Hatoum, M. B. & Nassereddine, H. (2023). Unleashing the Power of ChatGPT for Lean Construction: An Early Outlook. *Proceedings of the 31st Annual Conference of the International Group for Lean Construction (IGLC31),* 208–219. doi.org/10.24928/2023/0243

UNLEASHING THE POWER OF CHATGPT FOR LEAN CONSTRUCTION: AN EARLY OUTLOOK

Makram Bou Hatoum[1] and Hala Nassereddine [2]

ABSTRACT

Artificial Intelligence (AI) is one of the core technologies that was brought forward by the fourth industrial revolution. This technology is disrupting industries all around the globe, and the construction industry is no exception. Research targeting AI in construction has grown exponentially in the last decade as researchers investigate how to leverage AI across the project lifecycle. With the recent release of ChatGPT, AI research is expected to grow even more as the construction industry navigates this breakthrough and understands its impact.

This paper focuses on AI in the context of Lean Construction and has two main objectives. First, the paper reviews the database for the International Group of Lean Construction (IGLC) to identify AI-related publications, summarize their findings, and detect the research trends. A total of nineteen papers were identified, presenting various theoretical and practical aspects of AI in Lean Construction. Second, the paper provides an early outlook into ChatGPT and experiments with its capabilities through three simple use cases that explore ChatGPT's ability to educate and train on Lean aspects, perform conceptual analysis, and develop Lean applications. The early interaction with ChatGPT showed promising potential for the construction industry with encouraging results that can empower the Lean community.

KEYWORDS

Lean Construction, Artificial Intelligence, ChatGPT, Construction 4.0.

INTRODUCTION

Artificial Intelligence (AI) is a disruptive technology that has the power to revolutionize industries. The concept of AI can date back to the early 1300s (Press, 2016) but its science was officially established in the early 1930s (Ertel, 2017). The term "Artificial Intelligence" was first coined in the year 1955 by McCarthy et al. (1955) "2 month, 10 man study of artificial intelligence" proposal which led to the birth of the AI field in 1956 (McCarthy et al., 2006). The birth was a result of a strong period of technological developments that was accelerated by World War II and the desire to understand and connect the functioning of machines and organic beings (Council of Europe, 2023).

While there is no standardized definition of AI, the notes of 10 U.S. Code § 2358 use the following definitions: "(1) Any artificial system that performs tasks under varying and unpredictable circumstances without significant human oversight, or that can learn from experience and improve performance when exposed to data sets; (2) An artificial system developed in computer software, physical hardware, or another context that solves tasks requiring human-like perception, cognition, planning, learning, communication, or physical action; (3) An artificial system designed to think or act like a human, including cognitive

[1] Ph.D. Candidate, Department of Civil Engineering, University of Kentucky, Lexington, KY, USA, mbh.93@uky.edu, orcid.org/0000-0002-8824-3941.

[2] Assistant Professor, Department of Civil Engineering, University of Kentucky, Lexington, KY, USA, hala.nassereddine@uky.edu, orcid.org/0000-0001-7952-5034.

architectures and neural networks; (4) A set of techniques, including machine learning, that is designed to approximate a cognitive task; and (5) An artificial system designed to act rationally, including an intelligent software agent or embodied robot that achieves goals using perception, planning, reasoning, learning, communicating, decision-making, and acting."

AI AND THE CONSTRUCTION INDUSTRY

The construction industry is no exception to the disruptions caused by AI, a technology that is core to the Construction 4.0 transformation of the industry (Hatoum et al., 2021). A state-of-the-art review by Abioye et al. (2021) on AI in construction showed the valuable contribution of the technology to resource and waste optimization, supply chain management, health and safety analytics, estimation and scheduling, and job creation. The study also highlighted the potential to develop AI-driven contract comprehension, AI-driven audit systems for construction financials, AI-enabled head-mounted displays, voice user interfaces, and deep learning-based project assistive technologies (Abioye et al., 2021). Another study performed by Pan & Zhang, (2021) proposed a futuristic framework for construction engineering and management that builds on AI research and integrates it with other Construction 4.0 technologies such as robotics, AR, VR, IoT, blockchain, 3D printing, and digital twins, to enhance and optimize the design, planning, construction, and operation of projects. The importance of AI has also dubbed it as one of the ten emerging digital technologies in the Architecture, Engineering, Construction, and Operation (AECO) sector, as the interest in AI research has been growing almost exponentially in the past 10 years (Dou et al., 2023). Despite its importance however, major challenges remain at the level of cost, security, talent shortage, computer power requirements, internet connectivity requirements, policies and regulations, as well as ethical and cultural dilemmas (Abioye et al., 2021; Regona et al., 2022).

CHATGPT: AN AI BREAKTHROUGH

The release of ChatGPT in December 2022 has brought major disruptions, as its accessibility and capability prove that "AI is finally mainstream" (Vincent, 2022). ChatGPT is part of the Generative Pre-trained Transformer (GPT) family of languages developed by Open AI "which uses a transformer neural network to generate natural language text" (OpenAI, 2022). The model is trained using Reinforcement Learning from Human Feedback (RLHF), and unlike traditional chatbots, it can "provide answers, solutions, and descriptions to complex questions including potential ways to solve layout problems, write code, and answer optimization queries" (Haque et al., 2022; OpenAI, 2022) It can also remember what the user discussed earlier in the conversation for follow-up questions, refuse inappropriate requests, and question incorrect responses (Haque et al., 2022).

While the technology behind ChatGPT is not new and the model has several shortcomings, its impressive detailed and human-like text has made it a breakthrough in the AI chatbots that were ever released to the public, drawing more than 1 million users in its first five days and crossing the 100 million monthly users in January 2023 (Bæk, 2023) (Baek, 2023).

ChatGPT serves as the greatest example of the "Ready or Not, AI Comes" scenario, where its disruptions were rapidly noted in major aspects and industries (Lock, 2022; Roose, 2022). For example, concerns quickly grew over its effect on academia and research, prompting publishers to create policies on the use of ChatGPT in research articles, and causing universities and schools to constrain its impact on teaching, assignments, and examinations (Lock, 2022; Roose, 2022; Stokel-Walker, 2023).

As for the construction industry, the use of ChatGPT remains in its infant stages as researchers and practitioners are still trying to understand the technology and navigate its capabilities. Early articles by practitioners highlighted ChatGPT's power in helping construction professionals draft ideas, review communications, speed-up information inquiry, suggest solutions in various formats, highlight talking points, create document templates, fill templates with the required information, and automate administrative work (Mitchell, 2023; Sullivan, 2023). Another study conducted by Prieto et al. (2023) investigated the use of ChatGPT for scheduling construction projects. Results showed that while ChatGPT provided a logical sequence of tasks, its thought process behind the schedules was very linear. Not all of the proposed tasks agreed with the scope of work, but conversing with ChatGPT allowed it to correct some of its errors. The authors attributed the reason to the fact that ChatGPT has not been trained for specific construction purposes, making it not aware of all tasks that could be needed for construction. The study concluded that the overall performance was reasonable, the interaction experience with the interface was positive, and the results seem promising if ChatGPT can be further trained on specialized and specific construction project aspects (Prieto et al., 2023). The role of ChatGPT in generating construction schedules was also emphasized by Singh et al. (2023). The study highlighted the potential of ChatGPT as an aid for industry experts to create general project schedules while also acknowledging the tool's limitations in accounting for specific project constraints, risks, and requirements (Singh et al., 2023).

OBJECTIVE AND METHODOLOGY

With the importance of AI to the construction industry and the rise of ChatGPT, the objective of this study is to answer two research questions (RQs):

- ***RQ1.*** How is AI being researched in the context of Lean Construction?
- ***RQ2.*** Can ChatGPT benefit Lean Construction?

To answer RQ1, the database for the International Group of Lean Construction (IGLC) annual conferences was reviewed to identify all AI-related publications. The IGLC database was chosen because of its superior research in the field of Lean Construction and the significant impact of the IGLC annual conferences on the Lean community and the direction of Lean research. All AI-related publications were identified and summarized, and a keyword network was created to detect the general research trends of AI within Lean Construction.

As for RQ2, the authors conducted three simple use cases to experiment with ChatGPT and showcase its potential. The use cases explore ChatGPT's ability to educate and train on Lean aspects, perform conceptual analysis, and develop Lean applications. The use cases provide an early outlook into the capability of the technology and its support to the Lean construction community.

ARTIFICIAL INTELLIGENCE AND LEAN CONSTRUCTION

The first search within the IGLC database for papers that used the term "Artificial Intelligence" in their title, abstract, and/or keywords yielded nine publications. The second search for AI-related terms identified from the first search yielded eleven other publications.

PAPERS WITH DIRECT MENTIONS OF "ARTIFICIAL INTELLIGENCE"

The papers identified in the first search are summarized in Table 1. The nature of the papers varied between theoretical research and practical research. Theoretical research focused on AI's impact on the different Lean aspects like Lean principles and tools (Cisterna et al., 2022) and human-machine interaction (Arroyo et al., 2021), while the practical research utilized AI techniques to develop, verify, and validate AI models for different project purposes such as productivity (Zhao & Chua, 2003), and planning and scheduling (Benjaoran & Dawood, 2005).

A comprehensive keyword network was generated using VOSviewer for the papers as shown in Figure 1. The network aimed to identify the general themes of AI research by clustering the keywords using their association strength and detecting common key terms that Lean construction researchers use in their papers. Each color in the network represents a specific cluster, and the following trends are identified:

- Commitment, collaboration, and trust are needed for AI to empower digitization through smart data analysis techniques;
- The proper integration of AI and Lean construction can foster a cultural change that embraces continuous improvement;
- Decision-making using AI must adhere to social and ethical principles, and decision-makers should consider and limit AI bias;
- The proposed AI models most used neural networks for multiple project aspects including planning, scheduling, production lines, productivity, and waste;
- Knowledge management was a frequently investigated area where AI techniques such as decision trees, machine learning, data mining, and neural networks were used to analyze data and information and develop knowledge management systems.

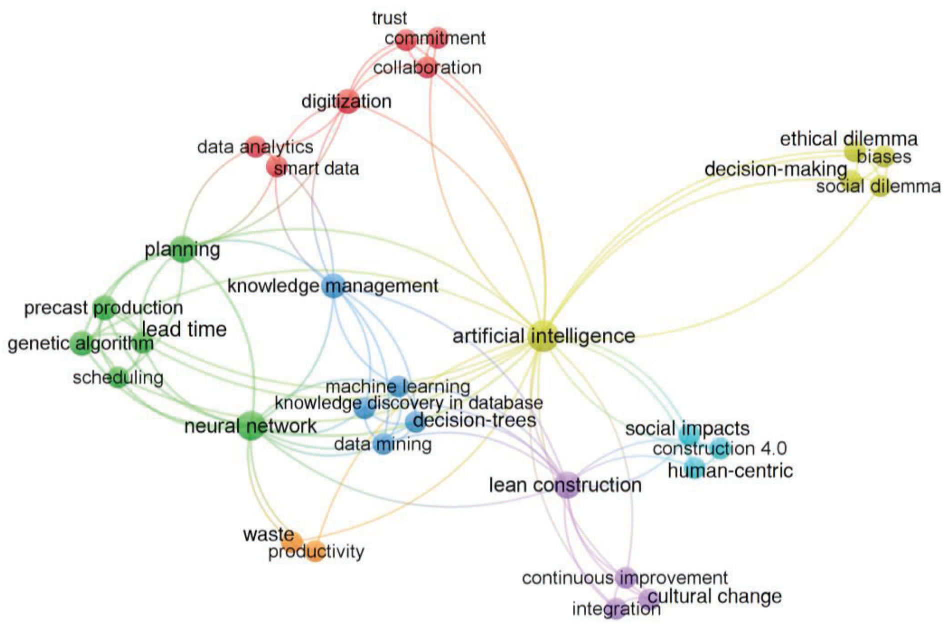

Figure 1: Keyword Network of the IGLC Papers that Used the Term "Artificial Intelligence"

Papers without Direct Mentions of "Artificial Intelligence"

The network in Figure 1 highlighted frequent key terms for different AI techniques used by Lean construction researchers. The key terms include "Neural Networks", "Machine Learning", "Decision Trees", "Genetic Algorithm", "Data Mining", and "Knowledge Discovery". Each of these where used to search the IGLC database for additional AI-related papers, and the search yielded eleven publications that did not appear in Round 1.

The papers are summarized in Table 2. The research was mostly practical in nature with direct applications of multiple AI techniques such as machine learning applications to create information systems (Caldas & Soibelman, 2002), genetic algorithms to reduce inventory (Ko, 2011), and artificial neural networks to benchmark and predict environmental performance indicators (Fernandes et al., 2019). Moreover, some AI techniques were used with common Lean decision-making tools such as genetic algorithms with Analytic Hierarchy Process (Lin, Wang, & Yu, 2009) and graph-based inference with Choosing by Advantages (Haymaker, Chau, & Xie, 2013).

Table 1: Summary of AI-related papers published in IGLC (Round 1)

Paper	Summary
Soibelman & Kim (2000)	Presented a framework required for implementing Knowledge Discovery in Databases (KDD) to uncover new patterns in construction projects by examining extensive project data. The procedure comprises five main stages: identifying issues, preparing data, mining data, analyzing data, and refining the process. The paper also developed a prototype of the KDD system And experimented with it utilizing the Resident Management System database from the US Corps of Engineers.
Benjaoran & Dawood (2003, 2005)	Proposed a system for automatic planning referred to as "artificial intelligence planner (AIP)" to minimize lead time and enhance the scheduling and planning of the precast concrete production process. AIP relies on two AI techniques - genetic algorithm (GA) and artificial neural networks (ANN). The original planner consists of four components that carry out different functions but communicate automatically with each other to achieve the AIP's overall purpose: "the central database, graphic data extractor, processing time estimator, and production planner". The authors followed it up with another paper where they enhanced AIP and presented a case study.
Zhao & Chua (2003)	Utilized a neural network to model the influence of wastes on measured productivity. The study formalized 20 types of waste, then analyzed a total of 75 sets of productivity data collected from formwork crews on multiple projects over 6 months. The model was able to successfully identify the 8 critical wastes affecting productivity and predict on-site performance with very good accuracy.
Oprach et al. (2019)	Focused on understanding the challenges in scheduling construction tasks with smart data and identifying possible solutions using existing applications of AI. The paper suggested three solutions including (i) naming of work packages by clustering with semantic wikis, (Sequential) pattern mining, and data recording with electronic devices; (ii) improvement of activity duration data by recording data with robots and drones and analyzing it with machine learning; and (iii) defining operationally significant locations through using BIM.
Schia et al. (2019)	Researched the successful implementation of digital tools and the understanding of human-machine relationships using literature, a case study, and interviews. The study utilized findings to provide technology, process, and culture factors that can "close the gap between the current and future use of AI in the construction industry" and evaluated the factors on three digital tools – Touchplan, Synchro, and ALICE
Arroyo et al. (2021)	Explored the ethical and social considerations of the AI application to spark discussion on AI within the Lean community. The study presented different examples, opinions, and use cases to elaborate on five main discussion points including (i) verifying the source of data and means of the data collection; (ii) trusting AI decisions; (iii) understanding AI bias; (iv) being cautious of pleasing the algorithm; and (v) understanding the impact on project team motivation and decision-making.
Cisterna et al. (2022)	Investigated the synergies between AI methods and Lean construction techniques where they highlighted two types of synergic interactions – interactions where Lean supports AI processes and interactions where AI supports Lean techniques. Findings were presented in an AI-Driven Construction Improvement Process (CIP) framework in which people were elevated to a pivotal position as a unifying element between the two fields.
Noueihed & Hamzeh (2022)	Explored the social impact of adopting Construction 4.0 technologies and addressed AI as a specific case of these technologies. The study emphasizes the need for human-centric approaches where technologies are means to support people to flourish and succeed, and should not be treated as means for dominancy. The study also highlighted that people should drive the design and implementation of technologies to make sure that "technologies fit their needs and preserve their rights of performing work freely, efficiently, and humanely".

Table 2: Summary of AI-related papers published in IGLC (Round 2)

Paper	Summary
Caldas & Soibelman (2002)	Utilized automated text classification methods to support the “implementation of pull techniques in construction management information systems”. The proposed system comprises six main modules namely: “data collection, data conversion, data preparation, dimensionality reduction, learning, and classification”. Multiple machine-learning algorithms were used in the learning module including Support Vector Machines. The prototype was created to automate the stages involved in the document classification process and enabled the generation of classification models for projects based on user-defined project components.
Filho et al. (2004)	Analyzed a large data set from a capital facility project to detect common patterns of sequences of non-completed activities. The analysis showed effectiveness in identifying problems in the production workflow and pinpointing relevant events that had not been noticed by the onsite workforce.
Bortolazza, Costa, & Formoso (2005)	Aimed to provide insights into the Last Planner System implementation in Brazil using a quantitative approach. The study aimed to analyze the percentage of plans completed (PPC) data from 115 residential, industrial, and low-income housing projects. The study also utilized data mining techniques including decision trees and neural networks to detect patterns and analyze causes for the non-completion of work packages. The major preliminary reasons indicated that most projects had limited success in the implementation of look-ahead planning.
Wu & Soibelman (2006)	Presented a case study on a novel approach developed by the authors to preprocess and represent network-based work plans from a project control system into abstraction-type descriptions in support of graphical analysis and pattern recognition. The analysis was performed on a Last Planner database of production control from a large capital facility project. The resulting patterns can allow project managers to better understand potential problems and make informed decisions to decrease variability and increase reliability in planning and control.
Srisuwanrat & Ioannou (2007)	Presented a unique investigation of lead-time buffering by focusing on “when to start a production line so that there is no interruption”. Two distinct methods of lead-time buffering were investigated – the “sequence step algorithm” (SQS-AL) and the “completed unit algorithm” (CU-AL). The authors employed STROBOSCOPE coupled with a search add-on that utilizes a genetic algorithm (GA). Results showed that incorporating a lead-time buffer leads to improved workflow and greater project profit that vary based on the workflow interruption’s penalty cost and indirect cost. The study highlighted the algorithms' advantages as well as limitations “depending on assumptions, simplicity of the simulation model, project characteristics, and uncertainty”.
Ko & Wang (2008)	Developed a flow-shop sequencing model to enhance weekly work planning. The model considers production constraints and buffer sizes and uses a genetic algorithm with multiple objectives to explore optimum solutions that minimize both makespan and tardiness penalties.
Lin et al. (2009)	Proposed an integrated model to facilitate the weightings and evaluation of “tenders involved in the best-value contractor selection process”. To weight criteria, an adaptive Analytical Hierarchy Process (AHP) was developed using a soft computing scheme and genetic algorithms “to recover the weights of the various criteria based on the derived pairwise weighting matrix”. As for tender evaluations, the authors proposed “a bid price evaluation submodel” to handle the quantitative criteria and “a performance-based evaluation submodel” to quantify the anticipated performances of other qualitative criteria for every bidder.

Paper	Summary
Ko (2011)	Developed a framework to reduce the precast fabrication inventory without changing production resources. The framework comprises three components including “(i) a time buffer evaluation is to avoid fabricators losing capacity by considering demand variability; (ii) a due date adjustment to shift the production curve closer to erection dates and reduce inventory; and (iii) a scheduling component that arranges production sequences to achieve multi-objectives using genetic algorithms”.
Haymaker et al. (2013)	Leveraged decision models and machine learning to support designers in dealing with decision-making challenges by automatically retrieving pertinent information from prior decisions. The authors employed the Belief Propagation (BP) graph-based inference to “develop a collaborative decision-making model” based on the Choosing by Advantages (CBA) methodology. The paper proposed the CBA-PB algorithm and implemented it to validate its efficiency and effectiveness.
Antunes & Poshdar (2018)	Suggested a theoretical framework to tackle construction production issues through the implementation of “an integrated automatic supervisory control and data acquisition for management and operations”. The system is segmented into planning, controlling, executing, and monitoring groups to track the project product as well as production. The system also employed machine learning models that can be trained with input sources from technologies to perform tasks and generate outputs that feed into the system.
Fernandes et al. (2019)	Proposed an equation that “predicts environmental performance indicators based on construction progress”. The model was developed via Python and utilized artificial neural networks using a database of 15 construction sites. Three equations were proposed for three environmental indicators – water consumption, energy consumption, and waste generation. The equations can provide managers with a benchmark to establish environmental performance targets and make managerial decisions as the construction progresses.

CHATGPT AND LEAN CONSTRUCTION

To understand how can ChatGPT benefit Lean construction professionals and researchers, the authors performed three simple use cases to experiment with the technology’s capabilities.

USE CASE ONE: EDUCATION AND TRAINING

The authors asked ChatGPT to define Lean Construction, list the major concepts and practices, and explain how ChatGPT can support the Lean Construction field. The responses are shown in Figure 2 (Left). The answers provided were both accurate and reliable. The authors also asked ChatGPT to provide the answer to Question 2 (Lean concepts and practices) in the form of an official training document, and ChatGPT changed the entire answer to a professional training template.

USE-CASE TWO: CONCEPTUAL ANALYSIS

The authors provided ChatGPT with a descriptive steel erection process beginning from the time the material was ordered and shipped from the manufacturer, through the construction production process, and ending with the material in its final position in the facility. The process was adopted from the Construction Industry Institute (CII) project RT-191. The authors requested ChatGPT to identify Lean waste and provide solutions, and the responses are shown in Figure 2 (Right). ChatGPT was successfully able to identify five waste types and provide solutions that meet the scope of the process. The answer provided by ChatGPT was very impressive given that ChatGPT was only given a descriptive summary of the process without any quantitative data for further analysis.

Authors: *Define Lean Construction.*
ChatGPT: "Lean construction is a management philosophy and production approach that aims to optimize the design and delivery of construction projects. It is based on the principles of the Toyota Production System, which has been successfully applied in manufacturing and other industries. In construction, the goal of lean construction is to eliminate waste, increase efficiency, and improve overall project performance by involving all members of the construction team in the continuous improvement process. This is accomplished through a series of tools and techniques, including value stream mapping, pull planning, and kaizen events, that help identify and eliminate non-value-adding activities. Lean construction also places a strong emphasis on collaboration and communication between all stakeholders in the project, including owners, designers, contractors, and subcontractors. The focus is on delivering projects that meet the needs of the customer, while also improving quality, reducing costs, and shortening the construction timeline."

Authors: *List the main Lean construction concepts and practices.*
ChatGPT: "The main concepts and practices of lean construction are as follows:

- Elimination of waste: Lean construction aims to eliminate waste in construction processes, including overproduction, waiting, defects, overprocessing, excess inventory, unnecessary motion, unused talent, and production of unnecessary products.
- Continuous improvement: Lean construction is focused on continuous improvement, which involves regularly reviewing and refining construction processes to identify and eliminate waste, and improve efficiency and quality
- Value stream mapping: This involves creating a visual representation of all the activities and processes involved in a construction project, from start to finish, to identify areas for improvement and eliminate waste.
- Just-in-time (JIT) production: JIT production is a key concept in lean construction, and involves producing materials and components just in time for when they are needed on the construction site, reducing the need for storage and inventory.
- Pull production: This involves producing materials and components in response to actual demand, rather than producing ahead of time, to reduce waste and improve efficiency.
- Kaizen: Kaizen is a Japanese term for continuous improvement, and involves regularly reviewing and refining construction processes to eliminate waste and improve quality and efficiency.
- Total productive maintenance (TPM): TPM involves involving all employees in the maintenance of equipment and machinery, to ensure that they are maintained in good condition, and to reduce downtime and waste.
- 5S: 5S is a set of five principles for workplace organization and efficiency, which include sorting, simplifying, sweeping, standardizing, and sustaining.
- Visual management: This involves using visual aids, such as visual schedules and status boards, to communicate project information and improve collaboration and communication.

In summary, these are the main concepts and practices of lean construction, which aim to eliminate waste, improve efficiency and quality, and promote continuous improvement in construction processes."

Authors: *How can ChatGPT support and enhance Lean Construction?*
ChatGPT: "ChatGPT can support and enhance the implementation of lean construction in several ways:

- Education and training: ChatGPT can be used as a virtual assistant to provide education and training to construction professionals on the principles and practices of lean construction. This can help to increase awareness and understanding of lean construction, and promote its adoption in the industry.
- Project management: ChatGPT can assist in the management of construction projects by providing real-time information and support to project teams. For example, it can help with the creation of project schedules, tracking of project progress, and identification of areas for improvement.
- Collaboration and communication: ChatGPT can facilitate collaboration and communication between all stakeholders in a construction project, including owners, designers, contractors, and subcontractors. This can help to promote teamwork, increase transparency, and reduce misunderstandings, which are key components of lean construction.
- Data analysis: ChatGPT can assist in the analysis of data related to construction projects, such as construction schedules, costs, and quality metrics. This can help to identify areas for improvement, and support the implementation of continuous improvement initiatives in the field.
- Knowledge management: ChatGPT can help to centralize and manage knowledge related to lean construction, allowing construction professionals to access and share information, best practices, and lessons learned.

In summary, ChatGPT can be a valuable tool for promoting and enhancing the implementation of lean construction in the construction industry. By providing support for education and training, project management, collaboration and communication, data analysis, and knowledge management, it can help to increase the efficiency and effectiveness of construction projects, and support the continuous improvement of construction processes."

Authors: The following paragraphs describe a structural steel erection process, beginning from the time the material was ordered and shipped from the manufacturer, through the construction production process, and ending with the material in final position in the facility. Information on delivery and handling of the steel joists was obtained from the project manager. Once it arrived onsite, the basic flow of the steel was as follows:

1. After the steel was manufactured, it remained onsite at the manufacturer's warehouse until needed.
2. Each steel shipment consisted of all structural steel members required in one bay. Steel could not be stored onsite in a large material lay-down yard due to safety restrictions. The steel for three to four bays was stored on truck trailers (minus the cab) in the parking lot until needed. It usually remained in the parking lot for one week before being handled again and moved to the second staging area - a small material lay-down area next to the bay being erected.
3. Each load was handled by a heavy-duty forklift. Depending on the steel member type, one to three separate lifting actions were needed by the forklift operator to remove the entire load from the truck bed.
4. The load from the truck was placed on the ground in the same manner as it was on the truck. No shakeout occurred from the truck to the ground.
5. The piles from the truck were organized by member type (columns with columns, trusses with trusses, etc.).
6. Each steel member had a number that correlated to a number on the drawings. Following the placement of each pile on the ground, a ground crewman located the number on each steel piece and related it back to the foreman. This number helped the erection crew foreman with the proper erection sequence.
7. No shakeout occurred after placement on the ground. The crane was required to swing over the material lay-down area in random picks to reach each steel piece. One piece was picked at a time. This created a large material transport time for the crane operator.
8. After the steel members were placed near their respective bay staging areas, the crane moved the girders, bar joists and columns from the staging position to final position in the structure.

Please identify all Lean waste in this procedure and suggest solutions.

ChatGPT: The following are the identified sources of Lean waste in the structural steel erection process:

- Waiting: The steel was stored at the manufacturer's warehouse until needed, and then in the parking lot for one week before being moved to the next staging area, resulting in waiting time for the material to be used.
- Excess Inventory: Steel for three to four bays was stored on truck trailers, creating excess inventory and taking up valuable space.
- Overprocessing: Depending on the steel member type, one to three separate lifting actions were needed by the forklift operator to remove the entire load from the truck bed, leading to overprocessing and increased handling time.
- Unnecessary Motion: The crane was required to swing over the material lay-down area in random picks to reach each steel piece, resulting in unnecessary motion and increased material transport time for the crane operator.
- Unused Talent: The ground crewman who located the numbers on each steel piece was only utilized in the material handling process and not in any other value-adding activities.

To eliminate these wastes, the following solutions can be considered:

- Reduce waiting time: Arrange for just-in-time (JIT) delivery of the steel members, so that they are delivered only when needed on the construction site, reducing the waiting time for the material to be used.
- Minimize excess inventory: Store only the necessary steel members required for the current bay in the parking lot, reducing the amount of excess inventory stored onsite.
- Streamline material handling process: Use equipment and processes that minimize the handling time of the steel members, such as using cranes to remove the entire load from the truck bed in one lift.
- Eliminate unnecessary motion: Arrange the material lay-down area in a way that reduces the movement required by the crane operator to reach each steel piece, such as organizing the piles by member type.
- Utilize all personnel: Encourage the ground crewman to take on additional responsibilities, such as assisting the crane operator, to utilize their full potential and skills.

Figure 2: Use-Case I (Left) and Use-Case II (Right)

USE-CASE THREE: APPLICATIONS DEVELOPMENT

The authors asked ChatGPT to code an application that can help Lean professionals fill in constraint logs. No details, descriptions, or any sort of information were provided for the application. In its reply, ChatGPT acknowledged that it cannot code the entire application, but it can provide a foundation to start developing it. The output resulted in a Graphic User Interface that allows the user to select the constrained type from a dropdown, describe the constraint, and specify its start and end date. Once the user clicks Submit, the input is exported to a text file. The use case showed the creativity of ChatGPT in developing applications. Another interesting aspect of the code is that ChatGPT utilized comments to explain the different sections of the code and their functionalities. This can make it easy for the user to understand the code when implementing and building up on it.

Unfortunately, I am not able to write a complete application for you, as it would require a significant amount of time and resources. However, here is some sample code that demonstrates how you could create a fillable form for constraint logs and track reliable promises in a construction project using the Python programming language:

```
# import necessary libraries
import tkinter as tk
from tkinter import ttk

# create the main window
root = tk.Tk()
root.title("Construction Project Constraint Log")

# create the frame for the constraint log form
frame = ttk.Frame(root, padding="10 10 10 10")
frame.grid(column=0, row=0, sticky="WENS")

# create the form fields
constraint_type = ttk.Combobox(frame, values=["Material", "Labor", "Equipment", "Weather", "Permits"])
constraint_type.grid(column=1, row=0)

constraint_description = ttk.Entry(frame)
constraint_description.grid(column=1, row=1)

start_date = ttk.Entry(frame)
start_date.grid(column=1, row=2)

end_date = ttk.Entry(frame)
end_date.grid(column=1, row=3)

# create the form labels
ttk.Label(frame, text="Constraint Type:").grid(column=0, row=0, sticky="W")
ttk.Label(frame, text="Constraint Description:").grid(column=0, row=1, sticky="W")
ttk.Label(frame, text="Start Date:").grid(column=0, row=2, sticky="W")
ttk.Label(frame, text="End Date:").grid(column=0, row=3, sticky="W")

# create the submit button
submit_button = ttk.Button(frame, text="Submit", command=lambda: log_constraint(constraint_type.get(),
constraint_description.get(), start_date.get(), end_date.get()))
submit_button.grid(column=0, row=4, columnspan=2, pady=10)

# create the function to log the constraint
def log_constraint(constraint_type, constraint_description, start_date, end_date):
    # add the constraint information to the constraint log
    with open("constraint_log.txt", "a") as log_file:
        log_file.write(f"{constraint_type} | {constraint_description} | {start_date} | {end_date}\n")

# run the main loop
root.mainloop()
```

This code creates a GUI application using the tkinter library that allows you to log constraints and track reliable promises in a construction project. The form includes fields for constraint type, constraint description, start date, and end date, and a submit button that adds the constraint information to a text file named constraint_log.txt.

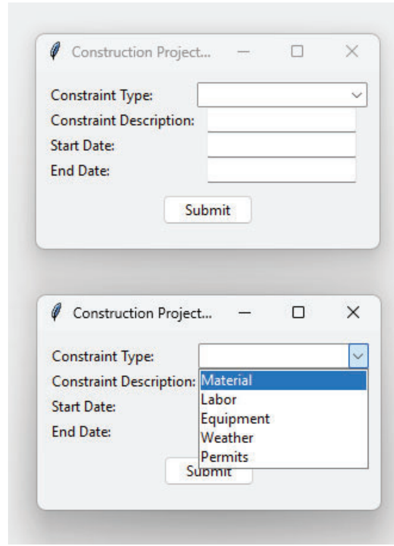

Figure 3: Use-Case III (code on the left and output on the right)

DISCUSSION

The review of the IGLC database on AI-related research showed that the Lean community has been invested in AI as early as the year 2000. Different publications have targeted both practical and theoretical research ranging from developing AI applications and models to understanding the implications of AI on people and Lean culture. With ChatGPT bringing AI to the mainstream, the research of AI within the Lean community is expected to rise even more. ChatGPT shows promising potential, and the three simple use cases presented in this paper showed a glimpse of how capable the technology can be for Lean Construction.

As illustrated in Figure 4, To successfully exploit ChatGPT and upcoming AI disruptions, Lean construction should embrace two types of people: innovators and doubters. On one hand, innovators represent individuals who will adopt ChatGPT early and will be eager to pilot the technology on different Lean aspects. They are often willing to take risks and embrace change, which can lead to new opportunities that leverage ChatGPT and AI in Lean Construction. On the other hand, doubters are individuals who are more cautious and skeptical of AI and ChatGPT. They will often want to understand the potential risks and downsides before embracing new ideas. The presence of both adopters and doubters will thus create a continuous improvement culture, where innovators will bring in new ideas and approaches to solving problems, while the doubters will help ensure that these ideas are thoroughly tested and evaluated before implementation. This interactive dynamic will result in a more thorough and well-informed use of the technology that enables trust, respect for people, adherence to ethical and social principles, and process enhancements.

The biggest threat to technology is resistance, a problem that remains widely common in the construction industry. Once doubters turn into resistors, the continuous improvement cycle of the technology will break as innovators will push ideas and resistors will block them. Thus, the Lean community needs to keep an open mind and embrace its scientific thinking to develop a community of innovators and doubters and exploit the potential of transformative technology.

Moreover, it is also important to acknowledge that AI tools like ChatGPT are still in their early stages of development and, as with any other technology, are expected to evolve and improve over time. Thus, in the meantime, it remains important to utilize the technology as intended, consider its limitations, and verify and validate its output using human intuition, expertise, and available AI content detectors.

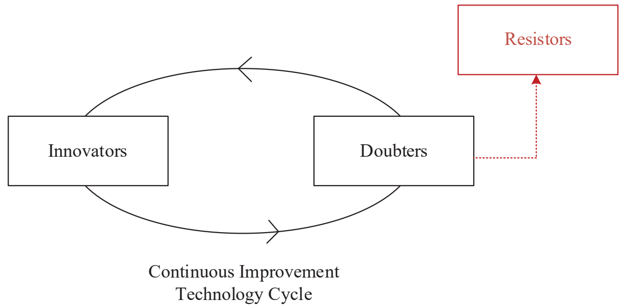

Figure 4: Conceptual Framework that Illustrates Lean and ChatGPT

CONCLUSIONS

This paper explored AI research in Lean Construction and presented preliminary findings on ChatGPT. A review of the IGLC database showed that AI has gained a lot of interest in Lean construction research, while the use cases on ChatGPT showed promising potential for Lean construction. The study however was limited to reviewing IGLC proceedings and performing simple use cases. Further studies can perform systematic literature reviews on other research databases to detect further trends. Future research is also expected to utilize ChatGPT in more complicated use cases that can fully leverage AI capabilities. Finally, in the words of ChatGPT:

Lean construction, so efficient and fast. A building process that's built to last.
With principles to eliminate waste. It aims to make every project great.
Along comes ChatGPT, a tool so bright. Bringing artificial intelligence to the site.
With its vast knowledge, it can assist. Making Lean construction more persistent.
Together they work, as a perfect team. Improving building processes like a dream.
Efficiency and accuracy are their goals. Building better structures for all roles.

REFERENCES

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade. O.O., Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, *44*, 103299. doi: https://doi.org/10.1016/j.jobe.2021.103299

Antunes, R., & Poshdar, M. (2018). Envision of an integrated information system for project-driven production in construction. *ArXiv:1807.04966*. doi: https://doi.org/10.24928/2018/0511

Arroyo, P., Schöttle, A., & Christensen, R. (2021). The Ethical and Social Dilemma of AI Uses in the Construction Industry. *Proc. 29th Annual Conference of the International Group for Lean Construction (IGLC)*, 227–236. Lima, Peru. doi: https://10.24928/2021/0188

Bæk, D. H. (2023). ChatGPT User Statistics & Facts (100 million users reached in January 2023). Retrieved February 11, 2023, from SEO website

Benjaoran, V., & Dawood, N. (2003). Development Framework of an Artificial Intelligence Planner Framework for Bespoke Precast Concrete Production. *11th Annual Conference of the International Group for Lean Construction*. Virginia, USA.

Benjaoran, V., & Dawood, N. (2005). An Application of Artificial Intelligence Planner for Bespoke Precast Concrete Production Planning: A Case Study. *13th Annual Conference of the International Group for Lean Construction*, 493–499. Sydney, Australia.

Bortolazza, R. C., Costa, D. B., & Formoso, C. T. (2005). A Quantitative Analysis of the Implementation of the Last Planner System in Brazil. *13th Annual Conference of the International Group for Lean Construction*, 413–420. Sydney, Australia.

Caldas, C. H., & Soibelman, L. (2002). Automated Classification Methods: Supporting the Implementation of Pull Techniques for Information Flow Management. In C. T. Formoso & G. Ballard (Eds.), *10th Annual Conference of the International Group for Lean Construction*. Gramado, Brazil.

Cisterna, D., Lauble, S., Haghsheno, S., & Wolber, J. (2022). Synergies Between Lean Construction and Artificial Intelligence: AI Driven Continuous Improvement Process. *Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC)*, 199–210. Edmonton, Canada. doi: https://doi.org/10.24928/2022/0122

Council of Europe. (2023). History of Artificial Intelligence. Retrieved February 12, 2023, from COE website: https://www.coe.int/en/web/artificial-intelligence/history-of-ai

Ertel, W. (2017). *Introduction to Artificial Intelligence* (2nd ed.). Cham, Switzerland: Springer International Publishing AG. doi: https://doi.org/10.1007/978-3-319-58487-4

Fernandes, L. L. A., Rocha, M. J., & Costa, D. B. (2019). Prediction of Environmental Performance Indicators for Construction Sites Based on Artificial Neural Networks. *Proc. 27th Annual Conference of the International Group for Lean Construction (IGLC)*, 1413–1424. Dublin, Ireland.

Filho, J. N. O., Solbeman, L., & Choo, J. (2004). Sequential Analysis of Reasons for Non-Completion of Activities: Case Study and Future Directions. In S. Bertelsen & C. T. Formoso (Eds.), *12th Annual Conference of the International Group for Lean Construction*. Helsingør, Denmark.

Haque, M. U., Dharmadasa, I., Sworna, Z. T., Rajapakse, R. N., & Ahmad, H. (2022). "I think this is the most disruptive technology": Exploring Sentiments of ChatGPT Early Adopters using Twitter Data. *ArXiv*, *Computer Science*, 1–12. doi: https://doi.org/10.48550/arXiv.2212.05856

Hatoum, M. B., Nassereddine, H., & Badurdeen, F. (2021). Reengineering Construction Processes in the Era of Construction 4.0: A Lean-Based Framework. *Proc. 29th Annual Conference of the International Group for Lean Construction (IGLC)*, 403–412. Lima, Peru.

Haymaker, J., Chau, D. H., & Xie, B. (2013). Inference-Assisted Choosing by Advantages. In Carlos Torres Formoso & P. Tzortzopoulos (Eds.), *21th Annual Conference of the International Group for Lean Construction* (pp. 339–348). Fortaleza, Brazil.

Ko, C.-H. (2011). Reducing Precast Fabrication Inventory. In J. Rooke & B. Dave (Eds.), *19th Annual Conference of the International Group for Lean Construction*. Lima, Peru.

Ko, C.-H., & Wang, S.-F. (2008). Arranging Weekly Work Plans in Concrete Element Prefabrication Using Genetic Algorithms. In *16th Annual Conference of the International Group for Lean Construction* (pp. 849–856). Manchester, UK.

Lin, C.-C., Wang, W.-C., & Yu, W.-D. (2009). Integrated Model of Weighting and Evaluating Decision Criteria for Supporting Best-Value Contractor Selection. In Y. Cuperus & E. H. Hirota (Eds.), *17th Annual Conference of the International Group for Lean Construction* (pp. 419–430). Taipei, Taiwan.

Lock, S. (2022). What is AI chatbot phenomenon ChatGPT and could it replace humans? Retrieved February 11, 2023, from The Gaurdian website.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12. doi: 10.1609/aimag.v27i4.1904

Mitchell, D. (2023). I Asked Chat GPT How It Can Help Construction Professionals. Retrieved from Archdesk: Construction Tips, News & Best Practices website.

Noueihed, K., & Hamzeh, F. (2022). The Need for a Human Centric Approach in C4.0 Technologies. *Proceedings of the 30th Annual Conference of the International Group for Lean Construction (IGLC)*, 820–831. Edmonton, Canada.

OpenAI. (2022). ChatGPT: Optimizing Language Models for Dialogue.

Oprach, S., Steuer, D., Krichbaum, V., & Haghsheno, S. (2019). Smart Data—Dealing With Task Complexity in Construction Scheduling. *Proc. 27th Annual Conference of the International Group for Lean Construction (IGLC)*, 347–358. Dublin, Ireland.

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, *122*, 103517. doi: https://doi.org/10.1016/j.autcon.2020.103517

Press, G. (2016). A Very Short History Of Artificial Intelligence (AI). Retrieved February 12, 2023, from Forbes website.

Prieto, S. A., Mengiste, E. T., & de Soto, B. G. (2023). Investigating the use of ChatGPT for the scheduling of construction projects. *ArXiv*, *Computer Science*, 1–14. doi: https://doi.org/10.48550/ARXIV.2302.02805

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and Adoption Challenges of AI in the Construction Industry: A PRISMA Review. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(1). doi: 10.3390/joitmc8010045

Roose, K. (2022). The Brilliance and Weirdness of ChatGPT. Retrieved from The New York Times website: https://www.nytimes.com/2022/12/05/technology/chatgpt-ai-twitter.html

Schia, M. H., Trollsås, B. C., Fyhn, H., & Lædre, O. (2019). The Introduction of AI in the Construction Industry and Its Impact on Human Behavior. *Proc. 27th Annual Conference of the International Group for Lean Construction (IGLC)*, 903–914. Dublin, Ireland.

Singh, A.K., Pal, A., Kumar, P., Lin, J.J., and Hsieh, S.H. (2023). Prospects of Integrating BIM and NLP for Automatic Construction Schedule Management. In *40th International Symposium on Automation and Robotics in Construction (ISARC 2023).* Chennai, India.

Soibelman, L., & Kim, H. (2000). Generating Construction Knowledge With Knowledge Discovery in Databases. *8th Annual Conference of the International Group for Lean Construction*. Brighton, UK.

Srisuwanrat, C., & Ioannou, P. G. (2007). The Investigation of Lead-Time Buffering Under Uncertainty Using Simulation and Cost Optimization. In *15th Annual Conference of the International Group for Lean Construction* (pp. 580–589). East Lansing, Michigan, USA.

Stokel-Walker, C. (2023). ChatGPT listed as author on research papers: Many scientists disapprove. *Nature*, *613*, 620–621.

Sullivan, M. (2023). The Pros and Cons of ChatGPT in Construction. Retrieved February 11, 2023, from Buildr website: https://buildr.com/blog/chatgpt-construction/

Vincent, J. (2022). ChatGPT proves AI is finally mainstream—And things are only going to get weirder. Retrieved February 11, 2023, from The Verge website.

Wu, J., & Soibelman, L. (2006). Graphical Analysis on Non-Conformances of Construction Production Processes: Ongoing Research and Case Study. *14th Annual Conference of the International Group for Lean Construction*, 393–405. Santiago, Chile.

Zhao, Y., & Chua, D. K. H. (2003). Relationship Between Productivity and Non Value-Adding Activities. *11th Annual Conference of the International Group for Lean Construction*. Virginia, USA.