

MAPPING AI AND LEAN CONSTRUCTION INTEGRATION: A NETWORK ANALYSIS FRAMEWORK FOR CONSTRUCTION PRODUCTIVITY

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ABSTRACT

The construction industry continues to face persistent productivity challenges, including inefficiencies, schedule delays, and resource underutilisation. While artificial intelligence has shown potential in construction applications for sensing, predicting, and explaining process behaviour, capabilities that align with lean construction's focus on flow reliability, waste visibility, and continuous learning, their systematic integration with lean principles remains fragmented. This study employs Social Network Analysis to systematically examine relationships between AI approaches and lean construction constructs. A systematic literature review of peer-reviewed studies (2015–2025) was conducted to map interconnections between AI approaches and 14 lean construction constructs, using weighted adjacency matrices and degree centrality measures to quantify relationship patterns. Key findings reveal significant variation in connectivity, with real-time analytics, machine learning, and computer vision showing the broadest coverage across lean constructs. The analysis identifies natural alignment opportunities: predictive analytics with continuous improvement processes, and computer vision with visual management and waste reduction. Based on these findings, we propose a three-tier integration framework enabling organisations to prioritise AI approaches based on (i) breadth of lean alignment and (ii) their lean priorities and implementation readiness. This research provides evidence-based prioritisation guidance for construction practitioners and contributes to theoretical understanding of digital transformation in lean construction.

KEYWORDS

AI, lean construction, construction productivity, digital transformation.

INTRODUCTION

The construction industry represents one of the world's largest economic sectors, yet it continues to lag behind other industries in productivity growth and technological adoption (Farmer, 2016; McKinsey & Company, 2020). Construction productivity remains a critical challenge, with persistent inefficiencies, fragmented value chains, and chronic underinvestment in innovation limiting sector competitiveness (Farmer, 2016; Hasan et al., 2018).

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Lean construction has emerged as a strategic methodology to enhance productivity by emphasising waste elimination, value creation, and continuous improvement through collaborative planning and execution (G. Ballard & Howell, 2003). Operationalised through tools such as the Last Planner System and takt planning, lean construction has demonstrated significant potential for improving project performance. However, successful lean implementation requires sustained engagement and considerable cultural transformation, presenting ongoing challenges for many organisations (McHugh et al., 2025; Rener et al., 2023). Realising lean's full potential requires real-time visibility of work constraints and performance, capabilities that AI sensing, analytics, and automation systems can provide (Abdelmegid et al., 2023; Poshdar et al., 2016).

Simultaneously, artificial intelligence has been increasingly explored as a transformative technology for addressing construction challenges. AI applications including machine learning, computer vision, natural language processing, robotics, and real-time analytics have been reported to offer potential for improving construction processes, reducing costs, enhancing safety, and accelerating project delivery (Abioye et al., 2021; Adebawale & Agumba, 2024). In other sectors such as manufacturing, AI-enabled Industry 4.0 integration has resulted in substantial process improvements, cost efficiencies, and sustained performance enhancement (Jamwal et al., 2021), suggesting considerable potential for construction sector adoption.

Although AI and lean construction have been increasingly explored in construction research in recent years, the literature lacks a consolidated, principle-level map of which AI approaches are most consistently linked to which lean construction principles and practices across studies. Furthermore, existing research has hindered comprehensive understanding of how specific AI approaches align with and enable lean construction objectives. Against this background, this study addresses this critical gap by systematically examining reported relationships between AI technologies and lean construction constructs to identify decision-relevant insights. Therefore, the research questions are (1) What relationships are reported between AI approaches and lean construction principles and practices in the reviewed literature? (2) How do reported AI-lean relationships vary in strength and coverage across different lean construction constructs? (3) What implementation priorities or decision-relevant insights emerge from mapping AI-lean relationships?

This research contributes to knowledge by providing a systematic network analysis of reported relationships between AI approaches and lean construction constructs based on analysis of 67 peer-reviewed studies, quantifying connectivity patterns through degree centrality analysis to support prioritisation decisions and developing an evidence-based three-tier framework for evaluating AI approaches relative to organisational lean objectives and implementation readiness.

LITERATURE REVIEW

LEAN CONSTRUCTION PRINCIPLES AND PRACTICES

Lean construction is grounded in foundational principles derived from the Toyota Production System, emphasising efficiency, waste elimination, and continuous improvement through the Transformation-Flow-Value (TFV) framework (G. Ballard & Howell, 2003; Koskela, 1992). The core lean construction principles include: (1) value generation, understanding and delivering what clients truly value; (2) flow optimisation, streamlining work processes to create smooth, continuous workflow; (3) waste elimination, identifying and removing non-value-adding activities; (4) learning and continuous improvement (kaizen), systematically seeking performance enhancements; (5) reliability, creating predictability in schedules and processes; (6) pull-based production, work is initiated by downstream demand rather than upstream push;

and (7) respect for people, engaging and empowering all project participants in collaborative improvement (G. Ballard & Howell, 2003; González et al., 2022).

To operationalise these principles, lean construction employs various tools and practices. The Last Planner System (LPS) operationalises reliability and collaboration principles through collaborative planning and constraint removal (H. G. Ballard, 2000). Takt planning implements flow and rhythm principles, creating predictable construction sequences that reduce variability and improve resource efficiency (Frandsen et al., 2013). Target Value Design (TVD) operationalises value principles by aligning project objectives with client values throughout design and construction phases (Johansen et al., 2021)(Frandsen et al., 2013). Value stream mapping implements waste elimination by systematically identifying and removing non-value-adding activities in construction processes (Pasqualini & Zawislak, 2005). Visual management systems, including Kanban boards, progress dashboards, and real-time status indicators, are tools that support multiple lean principles by enabling transparent information flow and supporting distributed team decision-making (Tezel et al., 2016). These systems are particularly effective at supporting the flow, learning, and reliability principles through continuous visibility of process status.

Despite the proven effectiveness of these approaches, sustained productivity improvements in construction have remained limited (Hasan et al., 2018). This suggests that lean implementation alone may require complementary enablers such as advanced technologies to more effectively operationalise lean principles across complex construction projects.

ARTIFICIAL INTELLIGENCE APPROACHES AND CAPABILITIES IN CONSTRUCTION

Artificial intelligence encompasses multiple approaches and capabilities including machine learning, computer vision, natural language processing, robotics, and real-time analytics, each offering distinct potential for construction applications (Abioye et al., 2021; Vickranth et al., 2019). For the purposes of this analysis, these AI-enabled capabilities are grouped into distinct approaches that were pragmatically defined based on the reviewed literature and represent functional groupings rather than exhaustive technology classification.

Machine Learning enables data-driven decision-making through pattern recognition in historical project data, with applications in cost estimation, schedule optimisation, risk prediction, and resource allocation (Bidhendi & Azizi, 2021). Computer Vision automates site monitoring, progress tracking, defect detection, and safety hazard identification through image and video analysis (Abioye et al., 2021). Natural Language Processing facilitates document analysis, automated report generation, and communication support across distributed teams (DIGIUDA et al., 2020). Robotics and Automation address labour constraints and safety risks through autonomous systems for repetitive and hazardous tasks (Singh et al., 2021). Digital Twins create virtual representations of construction processes enabling scenario analysis, planning optimisation, and performance prediction (Owais et al., 2024). Real-time Analytics Systems provide immediate visibility into construction process performance through continuous monitoring and KPI tracking (Dave et al., 2016).

While prior work has examined individual AI applications or digital support for specific lean practices, the literature lacks a consolidated, principle-level map of which AI approaches are most consistently linked to which lean construction principles and practices across studies. Prior research has identified promising individual applications (McHugh et al., 2025; Vickranth et al., 2019), but without systematic analysis enabling organisations to prioritise AI investments based on lean principles. This study addresses this mapping gap through systematic network analysis of AI-lean construction relationships.

RESEARCH METHODOLOGY

RESEARCH DESIGN

This study employs a hybrid research design combining systematic literature review (SLR) with Social Network Analysis (SNA) to examine relationships between AI approaches and lean construction constructs. SLR ensures systematic, reproducible identification of relevant evidence following established protocols, providing rigorous coverage of the research domain. SNA enables quantitative analysis of relationship patterns across the identified body of literature, identifying structural patterns and priorities. Together, these methods provide both methodological rigour and quantitative mapping of conceptual relationships.

Social Network Analysis was selected as the primary analytical framework due to its proven effectiveness for analysing complex relationships within construction management contexts (Bidhendi et al., 2025; Sheikhhoshkar et al., 2023; Tuivai et al., 2025). SNA provides mathematical and visual approaches for understanding how different concepts and practices interact within complex systems, making it particularly suitable for examining multifaceted relationships between AI and lean construction.

SYSTEMATIC LITERATURE REVIEW PROTOCOL

A systematic search was conducted across Scopus, and Google Scholar to identify peer-reviewed studies linking AI approaches with lean construction principles and practices. The search strategy employed Boolean operators combining AI technology keywords ("artificial intelligence," "machine learning," "deep learning," "computer vision," "natural language processing," "robotics," "real-time analytics," "digital twins," "predictive analytics") with lean construction terminology ("lean construction," "lean management," "Last Planner System," "visual management," "waste reduction," "continuous improvement," "value stream mapping," "takt planning") and construction domain terms ("construction," "built environment," "infrastructure," "AEC industry"). Search terms included truncation (lean*, productiv*) and synonyms to capture term variations.

Inclusion Criteria: Publications were included if they (1) addressed AI technologies or digital tools in construction contexts; (2) discussed lean construction principles, tools, or practices; (3) provided empirical evidence, case studies, or theoretical frameworks; (4) were published in peer-reviewed journals or conference proceedings; (5) were published between 2015 and 2025; and (6) were written in English.

Exclusion Criteria: Studies were excluded if they (1) focused solely on gaming or entertainment applications; (2) addressed industries other than construction without transferable insights; (3) lacked sufficient technical detail about implementation; or (4) were opinion pieces without original analysis.

Search Details and Screening Process: The search was conducted in December 2025 and updated in January 2026. Records were imported into Mendeley for duplicate removal. Title and abstract screening were conducted by authors. Full-text assessment for eligibility was conducted following PRISMA 2020 guidelines shown in Figure 1. An initial search identified 1,247 potentially relevant publications. Following title and abstract screening, 234 sources underwent full-text assessment for eligibility. The final corpus comprised 67 publications that provided sufficient empirical detail about AI approaches and lean construction constructs for relationship mapping.

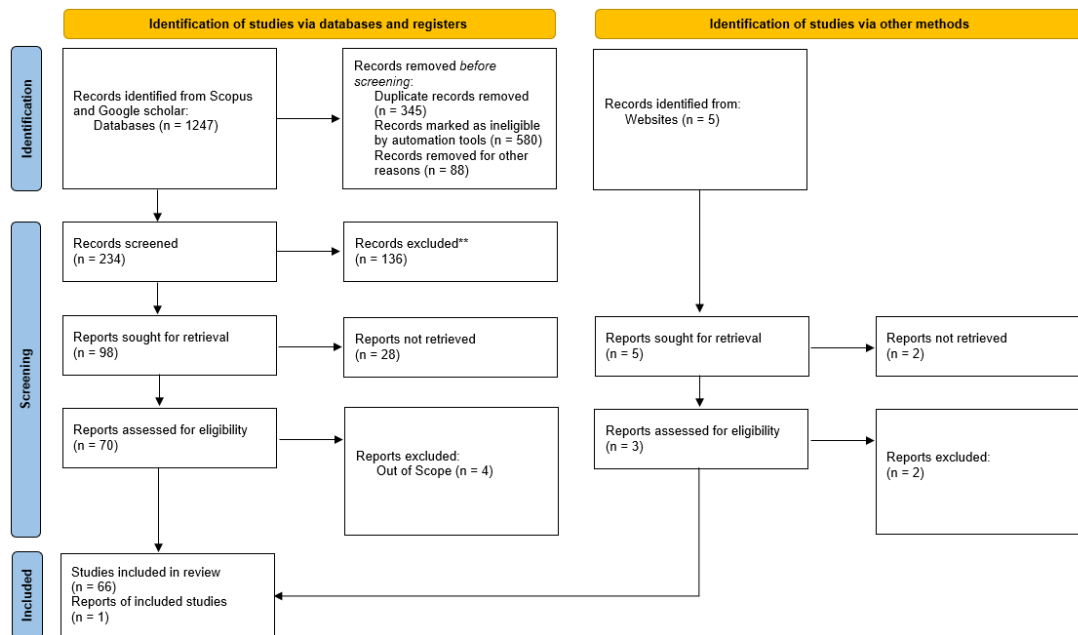


Figure 1: SLR process

SOCIAL NETWORK ANALYSIS METHODOLOGY

A reference matrix Q was developed with lean construction constructs as rows ($n=14$) and AI approaches as columns ($m=11$). Matrix cells were populated with binary values (0 or 1) indicating the presence or absence of documented relationships between specific constructs and AI approaches based on systematic literature analysis.

The reference matrix $Q_{(n \times m)}$ has lean constructs as rows ($n=14$) and AI approaches as columns ($m=11$), with binary entries (0/1) indicating documented relationships.

The weighted adjacency matrix was calculated using:

$$W_{(n \times n)} = Q_{(n \times m)} \times Q^T_{(n \times m)}, \text{ for } i \neq j$$

Where cells represent shared connections between pairs of lean principles.

Degree centrality for each AI approach was calculated as:

$$D_i = \sum W_{(i,j)} \text{ for } j=1 \text{ to } n, j \neq i$$

Where D_i represents the degree centrality of lean construct i , $W_{(i,j)}$ represents the weighted relationship between principle i and principle j from the weighted adjacency matrix.

Normalised centrality scores were calculated by dividing raw degree scores by the maximum possible score ($n-1 = 13$, representing complete connection to all other lean constructs), resulting in scores on a 0–1 scale.

RESULTS

IDENTIFIED AI APPROACHES

Through systematic analysis of the selected literature, eleven distinct AI approaches were identified and coded for network analysis as shown in Table 1. These approaches represent the most frequently discussed AI capabilities in construction contexts, with sufficient detail available to enable relationship mapping with lean construction constructs.

Table 1: Identified AI approaches.

ID	AI Approach	Application Focus
AIA01	Machine Learning for Predictive Analytics	Cost/schedule prediction, pattern recognition
AIA02	Computer Vision for Site Monitoring	Progress tracking, defect detection, hazard identification
AIA03	Real-time Analytics Systems	Performance monitoring, KPI tracking, process optimisation
AIA04	Natural Language Processing	Documentation, communication support, knowledge extraction
AIA05	Robotics and Automation	Repetitive task execution, hazardous work handling, cycle time reduction
AIA06	IoT-enabled Monitoring Systems	Real-time data collection, environmental monitoring, connectivity infrastructure
AIA07	Digital Twins for Simulation	Planning, scenario analysis, performance prediction
AIA08	Predictive Risk Management Systems	Risk identification, mitigation planning, early warning
AIA09	Automated Progress Tracking	Schedule adherence, milestone tracking, workflow status
AIA10	AI-enhanced Resource Optimisation	Material planning, equipment allocation, labour scheduling
AIA11	Knowledge Management Systems	Lessons learned capture, decision support

IDENTIFIED LEAN CONSTRUCTION CONSTRUCTS

For the purposes of this network analysis, recognised lean construction principles (value, flow, waste, learning, reliability, pull, and respect for people) and commonly documented lean practices were consolidated into a set of analytical constructs used to map AI–lean relationships. These constructs encompass both core lean principles and the key outcomes and practices through which these principles are operationalised in construction contexts. This categorisation serves the methodological purpose of network analysis and should not be interpreted as a normative or exhaustive taxonomy of lean construction principles. Fourteen core lean construction constructs were identified from the literature as shown in Table 2.

Table 2: Identified lean construction principles.

ID	Lean Construction Construct	Focus Area
LCP01	Optimal Scheduling and Planning	Process optimisation
LCP02	Pull-Based Production	Flow management
LCP03	Visual Management	Information visibility
LCP04	Continuous Improvement/Kaizen	Process enhancement
LCP05	Waste Reduction	Efficiency improvement
LCP06	Flexibility and Adaptability	Responsiveness
LCP07	Value Delivery	Customer satisfaction
LCP08	Stakeholder Collaboration	Coordination
LCP09	Process Efficiency and Productivity	Performance
LCP10	Resource Optimisation	Asset management
LCP11	Risk and Certainty Management	Project control
LCP12	Project Coordination	Integration
LCP13	Quality Management	Defect reduction
LCP14	Process Standardisation	Consistency

SNA DEGREE CENTRALITY AND RELATIONSHIP ANALYSIS

The network analysis revealed significant variation in connectivity patterns among AI approaches as shown in Table 3. Real-time analytics systems demonstrated the highest centrality score (0.91), followed closely by machine learning (0.89) and computer vision (0.87). These approaches showed strong coverage across multiple lean constructs in the reviewed studies, indicating broad integration across reported lean-AI relationships in the literature.

Table 3: AI approaches centrality analysis.

Rank	AI Approach	Centrality Score	Key Lean Connections (Top 5)
1	Real-time Analytics (AIA03)	0.91	LCP03, LCP04, LCP05, LCP09, LCP12
2	Machine Learning (AIA01)	0.89	LCP01, LCP04, LCP09, LCP10, LCP11
3	Computer Vision (AIA02)	0.87	LCP03, LCP05, LCP09, LCP13, LCP14
4	Digital Twins (AIA07)	0.84	LCP01, LCP04, LCP07, LCP10, LCP11
5	Predictive Risk Management (AIA08)	0.81	LCP04, LCP06, LCP11, LCP13, LCP14
6	Automated Progress Tracking (AIA09)	0.78	LCP01, LCP03, LCP09, LCP12, LCP14
7	IoT-enabled Monitoring (AIA06)	0.75	LCP03, LCP05, LCP09, LCP14, LCP11
8	AI-enhanced Resource Optimization (AIA10)	0.72	LCP05, LCP09, LCP10, LCP02, LCP08
9	Robotics and Automation (AIA05)	0.68	LCP05, LCP09, LCP14, LCP02, LCP13
10	Knowledge Management Systems (AIA11)	0.65	LCP04, LCP08, LCP14, LCP03, LCP12
11	Natural Language Processing (AIA04)	0.62	LCP08, LCP12, LCP14, LCP03, LCP04

The network analysis shown in Figure 2 and 3, identified three distinct clustering patterns based on the distribution of relationships and overlap in connected lean constructs:

Cluster 1 (Efficiency and Waste Reduction Focus): AIA03, AIA01, AIA02, AIA09 - these approaches show reported connections to efficiency, waste visibility, and performance monitoring objectives through real-time feedback and predictive capabilities.

Cluster 2 (Planning and Optimisation Focus): AIA07, AIA08, AIA10, AIA04 - these approaches show reported connections to planning, resource optimisation, and risk management through simulation, prediction, and resource analysis capabilities.

Cluster 3 (Coordination and Communication Focus): AIA11, AIA06, AIA05 - these approaches show reported connections to collaboration, information flow, and team coordination across distributed teams.

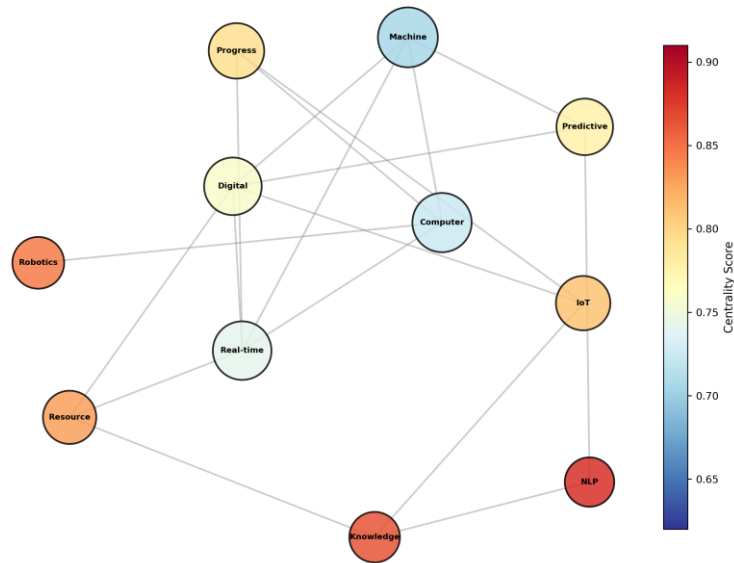


Figure 2: AI approaches network

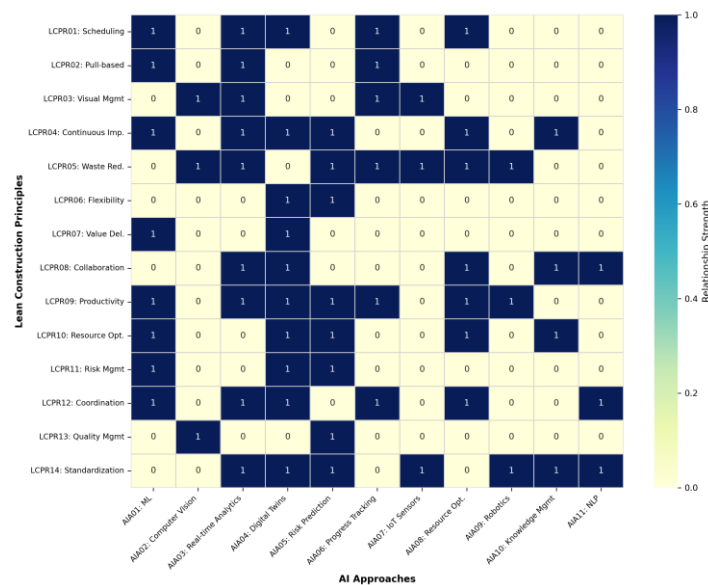


Figure 3: Bipartite incidence matrix of AI approaches and lean constructs

DISCUSSION

Based on the centrality analysis and connectivity patterns in the reviewed literature, we propose a three-tier integration framework to guide construction organisations in evaluating and prioritising AI approaches within lean construction contexts. The framework is based on evidence-map prominence rather than measured performance impact and enables decision-making tailored to organisational priorities while acknowledging implementation constraints. This tier reflects the breadth of documented relationships in the reviewed literature, not measured performance impact or real-world adoption effectiveness.

TIER 1 - HIGH- CONNECTIVITY APPROACHES (CENTRALITY > 0.85)

Three AI approaches demonstrate exceptionally broad coverage across lean constructs in the reviewed literature and are recommended as foundational evaluation priorities. These

approaches show strong documented connections across diverse lean objectives in published research, making them valuable starting points for organisations considering AI-enabled lean implementation.

Real-time Analytics Systems (AIA03, centrality score 0.91) demonstrate the highest connectivity across lean constructs in the literature. These systems provide immediate visibility into construction process performance, and are frequently studied in connection with waste reduction, reliability, and continuous improvement principles (Abioye et al., 2021). Reported applications include: Real-time KPI dashboards tracking workflow progress, resource utilisation, and schedule adherence (Alzubi et al., 2025). IoT-enabled monitoring of material flow and work-in-process status (Zhao, 2022). Constraint identification and removal supporting Last Planner System implementation (Garcés & Peña, 2023). Detection of idle resources and workflow bottlenecks (Chen et al., 2018).

Successful deployment typically requires robust data infrastructure, integrated information systems, and operator training. Organisations benefit from executive sponsorship, clear metric definition aligned with lean objectives, and integration with existing project management systems.

Machine Learning for Predictive Analytics (AIA01, centrality score 0.89) is frequently reported in the literature as enabling data-driven decision-making through pattern recognition. ML approaches show documented connections to planning, continuous improvement, risk management, and resource optimisation (Adebowale & Agumba, 2024). Key reported applications include: Predictive schedule risk assessment enabling more reliable planning (Li et al., 2025). Improved cost estimation supporting target value design principles (Johansen et al., 2021). Resource demand forecasting supporting just-in-time procurement (Kilic & Erkeyman, 2021). Identification of rework-prone tasks for proactive quality focus (Bidhendi & Azizi, 2021).

Success depends on data quality and availability, requiring organisations to invest in comprehensive historical project data governance. Additionally, ML insights should be integrated into actual project decision-making processes, and organisations benefit from collaborative industry data sharing initiatives and training programs for internal capability development.

Computer Vision for Site Monitoring (AIA02, centrality score 0.87) automates progress tracking and defect detection, with documented connections in the literature to visual management, waste identification, and quality objectives (Abioye et al., 2021). Reported applications include: Automated daily progress photography for schedule verification and documentation (Karmaoui et al., 2023). Real-time detection of material stockpiles and idle resources representing waste (Chen et al., 2018). Safety hazard identification during construction execution (Bidhendi & Azizi, 2021). Automated defect detection enabling immediate remediation (Haahr et al., 2019).

Implementation typically requires camera infrastructure across project sites, stable internet connectivity, and clear image quality standards. Success factors include precise specification of monitored areas and detection parameters, integration with project workflows, and establishment of privacy, security, and worker consent protocols appropriate to the regulatory context.

TIER 2 - MEDIUM- CONNECTIVITY APPROACHES (CENTRALITY 0.75-0.84)

These approaches demonstrate strong coverage with specific lean constructs and provide value in targeted organisational contexts. Implementation should be based on organisational priorities, existing lean maturity, and alignment with specific lean objectives rather than automatic adoption.

Digital Twins for Simulation (AIA07, centrality score 0.84) provide substantial value for organisations with significant planning complexity or those implementing advanced takt planning approaches. The literature documents connections to planning, optimisation, risk management, and continuous improvement (Owais et al., 2024). Digital twins create virtual representations enabling scenario analysis and what-if evaluation. Reported applications include construction sequence optimisation, resource allocation evaluation, and bottleneck analysis. However, implementation requires significant upfront modelling effort and assumes organisational BIM capability.

Predictive Risk Management Systems (AIA08, centrality score 0.81) support continuous improvement through early identification of potential disruptions, with documented connections to risk management, adaptability, and quality principles. These systems identify projects at elevated risk before problems materialise, creating opportunities for proactive mitigation. Reported applications include schedule risk prediction with systematic mitigation, quality and safety risk forecasting, and supply chain disruption early warning. Success requires organisational commitment to proactive management and integration with existing project controls frameworks. (Hasan et al., 2018).

Automated Progress Tracking (AIA09, centrality score 0.78) automates schedule adherence monitoring, with documented connections to planning and coordination (Schönbeck et al., 2020). Rather than relying on manual progress reporting, automated tracking provides near-real-time workflow status updates, daily milestone verification based on evidence, and constraint removal tracking.

TIER 3 - EMERGING APPROACHES (CENTRALITY < 0.75)

The third tier encompasses approaches with developing coverage in the literature that merit evaluation for specific organisational contexts. These approaches show connections to fewer lean constructs or lower degree centrality in the reviewed studies, suggesting more focused application areas: IoT-enabled Monitoring Systems (0.75) for data infrastructure and real-time monitoring supporting analytics. AI-enhanced Resource Optimisation (0.72) for just-in-time material and labour planning. Robotics and Automation (0.68) for waste reduction in repetitive, hazardous tasks. Knowledge Management Systems (0.65) for capturing and sharing lessons learned. Natural Language Processing (0.62) for documentation, communication support, and knowledge extraction

While individually showing narrower connectivity to lean constructs compared to Tier 1 approaches, these methods provide significant value in specific contexts. The network analysis identified potential alignment opportunities: computer vision and automated progress tracking enhance visual management by automating information capture; machine learning and predictive risk management accelerate continuous improvement by identifying patterns faster than traditional approaches; real-time analytics aligned with Last Planner principles enable proactive constraint removal.

CONCLUSION

This study employed Social Network Analysis to systematically map reported relationships between eleven AI approaches and fourteen lean construction constructs based on analysis of 67 peer-reviewed studies from 2015–2025. The research makes three primary contributions. First, it provides a systematic network analysis of reported AI-lean construction relationships, establishing that these represent complementary approaches based on documented literature patterns. The literature indicates recurring alignments suggesting that AI approaches and lean principles can be strategically integrated, with AI capabilities in sensing and analysis supporting lean principles focused on visibility, flow, and continuous improvement.

Second, the research quantifies connectivity patterns through degree centrality analysis, identifying real-time analytics (0.91), machine learning (0.89), and computer vision (0.87) as broadly connected approaches across many lean constructs, along with medium-connectivity and emerging approaches with more focused lean connections. These connectivity patterns reflect the breadth of documented relationships in the reviewed literature and provide a basis for prioritisation.

Third, the research proposes a practical three-tier framework enabling evidence-based evaluation of AI approaches relative to organisational lean objectives and readiness, supplemented by identification of alignment opportunities suggested by the network mapping. This framework supports practitioners to move beyond generic technology adoption toward strategically informed AI-lean evaluation tailored to organisational contexts.

The study acknowledges important limitations. This research mapped documented relationships between AI and lean constructs in academic literature rather than empirical project implementation data, potentially missing context-specific factors and organisational contingencies. Geographic concentration in developed economies may limit transferability. The network analysis is based on literature-derived indicators rather than measured implementation effectiveness or adoption patterns. Future research should include empirical validation through case studies and field implementations, longitudinal studies of AI adoption dynamics, context-specific frameworks for different project types and regions, and investigation of emerging technologies and organisational capability development.

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