

Work-in-Progress: Advancing Construction Management Education with Core Data Analytics Skills

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Introduction

Construction management (CM), as a crucial discipline within civil engineering, addresses the complexities of modern projects through a combination of technical, managerial, and organizational skills. It refers to various tasks, from planning, coordinating, and budgeting to controlling and monitoring construction projects through the project lifecycle. The construction industry is evolving rapidly due to urbanization, technological advancements, and increased project complexity, leading to a significant demand for effective management practices. This trend is evident in the growing number of academic programs and student enrollments in CM that are aligned with the industry's demand. According to the recent US Bureau of Labor Statistics report, the "employment of construction managers is projected to grow 9 percent from 2023 to 2033, much faster than the average for all occupations," [1] highlighting the robust demand for skilled CM professionals.

As construction projects become increasingly complex, a multidisciplinary approach incorporating elements from architecture, engineering, management, and leadership is essential [2]. Consequently, CM programs are evolving to include perspectives from economics, sociology, and information technology, making the field more appealing to civil engineering students for its practical and theoretical relevance [3]. In today's dynamic environment, the ability to solve complex problems is crucial. Traditional management skills and techniques often prove insufficient as projects grow in scale.

CM Education Status

The CM education has evolved from being a part of civil engineering programs to becoming a standalone discipline for many institutions in the US. This transition was driven by the growing demand for specialized knowledge that civil engineering curricula could not fully address. Additionally, the industry has supported this shift by emphasizing the need for specialized accreditation [4]. CM programs are designed to equip students with the skills required to excel as constructors, focusing on construction methods, materials, budgeting, scheduling, quality management, safety, and leadership.

In this vein, CM requires ongoing updates to academic curricula to align with the evolving demands of the workforce. The undergraduate CM program needs to implement a strategic plan to prepare future professionals to handle the increasing complexity of the construction industry. Key skills and attributes identified for success include problem-solving, analytical thinking, decision-making, and forecasting [5]. Additionally, the CM industry emphasizes the importance of analytical skills and the ability to navigate projects with multiple conflicting objectives [6]. Outstanding CM programs are proactively adopting integrated curriculum models to enhance learning outcomes, which aim to decompartmentalize knowledge and improve the quality of education by inculcating a more cohesive learning environment [7]. Therefore, skills in data

analytics, particularly Multi-objective Optimization (MO) and Machine Learning (ML), are becoming essential for aspiring professionals.

Significant Use of MO in CM

Various optimization models, including MO, are used to manage conflicting objectives and constraints. These techniques help achieve optimal or near-optimal solutions[8]. In construction management, MO plays a pivotal role in navigating the complexities of modern projects, where multiple, often conflicting objectives must be managed simultaneously. The ability to balance cost, time, and quality is essential for project success, and MO provides a structured approach to achieve this balance. For instance, project managers may face the challenge of minimizing costs while ensuring high-quality deliverables within strict timelines. By employing MO techniques, they can evaluate various strategies that allow them to identify the most cost-effective methods without sacrificing quality or extending project duration. This is particularly important in competitive bidding environments, where cost overruns and delays can significantly impact profitability and client satisfaction.

Additionally, MO is crucial in resource allocation, especially when dealing with limited resources or unexpected changes. For example, project managers may need to optimize labor, equipment, and materials during construction. By applying MO, they can analyze different scenarios to determine the optimal combination of these resources that meets project deadlines while minimizing costs. Studies have highlighted how the optimization technique can be used to allocate resources [9] [10] and risks [11] effectively in large-scale construction projects while ensuring that productivity is maximized without exceeding budgets.

Addressing the complex trade-offs between time, cost, and safety risks in construction scheduling problems is one of the main applications of MO [12]. By simultaneously considering these three objectives, project managers can develop schedules that not only minimize project duration and costs but also enhance safety outcomes. This method allows for identifying optimal scheduling solutions that balance tight deadlines with budget constraints while ensuring that safety standards are met. Stakeholders can evaluate various scenarios, facilitating informed decision-making that aligns with project goals and their priorities. Ultimately, this holistic approach leads to more sustainable and efficient construction practices.

Risk management is another area within construction projects. Project managers can make informed decisions that balance risk with project objectives by assessing multiple risk factors, such as safety, environmental impact, and financial exposure. For example, MO could help construction firms evaluate different safety measures while considering both cost implications and compliance with regulations, thus promoting safer work environments without incurring excessive costs [13].

In the context of sustainable construction, MO can facilitate the integration of environmental considerations, positive contribution to society, and balancing all with the economy in project planning. By simultaneously addressing multiple goals, from minimizing environmental impact to maximizing resource efficiency and safety, this approach enables project stakeholders to make

informed decisions aligning with economic and ecological objectives. It facilitates the identification of trade-offs between conflicting criteria, allowing for the selection of optimal solutions that meet regulatory requirements and promote long-term sustainability.

Multi-objective decision models can integrate carbon emissions with cost and time objectives to enhance sustainability in construction projects [14]. Also, project managers can use MO to balance sustainability goals with economic and performance metrics when selecting construction methods and materials. Stakeholders can better prioritize eco-friendly materials and practices than ever before while still meeting budgetary constraints and performance standards [15]. Integrating technologies like Building Information Modeling (BIM) and project management software has transformed traditional practices, enhancing efficiency and communication [16]. Integrating these models with BIM has recently been explored to simulate and validate resource optimization strategies, ensuring practicality in real-world situations [17].

In addition to all the mentioned applications, MO can enhance stakeholder satisfaction by incorporating diverse objectives from various stakeholders, including clients, contractors, and regulatory bodies. For example, engaging stakeholders in the decision-making process using MO can lead to better alignment of project goals, ensuring that the final outcomes reflect the interests of all parties involved. This collaborative approach not only improves project outcomes but also fosters a sense of ownership and commitment among stakeholders.

Transformative Use of ML In CM

The transformative field within artificial intelligence, known as ML, enables systems to learn from data and improve autonomously. The growth of ML is driven by the availability of large datasets and advancements in algorithms [18]. ML is increasingly being integrated into CM to enhance efficiency, accuracy, and data-driven decision-making processes. This integration addresses challenges of efficiency, schedule, productivity, safety, and cost-effectiveness.

One key area where ML is making a substantial impact is cost estimation and forecasting. Traditional methods often rely on historical data and expert judgment, which can be subjective and prone to errors. ML algorithms can analyze vast amounts of data from previous projects to provide more accurate cost predictions for horizontal and vertical construction projects, from highways to buildings and power infrastructure [19] [20]. Studies have found that ML models can predict construction costs more accurately than traditional estimation methods [21], achieving superiority rates of up to 90% [22]. This capability allows project managers to make more informed financial decisions and allocate resources more effectively.

ML significantly enhances CM capabilities when integrated with big data and virtual reality. For instance, engineering ML automation platforms can be employed for risk management and decision support, showcasing their ability to improve project efficiency [23]. Risks related to project delays can be assessed through evaluating factors such as weather conditions, labor availability, and material supply chains [24]. Project managers can implement mitigation strategies in advance by predicting these risks, saving time, and reducing costs.

Safety assessments in construction are also significantly enhanced through the application of ML. By leveraging historical accident data, ML can identify risk factors associated with construction sites. Predictive models enable project managers to implement preemptive safety measures, reducing the likelihood of accidents [25]. Research indicates that ML can predict the likelihood of accidents on construction sites using real-time data from wearables and sensors, leading to a safer working environment [26].

Regarding quality control, ML assists construction managers in evaluating processes and materials against required standards. Additionally, ML can significantly contribute to sustainable construction practices by optimizing energy and resource use while addressing environmental challenges [27]. Moreover, it can support scope management by analyzing project changes and assessing their implications on time and cost. ML algorithms effectively predict scope changes, enabling proactive project management [28]. By continuously monitoring project parameters, ML can alert managers to potential scope creep, allowing them to take corrective actions before issues escalate.

Resource allocation is another ML application domain for predicting labor productivity and equipment utilization. Florez-Perez et al. [29] illustrated how ML models could analyze past project data to forecast labor performance under varying conditions, enabling construction managers to schedule labor more effectively and reduce idle time. Last but not least, ML can enhance communication and collaboration among project stakeholders. It could analyze project documentation and extract relevant information for different parties involved, streamlining communication between architects, engineers, and contractors, reducing misunderstandings, and improving project coordination [30].

Research Objectives

Given the limited scope and depth of current CM curricula in addressing the evolving demands of the construction industry, this research was conducted to test two hypotheses:

- (1) CM professionals lack proficiency in data analytics, such as MO and ML, and
- (2) A video-based intervention can effectively enhance the knowledge of both undergraduate and graduate students in these areas.

To test these hypotheses, two groups of students participated in this research: CM graduate students, as CM professionals with work experience, and civil engineering undergraduate students enrolled in CM courses.

Methodology

To meet the research objectives, the methodology for this research can be defined in three steps:

- Step 1: Develop questionnaire surveys to assess students' current knowledge in data analytics, focusing on MO and ML.

- Step 2: Create educational modules introducing students to data analytics skills, focusing on MO and ML.
- Step 3: Conduct questionnaire surveys once more to evaluate the potential improved knowledge among students.

A total of 21 seniors enrolled in the CM course in the Fall 2025 and 23 in Spring 2025, and 13 CM master's students attended this research study. Over two to three weeks, participants were surveyed twice using multiple-choice and short-answer questions to evaluate their understanding of MO and ML. The survey included 10 technical questions to determine students' initial knowledge and a short-answer question requiring them to define MO and ML and their significance in our field. Additionally, students conducted a self-assessment of their knowledge, and the CM instructor provided further evaluations based on the short answers. Participants watched the educational video through EdPuzzle, facilitating engagement by tracking video completion.

Results and Discussion

Survey data were collected for both modules (MO and ML), with responses gathered for each module across three different groups of students (two undergraduate and one graduate) and two separate samples (before and after video watching). The first survey's responses were evaluated to determine current knowledge. All responses were assessed and evaluated after students were exposed to educational video modules, and the second survey was conducted.

It is important to note that students who attended only one of the two surveys for each module were excluded from the comparison analysis. After finalizing the participants, 19 undergraduates (group one), 23 undergraduates (group two), and 10 graduate students (group three) were included for MO. Regarding ML, 21 undergraduates (group one), 22 undergraduates (group two), and 11 graduate students (group three) were considered. Scores for all groups are presented in Tables 1, 2, and 3.

Table 1. Obtained scores from undergraduate students (group 1) before and after watching videos

Undergraduate Students	MO		ML	
	Before	After	Before	After
#1	50	90	80	100
#2	50	40	30	100
#3	50	80	70	90
#4	50	80	80	80
#5	40	80	80	100
#6	60	80	90	80
#7	50	100	70	90
#8	100	90	90	90
#9	80	80	80	90
#10	60	90	80	60

#11	70	100	80	90
#12	60	90	80	40
#13	70	80	90	80
#14	80	90	80	100
#15	50	90	90	90
#16	80	60	80	90
#17	80	90	70	100
#18	70	80	60	100
#19	90	90	80	100
#20			90	100
#21			100	100
Total Average	65.2%	83.2%	78.5%	89%

Table 2. Obtained scores from undergraduate students (group 2) before and after watching videos

Undergraduate Students	MO		ML	
	Before	After	Before	After
#1	70	90	50	90
#2	50	70	10	80
#3	10	100	40	100
#4	10	20	40	100
#5	70	90	20	60
#6	80	100	80	100
#7	50	90	100	100
#8	80	100	50	70
#9	70	80	40	90
#10	20	40	40	100
#11	60	80	70	60
#12	80	90	70	90
#13	40	90	60	100
#14	40	50	70	100
#15	0	50	80	30
#16	50	90	50	70
#17	20	90	80	80
#18	10	100	70	100
#19	0	30	30	70
#20	50	70	20	50
#21	80	100	80	100
#22	70	80	80	100
#23	50	90		
Total Average	46.1%	77.82%	55.9%	83.6%

Table 3. Obtained scores from graduate students (group three) before and after watching videos

Graduate Students	MO		ML	
	Before	After	Before	After
#1	30	70	40	60
#2	20	70	40	80
#3	60	100	50	80
#4	30	70	90	100
#5	100	70	100	90
#6	20	80	90	100
#7	90	80	80	100
#8	90	100	80	90
#9	20	80	70	100
#10	10	100	50	90
#11			40	100
Total Average	47%	82%	66.36%	90%

According to the sample size, a two-tailed t-test was conducted to test the null hypothesis of having the same mean values (average of total scores), with a *p-value* less than 0.05 as a common significance level [31]. Table 4 presents t-test results, in which having the same mean between two samples was rejected. This highlights the statistically significant improvements in students' knowledge of MO and ML after watching the videos in both graduate and undergraduate groups.

Table 4. *p*-values in the T-test for all comparisons

	Undergraduate Students Group I	Undergraduate Students Group II	Graduate Students
MO	0.001	0.0001	0.012
ML	0.045	0.0002	0.002

Our preliminary results for the MO module showed that the graduate and undergraduate groups had a baseline knowledge score of 47%, 65.2%, and 46.1%, respectively. After the intervention, the graduate group improved to 82%, a 35% increase, and the undergraduate students group one increased to 83.2%, and group two to 77.82% (Tables 1, 2, and 3). This suggests that the video significantly enhanced both groups' understanding. Individual question analysis revealed an improvement in the number of correct responses, up to 8 in the graduate group and up to 4 in the undergraduate group. Before the video, 81.8% of the graduate and 37.8% of undergraduate students rated their knowledge at the lowest level. Post-video, no one rated their knowledge at the lowest level, with a 100% rating between levels 2 and 4, out of which 63.6% of the graduate group and 75% of the undergraduate group were between levels 3 and 4. This improvement considerably highlights the increased confidence and knowledge.

For ML, our preliminary results showed the graduate and undergraduate groups had a baseline knowledge score of 66.36%, 78.5%, and 55.9%, respectively. After the intervention, the graduate group improved to 90%, and the undergraduate students group one improved to 89%, and group two to 83.6% (Tables 1, 2, and 3). These results suggest that the video significantly enhanced both groups' understanding. Individual question analysis revealed an improvement in the number of correct responses up to 6 and 5 in the graduate and undergraduate groups, respectively. Before the video, 54.5% of the graduate and 39.3% of undergraduate students' self-rating was at the lowest level. No one rated their knowledge at the lowest level post-video. These results highlight the students' improved confidence and knowledge.

The results reveal low current knowledge among all students. It was found that despite generally higher expectations from graduate students with more work experience, they still have a limited grasp of the subject. Our findings indicated that the educational video enhanced all students' knowledge and self-reported confidence in MO and ML within CM courses, particularly in the CM professionals' group.

Conclusion

CM requires continuous updates to academic curricula to meet the evolving demands of the workforce. Integrating key problem-solving and analytical thinking skills into the curriculum is essential to equipping students with the decision-making and forecasting tools necessary for success in CM. Among the critical data analytics skills are MO and ML.

MO is vital in CM to effectively balance cost, time, quality, and other essential factors. Construction project managers can leverage this skill to optimize resource allocation, manage risks, integrate sustainability, and enhance stakeholder satisfaction, ultimately leading to more successful and efficient construction projects. Additionally, the integration of ML in CM offers numerous advantages, including accurate cost estimation, improved risk management, enhanced safety, better quality control, and optimized resource allocation. As the construction industry continues to evolve, harnessing ML technologies will be crucial in driving efficiency and ensuring successful project outcomes.

This research indicates that CM professionals currently lack proficiency in core data analytics skills. Furthermore, it was found that a video-based module intervention can significantly enhance the knowledge of both undergraduate and graduate students in these areas, preparing them to make informed decisions in the complex and dynamic environment of the construction industry. It is essential to introduce undergraduate students, even those without advanced education, to these core analytical tools. The findings of this research can provide valuable insights to civil engineering and CM institutions on how to effectively enhance their CM education.

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References

- [1] Bureau of Labor Statistics, U.S. Department of Labor, "Occupational Outlook Handbook: Construction Managers," [Online]. Available: <https://www.bls.gov/ooh/management/construction-managers.htm>. [Accessed: Jan. 15, 2025].
- [2] A. K. Ali, "A case study in developing an interdisciplinary learning experiment between architecture, building construction, and construction engineering and management education," *Eng. Constr. Archit. Manag.*, vol. 26, no. 9, pp. 2040-2059, 2019.
- [3] A. Walker, *Project Management in Construction*. Hoboken, NJ, USA: John Wiley & Sons, 2015.
- [4] O. Abudayyeh, J. Russell, D. Johnston, and J. Rowings, "Construction Engineering and Management Undergraduate Education," *J. Constr. Eng. Manag.*, vol. 126, no. 3, pp. 169–175, May 2000, doi: 10.1061/(ASCE)0733-9364(2000)126:3(169).
- [5] S. Ahmed, C. Yaris, R. Farooqui, and M. Saqib, "Key Attributes and Skills for Curriculum Improvement for Undergraduate Construction Management Programs," *CoLab*. [Online]. Available: <https://colab.ws/articles/10.1080%2F15578771.2014.900833>. [Accessed: Jan. 15, 2025].
- [6] R. U. Farooqui and S. M. Ahmed, "Key Skills for Graduating Construction Management Students—A Comparative Study of Industry and Academic Perspectives," in *Proc. ASCE*, 2012, pp. 1439–1448.
- [7] Z. Torbica, "Design and Implementation of an Integrated Curriculum: A Case Study," in *Proc. Int. Conf. Future of Teaching and Education*, vol. 2, no. 1, Art. no. 1, Aug. 2023, doi: 10.33422/icfte.v2i1.59.
- [8] O. M. ElSahly, S. Ahmed, and A. Abdelfatah, "Systematic Review of the Time-Cost Optimization Models in Construction Management," *Sustainability*, vol. 15, no. 6, Art. no. 6, Jan. 2023, doi: 10.3390/su15065578.
- [9] Z. Zhan, Y. Hu, P. Xia, and J. Ding, "Multi-objective optimization in construction project management based on NSGA-III: Pareto front development and decision-making," *Buildings*, vol. 14, no. 7, pp. 2112, 2024.
- [10] M. Ghorqi et al., "Integration of resource supply management and scheduling of construction projects using multi-objective whale optimization algorithm and NSGA-II," *Soft Comput.*, pp. 1-19, 2024.
- [11] G. Khazaeni and A. Khazaeni, "Multi-objective optimal allocation of construction project risks, ant colony optimization algorithm," *Int. J. Build. Pathol. Adapt.*, 2024.
- [12] M. Yilmaz and T. Dede, "Multi-objective time-cost-safety risk trade-off optimization for the construction scheduling problem," *Eng. Constr. Archit. Manag.*, 2024.
- [13] K. Guo and L. Zhang, "Multi-objective optimization for improved project management: Current status and future directions," *Autom. Constr.*, vol. 139, Art. no. 104256, 2022.

- [14] Z. Zhan, Y. Hu, P. Xia, and J. Ding, "Multi-Objective Optimization in Construction Project Management Based on NSGA-III: Pareto Front Development and Decision-Making," *Buildings*, vol. 14, no. 7, Art. no. 7, Jul. 2024, doi: 10.3390/buildings14072112.
- [15] M. Askarifard et al., "A robust multi-objective optimization model for project scheduling considering risk and sustainable development criteria," *Environ. Dev. Sustain.*, vol. 23, pp. 11494-11524, 2021.
- [16] H. V. V. Tran and T. A. Nguyen, "A Review of Challenges and Opportunities in BIM Adoption for Construction Project Management," *Eng. J.*, vol. 28, no. 8, pp. 79-98, 2024.
- [17] W. He, W. Li, and W. Wang, "Developing a Resource Allocation Approach for Resource-Constrained Construction Operation under Multi-Objective Operation," *Sustainability*, vol. 13, no. 13, Art. no. 13, Jan. 2021, doi: 10.3390/su13137318.
- [18] S. T. Boppiniti, "Big Data Meets Machine Learning: Strategies for Efficient Data Processing and Analysis in Large Datasets," *International Journal of Creative Research in Computer Technology and Design*, vol. 2, no. 2, 2020.
- [19] "Cost estimation and prediction in construction projects: a systematic review on machine learning techniques | Discover Applied Sciences," Accessed: Jan. 15, 2025. [Online]. Available: <https://link.springer.com/article/10.1007/s42452-020-03497-1>.
- [20] T. N. Van and T. N. Quoc, "Research Trends on Machine Learning in Construction Management: A Scientometric Analysis," *Journal of Applied Science and Technology Trends*, vol. 2, no. 02, Art. no. 02, Sep. 2021, doi: 10.38094/jastt203105.
- [21] V. Sharma, M. Zaki, K. N. Jha, and N. A. Krishnan, "Machine learning-aided cost prediction and optimization in construction operations," *Engineering, Construction and Architectural Management*, vol. 29, no. 3, pp. 1241-1257, 2022.
- [22] M. O. Sanni-Anibire, R. M. Zin, and S. O. Olatunji, "Developing a preliminary cost estimation model for tall buildings based on machine learning," in *Big Data and Information Theory*, pp. 94-102, Routledge, 2022.
- [23] S.-W. Choi, E.-B. Lee, and J.-H. Kim, "The Engineering Machine-Learning Automation Platform (EMAP): A Big-Data-Driven AI Tool for Contractors' Sustainable Management Solutions for Plant Projects," *Sustainability*, vol. 13, no. 18, Art. no. 18, Jan. 2021, doi: 10.3390/su131810384.
- [24] A. Gondia, A. Siam, W. El-Dakhakhni, and A. H. Nassar, "Machine learning algorithms for construction projects delay risk prediction," *Journal of Construction Engineering and Management*, vol. 146, no. 1, p. 04019085, 2020.
- [25] F. Sattari, R. Macciotta, D. Kurian, and L. Lefsrud, "Application of Bayesian network and artificial intelligence to reduce accident/incident rates in oil & gas companies," *Safety Science*, vol. 133, p. 104981, 2021.
- [26] C. R. Ahn, S. Lee, C. Sun, H. Jebelli, K. Yang, and B. Choi, "Wearable sensing technology applications in construction safety and health," *Journal of Construction Engineering and Management*, vol. 145, no. 11, p. 03119007, 2019.
- [27] K. O. Kazeem, T. O. Olawumi, and T. Osunsanmi, "Roles of Artificial Intelligence and Machine Learning in Enhancing Construction Processes and Sustainable Communities," *Buildings*, vol. 13, no. 8, Art. no. 8, Aug. 2023, doi: 10.3390/buildings13082061.
- [28] M. M. Ajmal, M. Khan, A. Gunasekaran, and P. T. Helo, "Managing project scope creep in construction industry," *Engineering, Construction and Architectural Management*, vol. 29, no. 7, pp. 2786-2809, 2022.

- [29] 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.
- [30] R. Hasan, "Enhancing stakeholder engagement in project management through AI-driven predictive modeling," 2024.
- [31] T. K. Kim, "T test as a parametric statistic," *Korean Journal of Anesthesiology*, vol. 68, no. 6, pp. 540-546, 2015.