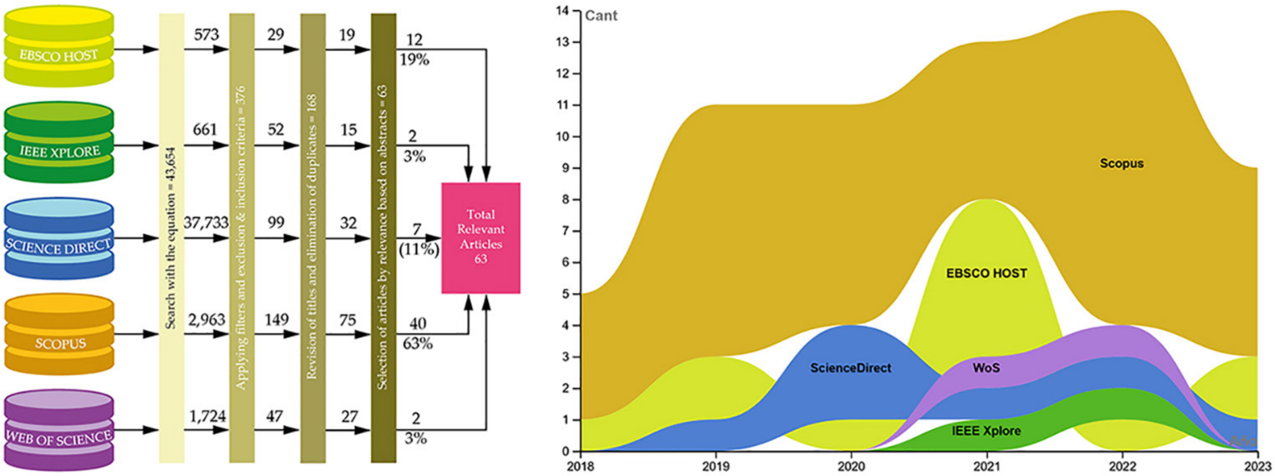

Fig. 3. Left: Results obtained by database and percentages; Right: Number of articles by year of publication

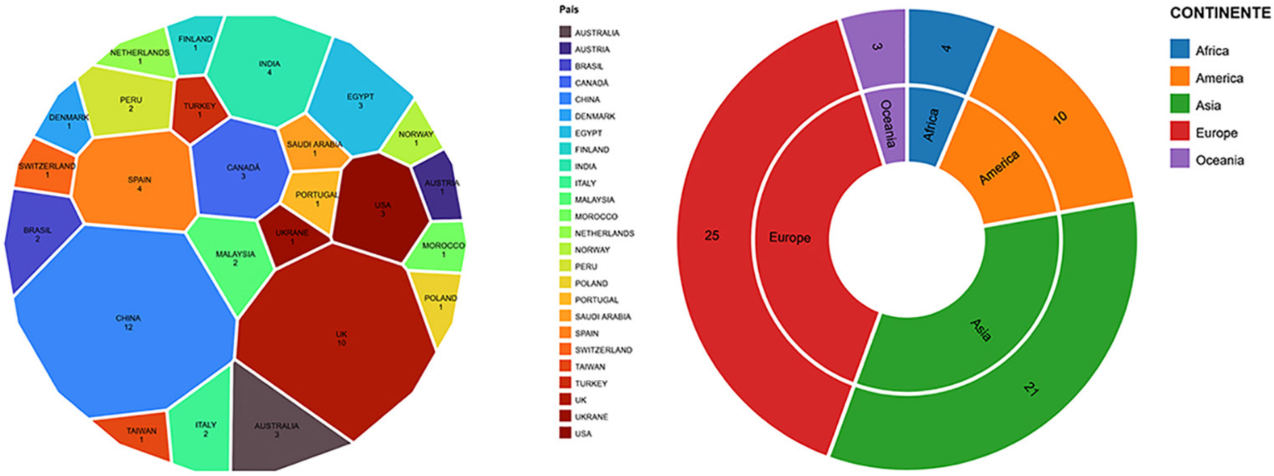

Fig. 4. Izquierda: Cantidad de artículos por país de publicación; Right: Number of articles per continent

China and the UK have the highest number of publications, with 12 and 10 articles, respectively, followed by India and Spain, with four articles each respectively. According to Figure 4, Australia, Canada, Egypt, and the USA have three individual articles, while other countries have only one or two publications. In Figure 4, Europe and Asia have the highest number of published articles, with 25 and 21, respectively. The Americas have ten publications, while Africa and Oceania have only four and three, respectively.

4.3 RQ1: What LC tools and strategies does the constructive PM use?

Lean construction is strengthening its position in the construction industry by focusing on continuous improvement and resource optimization. The use of LC methodology for PM has become almost mandatory as it leads to greater efficiency. As a result, [22] examines delays in construction projects to identify new technologies that can reduce them. One of the conclusions drawn is that the adoption of building information modeling (BIM) platforms is highly competitive and beneficial for project development in the construction industry. Similarly, in [20], lean tools used in PM are identified to achieve the benefits offered by LC, such as 5S, LPS, BIM, JIT, visual management (VM), and others. Similarly, in [21], 32 LC practices are identified, with LPS and JIT being the most extensively researched and documented in the industry. Table 3 presents the lean tools utilized in construction PM, as identified in this literature review.

Table 3. Lean techniques and/or tools applied to PM construction

	LC Techniques/Tools	Reference
1	5S	[32]
2	Augmented Reality – AR	[33–35]
3	Big Room	[32]
4	BIM 4D	[36]
5	Building Information Modeling – BIM	[32], [34], [35], [37–59]
6	Integradet Project Delivery – IPD	[44], [55]
7	Just in Time – JIT	[45], [57], [60–62]
8	Kanban	[63]
9	Last Planner System – LPS	[36], [39], [48], [51], [54], [57], [61–68]
10	Lean Six Sigma – LSS	[61]
11	Look Ahead	[36], [48]
12	Percent Plan Completed – PPC	[62]
13	Plan Do Check Adjust – PDCA	[62], [63]
14	Prefabrication, and Modularization	[61], [69]
15	Pull Planning	[55], [69]
16	Six Sgima – SS	[45], [60], [61], [68]
17	Interdependency Structure Matrix – ISM	[70]
18	Takt Time	[63]
19	Total Quality Management – TQM	[57], [61]
20	Value Stream Mapping – VSM	[68], [69]
21	Virtual Design and Construction – VDC	[44], [56]
22	Virtual Reality – VR	[33], [34], [50]
23	Visual Management – VM	[45], [54], [57], [61], [62]
24	Yokoten	[45]

4.4 RQ2: What are the most commonly used AI techniques and/or algorithms in constructive PM and how do they integrate with the LC philosophy to improve efficiency and productivity in construction?

This study identifies the most commonly used AI techniques to enhance PM in construction. In [26], ML is presented as a powerful tool in AI that relies on classifying and predicting information. It utilizes a range of architectures and algorithms to learn from the input data, ultimately resulting in the creation and training of a model capable of making predictions based on the analyzed and learned information. One of the main techniques used in machine learning is artificial neural networks (ANNs), which emulate the human brain and utilize other architectures, such as convolutional neural networks (CNN) and recurrent neural networks (RNN). It also utilizes methodologies such as fuzzy approaches and decision trees, as well as algorithms such as the backpropagation neural network (BPNN). The text also discusses deep learning (DL), a subfield of ML that utilizes a multi-level architecture and nonlinear analysis to process input and output information. In addition to CNNs and RNNs, DL also utilizes deep neural networks (DNN), among other techniques. The article also discusses natural language processing (NLP), which aims to facilitate communication with humans and extract information from written language. It also encompasses AI-based heuristics, reasoning methods based on partial evidence, as well as algorithms such as random forest (RF), support vector machine (SVM), and k-means. Researchers are studying ML techniques and tools that align with specific objectives. Choosing the appropriate tool can result in more precise and potent outcomes. Similarly, the article [30] highlights the most commonly used ML techniques, such as SVM, decision trees, RF, k-nearest-neighbor (kNN), ANN, and CNN. The research aims to automate the creation of precise digital building models using the mentioned algorithms, leveraging existing data such as plans or images, and employing BIM methodology. In reference [29], the study examines the synergy achieved by using LC tools such as VSM, BIM, discrete-event simulation, VR, etc., with the support of ML techniques. The ML techniques that are most conducive to achieving LC objectives in construction PM, such as ANN, fuzzy logic, decision support/expert systems, and genetic algorithms (GA), are identified and correlated. Tables 4 and 5 are presents the techniques and algorithms identified in the systematic literature review (SLR) that are used to enhance construction project management.

Table 4. AI techniques most commonly used in construction project management

Item	AI Field/Subfield	Techniques	References
1	ML	Artificial Neural Network – ANN	[42], [53], [71–77]
2	ML/DL	Convolutional Neural Network – CNN	[76], [78–81]
3		Deep Recurrent Neural Network – DRNN	[82]
4		Graph Neural Network – GNN	[83]
5		Long Short-Term Memory (LSTM)	[76]
6		Multilayer Perceptron	[76]
7	ML/SL	Decision Tree	[76]
8	Natural Language Processing (NLP)	Fast Recurrent Neural Network – Fast-RNN	[81]

Table 5. AI algorithms most used in construction project management

Item	AI Field/Subfield	Algorithms	References
1	ML/Clustering – Optimización/ Clustering optimization	Genetic Algorithm based K-means – GA-K-means	[84]
2	ML/DL	Backpropagation Neural Network – BPNN	[85]
3	ML/SL	C4.5	[71]
4		k-Nearest-Neighbors – kNN	[71]
5		Naïve Bayes – NB	[59], [71], [76]
6		Random Forest – RF	[71], [75], [86], [87]
7		Support Vector Machine – SVM	[71], [73], [75], [76], [88], [89]
8	Computer vision	YOLO You Only Look Once	[81]

4.5 RQ3: What are the main benefits and advantages of the combination of LC and ML strategies in constructive PM, in terms of cost, time and risk?

[29] argue that the benefits provided by the use of LC tools with the support of ML techniques are directly related to the principles of the Lean philosophy, such as: (1) waste reduction; (2) time reduction; (3) reduction of variability in terms of time, costs, workflows, and processes; (4) improved safety management; (5) increased productivity; (6) development of a system for project delivery; and (7) improved construction efficiency. For the present research, Table 6 presents the benefits identified in SLR, which are categorized into four general levels encompassing benefits in this area: efficiency, quality, and safety; optimization of schedules and budgets; and risk reduction.

Table 6. Benefits of the combination of LC and ML strategies in constructive PM

Item	Category	Benefits	References
1	Efficiency	Elimination of construction waste and losses. Optimization of processes and work flow. Estimates, improves and automates productivity and labor performance. Increased efficiency in resource allocation. Improved information processing.	[34], [36], [47], [58], [73], [75], [76], [82], [83]
2	Quality and Safety	Real-time remote monitoring support. High accuracy of generating intelligent reports in time on the development of the construction. Continuous monitoring. Increased focus on job site safety.	[71], [79], [88]
3	Optimization of deadlines and budgets	Improves project planning and scheduling. Estimates construction schedules. Performs budget and cost estimates. Generates higher profitability.	[34], [53], [76], [77], [82], [83], [87], [89]
4	Risk Reduction	Identifies and predicts potential risks. Reduces unexpected problems. Facilitates decision making	[50], [58], [59], [74], [81], [84], [87], [90]

5 CONCLUSIONS

The reviewed articles demonstrate a growing interest in the LC methodology and its tools for construction PM, which confirms its position and relevance in the sector. The most researched tools in this SLR are BIM and LPS, with 25 and 13 articles, respectively. These two tools are considered to be the most representative of the group. They are followed by VM and JIT, each with five research articles.

It is important to conduct further research on additional lean tools and their synergies to enhance the management of construction projects.

Researchers agree that the BIM methodology is competitive and effective in reducing delays and improving collaboration among all parties involved. LC researchers have discovered similar advantages, including enhanced operational efficiency with decreased waste, process optimization, increased productivity and performance, and reduced time and costs.

The most studied ML technique in the reviewed articles is ANN, followed by SVM. All of the ML tools presented demonstrate positive effects on PM processes. It is important to choose the ML technique that is suitable for the specific objectives in order to achieve more accurate results with greater precision and power.

The use of LC and ML strategies in construction PM allows for the improvement of costs, schedules, processes, and productivity, aligning with Lean principles. This combination is a potent tool for achieving success and efficiency in the industry.

Limitations encountered in this research on the integration of LC strategies with ML techniques include the availability and quality of the data used to train the algorithms, potential bias in the selection of studies for the literature review, inherent limitations of ML techniques, the scarcity of specific research in this field, and challenges in integrating these methodologies in the construction industry due to resistance to change. Addressing these aspects is crucial to their successful application.

To delve deeper into the practical application of combining LC and ML in construction project management, the author recommends conducting case studies and pilot projects to validate real-world results. Specific tools and platforms should be designed to integrate ML techniques into the industry. Customized algorithms tailored to meet project management requirements should be developed, along with cost-benefit analyses to assess economic viability. These approaches will enhance efficiency, reduce costs and risks, and promote sustainability in construction.

6 REFERENCES

[1] G. Ballard and G. A. Howell, "Lean project management," *Building Research & Information*, vol. 31, no. 2, pp. 119–133, 2010. https://doi.org/10.1080/09613210301997

[2] E. Safapour and S. Kermanshachi, "Identifying early indicators of manageable rework causes and selecting mitigating best practices for construction," *Journal of Management in Engineering*, vol. 35, no. 2, 2019. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000669

[3] U. H. Issa, "Implementation of lean construction techniques for minimizing the risks effect on project construction time," *Alexandria Engineering Journal*, vol. 52, no. 4, pp. 697–704, 2013. https://doi.org/10.1016/j.aej.2013.07.003

[4] P. Nowotarski, J. Pasławski, and J. Matyja, "Improving construction processes using lean management methodologies – Cost case study," *Procedia Eng.*, vol. 161, 2016, pp. 1037–1042. https://doi.org/10.1016/j.proeng.2016.08.845
[5] G. A. Howell, G. Ballard, I. D. Tommelein, and L. Koskela, "Discussion of 'reducing variability to improve performance as a lean construction principle' by H. Randolph Thomas, Michael J. Horman, Ubiraci Espinelli Lemes de Souza, and Ivica Zavřski," *J. Constr. Eng. Manag.*, vol. 130, no. 2, pp. 299–300, 2004. https://doi.org/10.1061/(ASCE)0733-9364(2004)130:2(299)
[6] P. T. Nguyen, "Application machine learning in construction management," *TEM Journal*, vol. 10, no. 3, pp. 1385–1389, 2021. https://doi.org/10.18421/TEM103-48
[7] T. D. Akinosho *et al.*, "Deep learning in the construction industry: A review of present status and future innovations," *Journal of Building Engineering*, vol. 32, p. 101827, 2020. https://doi.org/10.1016/j.jobe.2020.101827
[8] L. Florez-Perez, Z. Song, and J. C. Cortissoz, "Using machine learning to analyze and predict construction task productivity," *Computer-Aided Civil and Infrastructure Engineering*, vol. 37, no. 12, pp. 1602–1616, 2022. https://doi.org/10.1111/mice.12806
[9] L. J. Koskela, I. Tommelein, and G. Ballard, "The foundations of lean construction." Accessed: Jan. 25, 2023. [Online]. Available: https://www.researchgate.net/publication/28578914_The_foundations_of_lean_construction.
[10] H. T. H. S. ALRikabi, I. A. Aljazaery, J. S. Qateef, A. H. M. Alaidi, and R. M. Al_airaji, "Face patterns analysis and recognition system based on Quantum Neural Network QNN," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 8, pp. 34–48, 2022. https://doi.org/10.3991/ijim.v16i08.30107
[11] N. Bauyrzhan, B. Sakysh, A. Zhanar, P. Nikolay, K. Ardak, and U. Kumys, "Using machine learning to analyze the learning process for solving mathematical problems," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 21, pp. 114–124, 2022. https://doi.org/10.3991/ijim.v16i21.36065
[12] S. O. Abioye *et al.*, "Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges," *Journal of Building Engineering*, vol. 44, 2021. https://doi.org/10.1016/j.jobe.2021.103299
[13] O. Iparraguirre-Villanueva, L. Obregon-Palomino, W. Pujay-Iglesias, F. Sierra-Liñan, and M. Cabanillas-Carbonell, "Productivity of incident management with conversational bots-a review," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 4, pp. 1543–1556, 2023. https://doi.org/10.11591/ijai.v12.i4.pp1543-1556
[14] T. V. Fridgeirsson, H. T. Ingason, H. I. Jonasson, and H. Jonsdottir, "An authoritative study on the near future effect of artificial intelligence on project management knowledge areas," *Sustainability (Switzerland)*, vol. 13, no. 4, pp. 1–20, 2021. https://doi.org/10.3390/su13042345
[15] L. Shehab, D. Salhab, E. Pourrahimian, K. Noueihed, G. Lucko, and F. R. Hamzeh, "Machine learning framework to predict last planner system performance metrics," *Construction Research Congress 2022: Project Management and Delivery, Controls, and Design and Materials – Selected Papers from Construction Research Congress 2022*, vol. 3–C, pp. 292–301, 2022. https://doi.org/10.1061/9780784483978.031
[16] M. Aslam, Z. Gao, and G. Smith, "Framework for selection of lean construction tools based on lean objectives and functionalities," *International Journal of Construction Management*, vol. 22, no. 8, pp. 1559–1570, 2020. https://doi.org/10.1080/15623599.2020.1729933
[17] S. Goyal, H. Jha, and A. Gupta, "Prediction in industry 4.0 with lean six sigma," *Lecture Notes in Networks and Systems*, vol. 540, pp. 569–575, 2023. https://doi.org/10.1007/978-981-19-6088-8_51

[18] D. Bassir, H. Lodge, H. Chang, J. Majak, and G. Chen, "Application of artificial intelligence and machine learning for BIM: Review," *International Journal for Simulation and Multidisciplinary Design Optimization*, vol. 14, p. 5, 2023. https://doi.org/10.1051/smdo/2023005

[19] A. M. Huenerfauth, "Mobile technology applications for manufacturing, reduction of muda (waste) and the effect on manufacturing economy and efficiency," *International Journal of Interactive Mobile Technologies*, vol. 8, no. 4, pp. 20–23, 2014. https://doi.org/10.3991/ijim.v8i4.3797

[20] S. Singh and K. Kumar, "Review of literature of lean construction and lean tools using systematic literature review technique (2008–2018)," *Ain Shams Engineering Journal*, vol. 11, no. 2, pp. 465–471, 2020. https://doi.org/10.1016/j.asej.2019.08.012

[21] O. Babalola, E. O. Ibem, and I. C. Ezema, "Implementation of lean practices in the construction industry: A systematic review," *Build Environ.*, vol. 148, pp. 34–43, 2019. https://doi.org/10.1016/j.buildenv.2018.10.051

[22] A. P. Gurgun, K. Koc, and H. Kunkcu, "Exploring the adoption of technology against delays in construction projects," *Engineering, Construction and Architectural Management*, vol. ahead-of-print, 2022. https://doi.org/10.1108/ECAM-06-2022-0566

[23] Y. Pan and L. Zhang, "Roles of artificial intelligence in construction engineering and management: A critical review and future trends," *Autom. Constr.*, vol. 122, p. 103517, 2021. https://doi.org/10.1016/j.autcon.2020.103517

[24] V. Maphosa and M. Maphosa, "Artificial intelligence in project management research: A bibliometric analysis," *J. Theor. Appl. Inf. Technol.*, vol. 100, no. 16, pp. 5000–5012, 2022.

[25] S. Bento, L. Pereira, R. Gonçalves, Á. Dias, and R. L. da Costa, "Artificial intelligence in project management: Systematic literature review," *International Journal of Technology Intelligence and Planning*, vol. 13, no. 2, pp. 143–163, 2022. https://doi.org/10.1504/IJTIP.2022.126841

[26] I. Taboada, A. Daneshpajouh, N. Toledo, and T. de Vass, "Artificial intelligence enabled project management: A systematic literature review," *Applied Sciences 2023*, vol. 13, no. 8, p. 5014, 2023. https://doi.org/10.3390/app13085014

[27] J. M. Mesa Fernández, J. J. González Moreno, E. P. Vergara-González, and G. Alonso Iglesias, "Bibliometric analysis of the application of artificial intelligence techniques to the management of innovation projects," *Applied Sciences (Switzerland)*, vol. 12, no. 22, 2022. https://doi.org/10.3390/app122211743

[28] A. Khodabakhshian, T. Puolitaival, and L. Kestle, "Deterministic and probabilistic risk management approaches in construction projects: A systematic literature review and comparative analysis," *Buildings 2023*, vol. 13, no. 5, p. 1312, 2023. https://doi.org/10.3390/buildings13051312

[29] J. Dumrak and S. A. Zarghami, "The role of artificial intelligence in lean construction management," *Engineering, Construction and Architectural Management*, 2023. https://doi.org/10.1108/ECAM-02-2022-0153

[30] P. Schönfelder, A. Aziz, B. Faltin, and M. König, "Automating the retrospective generation of As-is BIM models using machine learning," *Autom. Constr.*, vol. 152, 2023. https://doi.org/10.1016/j.autcon.2023.104937

[31] J. J. Yepes-Nuñez, G. Urrútia, M. Romero-García, and S. Alonso-Fernández, "Declaración PRISMA 2020: una guía actualizada para la publicación de revisiones sistemáticas," *Rev Esp Cardiol*, vol. 74, no. 9, pp. 790–799, 2021. https://doi.org/10.1016/j.recesp.2021.06.016

[32] S. Singh and K. Kumar, "A study of lean construction and visual management tools through cluster analysis," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 1153–1162, 2021. https://doi.org/10.1016/j.asej.2020.04.019

[33] J. M. Davila Delgado, L. Oyedele, P. Demian, and T. Beach, "A research agenda for augmented and virtual reality in architecture, engineering and construction," *Advanced Engineering Informatics*, vol. 45, 2020. https://doi.org/10.1016/j.aei.2020.101122
[34] U. S. Igwe, S. F. Mohamed, M. B. M. Dzahir Azwarie, R. A. Ugulu, and O. Ajayi, "Acceptance of contemporary technologies for cost management of construction projects," *Journal of Information Technology in Construction*, vol. 27, pp. 864–883, 2022. https://doi.org/10.36680/j.itcon.2022.042
[35] J. Ratajczak, M. Riedl, and D. T. Matt, "BIM-based and AR application combined with location-based management system for the improvement of the construction performance," *Buildings*, vol. 9, no. 5, 2019. https://doi.org/10.3390/buildings9050118
[36] O. Doukari, B. Seck, and D. Greenwood, "The creation of construction schedules in 4D BIM: A comparison of conventional and automated approaches," *Buildings*, vol. 12, no. 8, 2022. https://doi.org/10.3390/buildings12081145
[37] X. Du, "Research on engineering project management method based on BIM technology," *Sci. Program.*, vol. 2021, 2021. https://doi.org/10.1155/2021/7230585
[38] X. Du, "Construction cost simulation based on artificial intelligence and BIM," *Sci. Program.*, vol. 2021, 2021. https://doi.org/10.1155/2021/9744286
[39] D. Heigermoser, B. García de Soto, E. L. S. Abbott, and D. K. H. Chua, "BIM-based last planner system tool for improving construction project management," *Autom. Constr.*, vol. 104, pp. 246–254, 2019. https://doi.org/10.1016/j.autcon.2019.03.019
[40] W. H. Collinge, K. Farghaly, M. H. Mosleh, P. Manu, C. M. Cheung, and C. A. Osorio-Sandoval, "BIM-based construction safety risk library," *Autom. Constr.*, vol. 141, 2022. https://doi.org/10.1016/j.autcon.2022.104391
[41] R. K. Soman, M. Molina-Solana, and J. K. Whyte, "Linked-data based constraint-checking (LDCC) to support look-ahead planning in construction," *Autom. Constr.*, vol. 120, 2020. https://doi.org/10.1016/j.autcon.2020.103369
[42] I. Taboada, A. Daneshpajouh, N. Toledo, and T. de Vass, "Artificial intelligence enabled project management: A systematic literature review," *Applied Sciences (Switzerland)*, vol. 13, no. 8, 2023. https://doi.org/10.3390/app13085014
[43] A. M. Eldeep, M. A. M. Farag, and L. M. Abd El-hafez, "Using BIM as a lean management tool in construction processes – A case study: Using BIM as a lean management tool," *Ain Shams Engineering Journal*, vol. 13, no. 2, 2022. https://doi.org/10.1016/j.asej.2021.07.009
[44] S. Rashidian, R. Drogemuller, and S. Omrani, "The compatibility of existing BIM maturity models with lean construction and integrated project delivery," *Journal of Information Technology in Construction*, vol. 27, pp. 496–511, 2022. https://doi.org/10.36680/j.itcon.2022.024
[45] E. N. Shaqour, "The impact of adopting lean construction in Egypt: Level of knowledge, application, and benefits," *Ain Shams Engineering Journal*, vol. 13, no. 2, 2022. https://doi.org/10.1016/j.asej.2021.07.005
[46] H. G. Bayhan, S. Demirkesen, C. Zhang, and A. Tezel, "A lean construction and BIM interaction model for the construction industry," *Production Planning and Control*, 2021. https://doi.org/10.1080/09537287.2021.2019342
[47] M. Locatelli, E. Seghezzi, L. Pellegrini, L. C. Tagliabue, and G. M. Di Giuda, "Exploring natural language processing in construction and integration with building information modeling: A scientometric analysis," *Buildings*, vol. 11, no. 12, 2021. https://doi.org/10.3390/buildings11120583
[48] M. D. Andújar-Montoya, A. Galiano-Garrigós, V. Echarri-Iribarren, and C. Rizo-Maestre, "BIM-LEAN as a methodology to save execution costs in building construction-An experience under the spanish framework," *Applied Sciences (Switzerland)*, vol. 10, no. 6, 2020. https://doi.org/10.3390/app10061913

[49] F. Mellado and E. C. W. Lou, "Building information modelling, lean and sustainability: An integration framework to promote performance improvements in the construction industry," *Sustain Cities Soc.*, vol. 61, 2020. https://doi.org/10.1016/j.scs.2020.102355

[50] F. Pour Rahimian, S. Seyedzadeh, S. Oliver, S. Rodriguez, and N. Dawood, "On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning," *Autom. Constr.*, vol. 110, 2020. https://doi.org/10.1016/j.autcon.2019.103012

[51] M. Darabseh, "Lean applications in construction: Review article," *U. Porto Journal of Engineering*, vol. 5, no. 2, pp. 29–37, 2019. https://doi.org/10.24840/2183-6493_005.002_0004

[52] R. Jin, Y. Zou, K. Gidado, P. Ashton, and N. Painting, "Scientometric analysis of BIM-based research in construction engineering and management," *Engineering, Construction and Architectural Management*, vol. 26, no. 8, pp. 1750–1776, 2019. https://doi.org/10.1108/ECAM-08-2018-0350

[53] M. Juszczyk, K. Zima, and W. Lelek, "Forecasting of sports fields construction costs aided by ensembles of neural networks," *Journal of Civil Engineering and Management*, vol. 25, no. 7, pp. 715–729, 2019. https://doi.org/10.3846/jcem.2019.10534

[54] D. A. Brady, P. Tzortzopoulos, J. Rooke, C. T. Formoso, and A. Tezel, "Improving transparency in construction management: A visual planning and control model," *Engineering, Construction and Architectural Management*, vol. 25, no. 10, pp. 1277–1297, 2018. https://doi.org/10.1108/ECAM-07-2017-0122

[55] L. M. Khodeir and R. Othman, "Examining the interaction between lean and sustainability principles in the management process of AEC industry," *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 1627–1634, 2018. https://doi.org/10.1016/j.asej.2016.12.005

[56] X. Ma, A. P. C. Chan, H. Wu, F. Xiong, and N. Dong, "Achieving leanness with BIM-based integrated data management in a built environment project," *Construction Innovation*, vol. 18, no. 4, pp. 469–487, 2018. https://doi.org/10.1108/CI-10-2017-0084

[57] M. E. A. M. Ahmed and L. S. Wong, "Assessment of lean construction practice at selected construction sites in Klang Valley," *International Journal of Engineering and Technology (UAE)*, vol. 7, no. 4, pp. 125–130, 2018. https://doi.org/10.14419/ijet.v7i4.35.22340

[58] K. Kyivska and S. Tsiutsiura, "Implementation of artificial intelligence in the construction industry and analysis of existing technologies," *Technology Audit and Production Reserves*, vol. 2, no. 2(58), pp. 12–15, 2021. https://doi.org/10.15587/2706-5448.2021.229532

[59] L. Chenya, E. Aminudin, S. Mohd, and L. S. Yap, "Intelligent risk management in construction projects: Systematic literature review," *IEEE Access*, vol. 10, pp. 72936–72954, 2022. https://doi.org/10.1109/ACCESS.2022.3189157

[60] R. Sindhwani, O. S. Vaidya, J. Antony, and A. Shokri, "Evaluating performance of projects using Six Sigma approach," *IEEE Trans. Eng. Manag.*, 2021. https://doi.org/10.1109/TEM.2021.3092885

[61] M. H. Rad, M. Mojtahedi, M. J. Ostwald, and S. Wilkinson, "A conceptual framework for implementing lean construction in infrastructure recovery projects," *Buildings*, vol. 12, no. 3, 2022. https://doi.org/10.3390/buildings12030272

[62] X. Wu, W. Zhao, T. Ma, and Z. Yang, "Improving the efficiency of highway construction project management using lean management," *Sustainability (Switzerland)*, vol. 11, no. 13, 2019. https://doi.org/10.3390/su11133646

[63] S. Besklubova and X. Zhang, "Improving construction productivity by integrating the lean concept and the clancey heuristic model," *Sustainability (Switzerland)*, vol. 11, no. 17, 2019. https://doi.org/10.3390/su11174535

[64] J. Zhao, O. Seppänen, A. Peltokorpi, B. Badihi, and H. Olivieri, "Real-time resource tracking for analyzing value-adding time in construction," *Autom. Constr.*, vol. 104, pp. 52–65, 2019. https://doi.org/10.1016/j.autcon.2019.04.003

[65] M. Gao, X. Wu, Y. Hui Wang, and Y. Yin, "Study on the mechanism of a lean construction safety planning and control system: An empirical analysis in China," *Ain Shams Engineering Journal*, vol. 14, no. 2, 2023. https://doi.org/10.1016/j.asej.2022.101856

[66] J. C. Quiroz-Flores, F. Acuña-Cervantes, A. Quicaña-Arbieto, and S. Nallusamy, "Lean operations management model to increase on-time project delivery in a construction company," *SSRG International Journal of Civil Engineering*, vol. 10, no. 4, pp. 22–28, 2023. https://doi.org/10.14445/23488352/IJCE-V10I4P104

[67] E. I. Daniel, C. Pasquire, and G. Dickens, "Development of approach to support construction stakeholders in implementation of the last planner system," *Journal of Management in Engineering*, vol. 35, no. 5, 2019. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000699

[68] X. Meng, "Lean management in the context of construction supply chains," *Int. J. Prod. Res.*, vol. 57, no. 11, pp. 3784–3798, 2019. https://doi.org/10.1080/00207543.2019.1566659

[69] A. Tezel, M. Taggart, L. Koskela, P. Tzortzopoulos, J. Hanahoe, and M. Kelly, "Lean construction and BIM in Small and Medium-sized Enterprises (SMEs) in construction: A systematic literature review," *Canadian Journal of Civil Engineering*, vol. 47, no. 2, pp. 186–201, 2020. https://doi.org/10.1139/cjce-2018-0408

[70] J. G. Sarhan, B. Xia, S. Fawzia, A. Karim, A. O. Olanipekun, and V. Coffey, "Framework for the implementation of lean construction strategies using the Interpretive Structural Modelling (ISM) technique: A case of the Saudi construction industry," *Engineering, Construction and Architectural Management*, vol. 27, no. 1, pp. 1–23, 2020. https://doi.org/10.1108/ECAM-03-2018-0136

[71] M. Martínez-Rojas, J. M. Soto-Hidalgo, N. Marín, and M. A. Vila, "Using classification techniques for assigning work descriptions to task groups on the basis of construction vocabulary," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, no. 11, pp. 966–981, 2018. https://doi.org/10.1111/mice.12382

[72] G. G. Tiruneh, A. R. Fayek, and V. Sumati, "Neuro-fuzzy systems in construction engineering and management research," *Autom. Constr.*, vol. 119, 2020. https://doi.org/10.1016/j.autcon.2020.103348

[73] S. Bang and B. Andersen, "Utilising artificial intelligence in construction site waste reduction," *Journal of Engineering, Project, and Production Management*, vol. 12, no. 3, pp. 239–249, 2022. https://doi.org/10.32738/JEPPM-2022-0022

[74] Z. Liu, X. Zhao, J. Tan, and H. Tian, "Model and simulation of engineering safety risk control based on artificial intelligence algorithm," *International Transactions on Electrical Energy Systems*, vol. 2022, 2022. https://doi.org/10.1155/2022/3204317

[75] J. M. Mesa Fernández, J. J. González Moreno, E. P. Vergara-González, and G. Alonso Iglesias, "Bibliometric analysis of the application of artificial intelligence techniques to the management of innovation projects," *Applied Sciences (Switzerland)*, vol. 12, no. 22, 2022. https://doi.org/10.3390/app122211743

[76] E. L. Jacobsen, J. Teizer, and S. Wandahl, "Work estimation of construction workers for productivity monitoring using kinematic data and deep learning," *Autom. Constr.*, vol. 152, 2023. https://doi.org/10.1016/j.autcon.2023.104932

[77] A. Darko, A. P. C. Chan, M. A. Adabre, D. J. Edwards, M. R. Hosseini, and E. E. Ameyaw, "Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities," *Autom. Constr.*, vol. 112, 2020. https://doi.org/10.1016/j.autcon.2020.103081

[78] G. Ma, Z. Wu, J. Jia, and S. Shang, "Safety risk factors comprehensive analysis for construction project: Combined cascading effect and machine learning approach," *Saf. Sci.*, vol. 143, 2021. https://doi.org/10.1016/j.ssci.2021.105410

[79] B. A. S. Oliveira, A. P. De Faria Neto, R. M. A. Fernandino, R. F. Carvalho, A. L. Fernandes, and F. G. Guimaraes, "Automated monitoring of construction sites of electric power substations using deep learning," *IEEE Access*, vol. 9, pp. 19195–19207, 2021. https://doi.org/10.1109/ACCESS.2021.3054468

[80] L. W. Lung and Y. R. Wang, "Applying deep learning and single shot detection in construction site image recognition," *Buildings*, vol. 13, no. 4, 2023. https://doi.org/10.3390/buildings13041074

[81] M. M. Alateeq, F. R. Fathimathul, and M. A. S. Ali, "Construction site hazards identification using deep learning and computer vision," *Sustainability (Switzerland)*, vol. 15, no. 3, 2023. https://doi.org/10.3390/su15032358

[82] J. Senthil, M. Muthukannan, M. Urbański, M. Stępień, and G. Kądzielawski, "MSCA based deep recurrent neural network for statistics risk management in construction projects," *Acta Montanistica Slovaca*, vol. 26, no. 3, pp. 481–497, 2021. https://doi.org/10.46544AMS.v26i3.08

[83] C. Wu, X. Li, R. Jiang, Y. Guo, J. Wang, and Z. Yang, "Graph-based deep learning model for knowledge base completion in constraint management of construction projects," *Computer-Aided Civil and Infrastructure Engineering*, 2022. https://doi.org/10.1111/mice.12904

[84] D. B. Chattapadhyay, J. Putta, and P. Rama Mohan Rao, "Risk identification, assessments, and prediction for mega construction projects: A risk prediction paradigm based on cross analytical-machine learning model," *Buildings*, vol. 11, no. 4, 2021. https://doi.org/10.3390/buildings11040172

[85] L. Yu, "Project engineering management evaluation based on GABP neural network and artificial intelligence," *Soft Comput.*, vol. 27, pp. 6877–6889, 2023. https://doi.org/10.1007/s00500-023-08133-9

[86] A. K. Langroodi, F. Vahdatikhaki, and A. Doree, "Activity recognition of construction equipment using fractional random forest," *Autom. Constr.*, vol. 122, 2021. https://doi.org/10.1016/j.autcon.2020.103465

[87] B. Mohamed and O. Moselhi, "Conceptual estimation of construction duration and cost of public highway projects," *Journal of Information Technology in Construction*, vol. 27, pp. 595–618, 2022. https://doi.org/10.36680/j.itcon.2022.029

[88] I. Hartl, M. Sorger, K. Hartl, B. J. Ralph, and I. Schlögel, "Passive seismic monitoring in conventional tunnelling – An innovative approach for automatic process recognition using support vector machines," *Tunnelling and Underground Space Technology*, vol. 137, 2023. https://doi.org/10.1016/j.tust.2023.105149

[89] M. Kassem, E. Mahamedi, K. Rogage, K. Duffy, and J. Huntingdon, "Measuring and benchmarking the productivity of excavators in infrastructure projects: A deep neural network approach," *Autom. Constr.*, vol. 124, 2021. https://doi.org/10.1016/j.autcon.2020.103532

[90] T. D. Akinosho *et al.*, "Deep learning in the construction industry: A review of present status and future innovations," *Journal of Building Engineering*, vol. 32, 2020. https://doi.org/10.1016/j.jobe.2020.101827

7 AUTHORS

Lesly Velezmoro-Abanto, Universidad Peruana de Ciencias Aplicadas, Lima, Perú.

Rocío Cuba-Lagos, University of Birmingham, Birmingham, United Kingdom (E-mail: rmc025@alumni.bham.ac.uk).

Bryan Taico-Valverde, Escuela Universitaria de Posgrado, Universidad Nacional Federico Villarreal, Lima, Perú.

Orlando Iparraguirre-Villanueva, Universidad Tecnológica del Perú, Chimbote, Perú.

Michael Cabanillas-Carbonell, Facultad de Ingeniería, Universidad Privada del Norte, Lima, Perú.