

# ESTABLISH A LEAN AI-DRIVEN DEFECT MANAGEMENT FRAMEWORK

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## ABSTRACT

The construction industry continues to face significant performance challenges due to defective work, with rework estimated to account for a substantial portion of project costs. Despite the adoption of Lean Construction principles, effective learning from defects remains hindered by fragmented workflows and the unstructured nature of defect data. Furthermore, while Artificial Intelligence (AI) has shown promise in quality management, existing research predominantly focuses on Computer Vision for reactive detection rather than leveraging textual data for proactive prevention. To address this gap, this study adopts a conceptual research methodology to propose the Lean AI-Driven Defect Management Framework. This framework integrates the philosophical pillars of Lean Construction: Respect for People, Flow, and Value, with the analytical capabilities of Large Language Models (LLMs). The proposed model conceptualises defect data not as a compliance metric, but as a strategic resource for organisational learning. By utilizing LLMs to process unstructured defect records and identify recurring patterns, the framework supports "just-in-time" decision-making and targeted Lean interventions, such as strategic "Muda walks." This study contributes to the field by offering a theoretical foundation for integrating human-centric Lean values with AI-driven knowledge systems, shifting defect management from reactive correction to continuous, data-driven improvement.

## KEYWORDS

Lean construction, defect management, artificial intelligence, large language model, Lean Construction 4.0.

## INTRODUCTION

The construction industry plays a critical role in national economies, yet its performance continues to be constrained by significant levels of waste. Among the most prominent sources of waste is defective work resulting from errors, which contributes to cost overruns, schedule delays, reduced productivity, and diminished client satisfaction (Bølviken et al. 2014). In the United Kingdom, the Get It Right Initiative (2016) estimates that construction errors account for 10–25% of total project costs, equating to annual losses of £10–25 billion.

Lean Construction seeks to minimise waste and maximise value through the contextual application of Lean principles, techniques, and tools. From a Lean perspective, rework arising from defects, quality deviations, and non-conformance represents a direct loss of time, material, and value. Central to Lean thinking is learning from defects. Systematic identification, analysis, and feedback from defective work enable organizations to improve quality, eliminate waste,

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and foster continuous improvement (Hopkin et al. 2019). Despite this recognition, effective learning from defects remains challenging in practice. Social barriers, such as blame-oriented cultures, coexist with technical challenges related to the capture, analysis, and reuse of defect information (Love et al. 2023; Matthews et al. 2023). Defect management processes are often characterized by fragmented workflows, unstructured defect data, insufficient information input, and limited retrieval mechanisms (Hopkin et al. 2019; Lee et al. 2016). These limitations constrain organizational learning and undermine Lean objectives related to flow reliability, quality at the source, and continuous improvement, highlighting the need for more effective and technology-enabled approaches to defect management (Luo et al. 2022).

Artificial Intelligence (AI) techniques, including computer vision, machine learning, and natural language processing, have been applied to defect detection and classification, improving inspection accuracy. However, most applications remain reactive and detection-oriented, with limited support for cross-project learning and prevention (Luo et al. 2022). Lean Construction 4.0 research argues that Lean principles should guide digital transformation, with technologies acting as enablers of information flow and learning (González et al. 2022). Critically, evidence shows that technology adoption alone does not improve defect outcomes (London et al. 2021): without Lean principles structuring how outputs are acted upon, digital tools risk automating existing waste rather than eliminating it. Existing work has proposed AI-Lean linkages (Cisterna et al. 2022), yet defect prevention through systematic cross-project learning remains underexplored. In particular, Large Language Models (LLMs), which are suited for interpreting the unstructured textual data that dominates defect records, have received limited attention in this context (Cusumano et al. 2025).

To address this gap, this study proposes the Lean AI-Driven Defect Management Framework, a conceptual model that integrates Lean Construction principles with AI capabilities to support proactive, data driven, and learning oriented defect management. Rather than treating defects solely as issues requiring resolution, the framework conceptualises defect data as a strategic resource for organisational learning. It embeds core Lean principles, including Respect for People, Flow, and Value, while leveraging AI, particularly large language models, to enhance information flow, analytical capability, and cross-project learning. The framework makes three theoretical contributions. First, it establishes LLMs as a distinct enabling capability within Lean Construction 4.0, one that addresses the unstructured textual data challenge constraining systematic learning from defects. Second, it reframes defect data as a strategic organisational asset grounded in Argyris and Schön (1978) double-loop learning theory: current defect management operates at the single-loop level, fixing individual defects without revising the systemic conditions producing them; the framework is designed to enable double-loop learning by transforming defect data into cross-project knowledge that revises practice. Third, it provides an operational mechanism linking data capture, AI-enabled pattern recognition, and targeted Lean action, closing the gap left by prior frameworks that establish philosophical compatibility between Lean and AI without specifying how they interact in practice in relation to defect management

## LITERATURE REVIEW

### LEAN CONSTRUCTION AND DEFECT MANAGEMENT

Lean Construction, grounded in Koskela's (2000) Transformation-Flow-Value framework, treats defective work as a direct form of waste and learning from defects as a prerequisite for continuous improvement. From a quality perspective, defective work represents a critical form of waste, leading to material loss, time loss, and value loss (Bølviken et al. 2014). Learning from defects is therefore fundamental to Lean thinking, as it enables organisations to identify root causes, prevent recurrence, and improve process reliability over time. However, recent

studies has shown that in practice, learning from defects often remains manual, localised, and dependent on individual experience, which limits the ability of Lean systems to support systematic and organisation-wide learning (Love et al. 2023; Love and Matthews 2022).

The Lean construction institute identify six core tenet that guides lean, which includes:

- **Respect for People** underpins defect learning by fostering psychological safety and a no-blame culture where errors and quality issues can be reported early (Korb 2016; Love et al. 2023). This shifts defect management from fault-finding to organisational learning.
- **Value Generation** defines quality through customer requirements, including both downstream trades and end users (Koskela, 2000). Defects represent value failure when these requirements are not consistently translated into production.
- **Waste Elimination** treats defects as a major form of waste, producing rework, delays, and products unfit for use (Bølviken et al., 2014). Reducing defects therefore directly reduces non-value-adding activities.
- **Continuous Improvement** relies on Kaizen and PDCA cycles, where defect data becomes meaningful only when systematically analysed and converted into preventive actions (Amdal and Drevland 2024; Cisterna et al. 2022).
- **Optimising the Whole** recognises that defects are often system-induced, emerging from cross-team interactions, upstream decisions, and process breakdowns rather than isolated workmanship issues (London et al. 2021). Prevention, therefore, requires root-cause learning at the system level.
- **Focus on Flow** distinguishes Lean from traditional transformation-based management by emphasising stable production and information flow (Koskela, 1992; Bertelsen et al., 2006). Since defects frequently stem from late, missing, or inconsistent information, improving information flow is critical for defect reduction (Tommelein et al., 2022).

Lean construction practices are methods of achieving the lean philosophy and principles at the various phases of a construction project. Several Lean tools are directly relevant to improving quality and minimising defects:

- Last Planner System (LPS) reduces variability by improving workflow reliability and collaborative planning (Ballard 2021).
- Poka-yoke (mistake-proofing) reduces the likelihood of human error by embedding process constraints (Tommelein 2008).
- Five Whys and root cause analysis identify defects' underlying systemic causes (Aziz and Hafez 2013).
- Visual management ensures that deviations are visible and easily correctable (Aziz and Hafez 2013).
- First Run Studies simulate upcoming tasks to identify potential errors in advance (Aziz and Hafez 2013).

However, while these practices have demonstrated effectiveness in reducing variability and improving coordination, their success relies heavily on timely, accurate, and interpretable information (Caldas and Soibelman 2002).

## DEFECT MANAGEMENT AND KEY CHALLENGES IN LEARNING FROM DEFECTS

Defect management is an important part of quality control in the production phase. It involves identifying, documenting, reporting and rectifying executed work that is not in accordance with the specifications or designs (Lee et al. 2016). The primary purpose of defect management is to ensure adherence to standards. In recent times, construction organisations, particularly in

developed countries, have shifted from a purely manual approach to leveraging the use of various digital technologies. However, despite the introduction of digital technologies such as BIM, mobile inspection tools, and database systems to support defect management (Lee et al., 2016), several persistent challenges continue to hinder effective learning from defects. Firstly, defect records are often unstructured, incomplete, and inconsistent, with descriptions relying heavily on free-text entries that vary by individual, trade, and project (Fan, 2022; Lundkvist et al., 2014; Matthews et al., 2022). Secondly, the absence of standardised defect taxonomies limits comparability across projects and undermines pattern recognition (Bazzan et al., 2024; Lundkvist et al., 2014). Also, existing defect databases typically offer limited analytical and retrieval capabilities, relying on keyword-based searches that struggle with inconsistent terminology (Bazzan et al., 2024). Finally, feedback mechanisms remain weak, resulting in repeated defects across projects and limited knowledge transfer (Jeon & Lee, 2025). All these challenges prevent defect data from being transformed into actionable organisational knowledge.

From a Lean perspective, poor information flow and inadequate feedback loops undermine continuous improvement, flow reliability, and quality at the source. As a result, defects persist despite the widespread adoption of Lean practices. These persistent barriers can be understood through Argyris and Schön's (1978) organisational learning theory, which distinguishes between two levels of learning. Single-loop learning occurs when an organisation detects and corrects an error without questioning the underlying norms, assumptions, or processes that produced it. Double-loop learning, by contrast, involves revisiting and revising the governing conditions themselves, producing durable change rather than repeated correction. Current defect management practice operates predominantly at the single-loop level: defects are identified, rectified, and closed out, but the systemic conditions that generated them, fragmented data, absent causal records, and dissolved project knowledge are left unchanged. The consequence is precisely what the literature documents: the same defect types recur across projects because the knowledge needed to prevent them is never converted into organisational learning. For double-loop learning to occur in construction defect management, defect data must be transformed from isolated occurrence records into cross-project, cause-linked knowledge that feeds back into practice. This is the theoretical gap the proposed framework is designed to close.

## **ARTIFICIAL INTELLIGENCE IN CONSTRUCTION DEFECT MANAGEMENT**

Recent advances in AI have generated growing interest in its application to construction quality management. AI techniques such as machine learning, deep learning, computer vision, and natural language processing have been applied to automate defect detection, inspection, and classification (Luo et al. 2022). Most existing studies focus on visual inspection using computer vision and deep learning to identify cracks, surface defects, and material deterioration, which has improved inspection accuracy and efficiency. While these approaches demonstrate the analytical potential of AI, they remain largely reactive and detection-oriented. Moreover, many AI-based systems depend on structured or image-based data and offer limited support for learning, feedback, and defect prevention. Also, the challenge of extracting knowledge from large volumes of unstructured defect text and embedding insights into Lean improvement cycles remains unresolved.

## **RESEARCH GAP**

Lean Construction 4.0 represents the convergence of Lean philosophy with Industry 4.0 technologies, emphasising that Lean provides the guiding principles (“the why”), while digital technologies provide the enabling mechanisms (“the how”)(Hamzeh et al. 2021). When effectively integrated, digital technologies can enhance Lean practices by improving

information flow, enabling real-time feedback, and strengthening root cause analysis (González et al. 2022). However, without the appropriate processes and learning-oriented systems, digital tools risk just automating existing waste.

Within Lean construction 4.0 research, attention has primarily focused on technologies such as computer vision, sensors, and automation (Brissi & Debs, 2019). LLMs, however, represent a critical yet underexplored capability. LLMs are uniquely suited to defect management due to their ability to interpret unstructured text, capture semantic meaning, standardise heterogeneous defect descriptions, and support conversational access to organisational knowledge (Cusumano et al. 2025; Naveed et al. 2024). By enabling automated defect standardisation, cross-project pattern detection, and real-time knowledge retrieval, LLMs offer the potential to address long-standing challenges in defect information management. Importantly, these capabilities align closely with Lean principles by strengthening information flow, supporting continuous improvement, and enabling learning-oriented defect prevention. Despite this potential, the integration of LLMs within Lean-based defect management frameworks remains limited in the literature.

Across these three domains, a consistent misalignment emerges: Lean Construction requires reliable information flow and systematic learning to achieve continuous improvement, yet defect management generates data too unstructured for pattern analysis, and existing AI applications address detection rather than learning. LLMs represent the specific capability that closes this triangle, operating on the textual language of defect records to enable standardisation, cross-project pattern detection, and actionable knowledge retrieval within a Lean operational framework.

## METHODOLOGY

This study adopts a conceptual research methodology to develop a theoretically grounded framework that integrates Lean Construction principles with artificial intelligence capabilities for defect management. Conceptual research is appropriate for synthesising existing knowledge into new explanatory models and theoretical constructs, particularly in emerging research domains where empirical evidence remains limited (Snyder 2019). In such contexts, the primary aim is not hypothesis testing, but the development of explanatory structures and integrative models that can guide future empirical investigation and practical implementation.

The research is positioned within the Lean Construction and organisational learning paradigm, which emphasises continuous improvement, information flow, and respect for people. Artificial intelligence, particularly large language models, is conceptualised not as a replacement for human decision-making but as an enabling mechanism that strengthens learning, sense-making, and feedback within Lean systems. Accordingly, the methodological focus is on synthesising established theory and prior empirical insights into a coherent, learning-oriented framework for defect management. The synthesis employed concept mapping to identify structural relationships across the three knowledge domains, with each domain deconstructed into its core mechanisms and limitations before gaps and leverage points were identified. The framework is explicitly designed as a precursor to empirical validation, providing the conceptual architecture that guides a broader programme involving expert interviews, computational analysis of industry defect records, and prototype system development. As a limitation inherent to conceptual research, the propositions and mechanisms advanced here are theoretically grounded but not yet empirically tested; their validity is contingent on the quality of the source literature and the coherence of the synthesis logic rather than on direct observation.

## **LITERATURE IDENTIFICATION AND SYNTHESIS STRATEGY**

A structured literature synthesis was undertaken to inform framework development. Relevant studies were identified through searches of major academic databases, including Scopus, Web of Science, and Google Scholar. Search terms were organised into three primary clusters:

- Lean construction, learning, quality, continuous improvement
- Defect management, rework, non-conformance, quality defects
- Artificial intelligence, machine learning, natural language processing, large language models, Construction 4.0

Peer-reviewed journal articles and high-quality conference papers particularly those from IGLC were prioritised. Seminal Lean Construction works were included irrespective of publication year, while AI-related studies were primarily drawn from the last 15 years to reflect recent technological developments. Studies were included if they addressed at least one of the following: (1) learning from defects in construction, (2) digital or AI-supported defect management, or (3) integration of Lean principles with digital technologies.

Rather than aiming for exhaustive coverage, the synthesis focused on identifying recurring concepts, mechanisms, limitations, and points of misalignment across the three knowledge domains.

## **FRAMEWORK DEVELOPMENT PROCESS**

The development of the framework followed three iterative phases adapted from Jabareen (2009) conceptual framework analysis methodology. In Phase 1 (theoretical deconstruction), each domain, was analysed systematically for its core mechanisms, enabling conditions and documented failure points, based on the structure literature synthesis described above. In Phase 2 (Gap Analysis and Conceptual Mapping), the three domains were mapped against each other using a functional complementarity criterion: each domain was assessed for what it structurally requires to achieve its stated purpose and what it currently cannot supply alone. This analysis revealed a specific structural fit: Lean Construction's continuous improvement logic requires reliable, cross-project information flow (Cisterna et al. 2022); defect management generates the raw material for that flow but in a form too unstructured for systematic analysis (Park et al. 2013); and LLMs are the specific capability that can process that unstructured material and return it as actionable knowledge (Naveed et al. 2024). The integration is not asserted as general synergy but derived from this functional dependency; each component's output becomes the next component's required input, which was adopted as the internal coherence criterion for framework design. In Phase 3 (Framework Synthesis), the integrated model was constructed by positioning LLMs at the intersection of these identified gaps, then embedding the entire mechanism within Lean's philosophical structure.

## **THE CONCEPTUAL FRAMEWORK: LEAN AI-DRIVEN DEFECT MANAGEMENT**

The Lean AI-Driven Defect Management Framework (Figure 1) integrates Lean philosophy, digital defect management, and Artificial Intelligence (AI) to drive quality in construction. The framework is structured into two primary layers: the philosophical foundation and operational engine. As the defect data is captured, analysed and acted upon through the operational cycle, that accumulated learning flows upward towards the apex goal of Build in Quality.

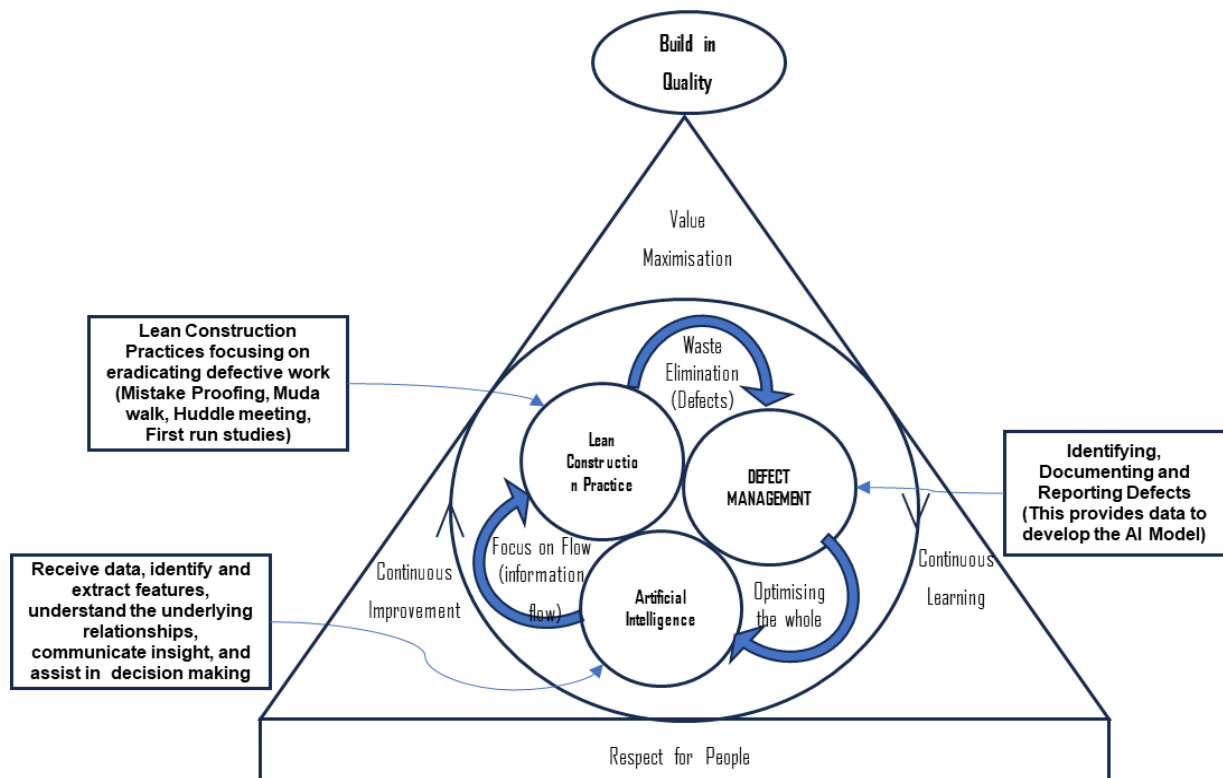


Figure 1: Lean AI-Driven Defect Management Framework

## THE PHILOSOPHICAL FOUNDATION

The triangle serves as the boundary for all activities, ensuring that technological implementation and defect management activities occur within Lean values (McHugh et al., 2022).

- Respect for People:** The framework is grounded in Respect for People, ensuring that the system supports the workforce rather than replacing or burdening it (Noueihed & Hamzeh, 2022). This includes reducing non-value adding administrative effort and fostering psychological safety so defects can be reported without fear of blame (Love et al., 2023). Defects are treated as learning opportunities, while LLMs support decision making by automating routine tasks and providing timely clarity and feedback. This principle extends that workers, supervisors and managers must see LLM as tools that enhance their professional judgement rather than as mechanisms for surveillance or performance monitoring.
- Continuous Improvement and Continuous Learning:** These principles drive value creation by enabling regular reflection, rapid learning from mistakes, and adjustment based on feedback (Amdal & Drevland, 2024). AI strengthens these mechanisms by enabling access to defect histories, supporting real time root cause insights, and identifying cross project trends. LLM based knowledge retention ensures learning is preserved and reused, supporting sustained continuous improvement (Cisterna et al., 2022).
- Build in Quality (Value Maximisation):** The ultimate goal of the framework is to build quality into the process from the outset, rather than relying on reactive inspection, thereby supporting right first time delivery (Marosszeky et al., 2002). LLMs act as the intelligence layer that synthesises unstructured project information such as inspection notes and historical reports to identify conditions likely to cause defects and provide actionable preventive insights (Lagos et al., 2024).

## THE CORE: THREE INTERLOCKING CIRCLES

The core of the framework consists of three interlocking operational domains. As shown in Figure 1, these circles do not function in isolation; rather, they form a continuous feedback loop where data is transformed into intelligence, and intelligence is translated into site-level action.

- Defect Management (The Data Source):** This focuses on identifying, documenting, and reporting defects (Lee et al., 2016). Within this framework, these activities are not merely administrative; they provide the critical "data fuel" required to develop and refine the AI model (Cisterna et al. 2022). Defects become data points for learning, not just problems to fix. The record should capture not just what broke but the conditions present when it broke, including inspection notes, meeting records, and project documentation, ensuring the data corpus reflects the full project context (optimising the whole).
- Artificial Intelligence: The LLM Analytical Engine:** AI specifically Large Language Models (LLMs) serves as the "brain" or the sense-making mechanism of the cycle. Unlike traditional analytics, LLMs excel at processing the high volume of unstructured text typical of construction reports. The primary data inputs to the LLM are digital free-text records generated during defect management, including mobile inspection reports, site diary entries and meeting minutes, which are usually in unstructured or semi-structured formats. The LLM receives raw text data from the defect management process and performs three analytical tasks. The first is defect standardisation, which can be achieved through a few-shot prompted classifications: The LLM is provided with example mappings from raw descriptions to standardised defect types drawn from a defect taxonomy, and generalises this mapping across new records. The Second is Pattern detection across project. This is not performed by the LLM alone; it requires the LLM to work in conjunction with a structured knowledge representation, such as a knowledge graph, that aggregates data into query able relational structures (Jeon and Lee 2025). The LLM then interprets and communicates the patterns surfaced in natural language. Insight generation uses retrieval-augmented generation: relevant entities, relationships, and precedents are retrieved from the knowledge store and passed to the LLM as context, which synthesises them into a plain-language advisory for the practitioner. The insights are communicated to the team in natural language, providing "just-in-time" knowledge that supports proactive decision-making. The focus here is to ensure "information flow" is optimised, getting the right insight to the right person at the right time (Caldas and Soibelman 2002).
- Lean Construction Practice (The Action Engine):** This represents the "on-the-ground" execution where AI-generated intelligence is operationalised through established Lean tools and behaviours. Within this cycle, Mistake Proofing (Poka-yoke) utilises AI insights to guide the design of physical or procedural constraints, effectively preventing the recurrence of identified failure modes. Rather than performing generalised site tours, managers conduct Strategic Muda Walks, which are "Waste Walks" specifically targeted at high-risk hotspots previously identified by the LLM. The focus here is on proactive waste elimination and ensuring quality is gotten right at the source.

## ILLUSTRATIVE USE CASE: FINISHING DEFECTS

To ground the framework in practice, this section presents an illustrative use case explaining how the three core interlocking circles can work as per Figure 1. This is because these three circles present the operational level of the framework. The purpose is to demonstrate conceptual feasibility rather than empirical validation, although the illustration aligns with an ongoing

empirical study. Therefore, we present a use case in finishing defects scenario, and only high-level information is provided here.

**Defect management:** At this stage, the primary priority is to capture defects data. Take Australia's residential construction sector for example, during pre-handover inspections stage, the site supervisors document various finishing defects, such as paint inconsistencies, incomplete caulking, and surface scratches, using a mobile inspection application. Each record includes location, a photograph, responsible parties, and a short textual description. In practice, however, these descriptions are brief and inconsistent: one record may read "paint touch-up required," while other logs the same condition as "surface blemish" or "finish not acceptable." Fields for root cause, associated work activity, and prevention strategy are left blank. This pattern is well documented in the literature: defect records are characterised by missing records, with causal and prevention fields systematically absent (Fan, 2022; Matthews et al., 2022). Despite identifying, documenting, and rectifying these defects at project closeout, the underlying conditions that allowed them to recur are not available to inform future projects.

**LLM Analysis:** Within the proposed framework, the accumulated defect records across multiple projects are input into an LLM analytical engine. The LLM performs three analytically distinct tasks, each relying on a different mechanism. First, *standardisation*: the LLM is provided with a domain defect taxonomy and example mappings through few-shot prompting, enabling it to classify heterogeneous descriptions such as "paint touch-up," "surface blemish," and "finish not acceptable" under a common standardised defect type, resolving the inconsistency that prevents meaningful cross-project comparison (Bazzan et al., 2024; Lundkvist et al., 2014; Cusumano et al., 2025). Second, *pattern detection* is conducted through aggregation of defect data into a structured knowledge representation, such as a knowledge graph that supports relational querying. The LLM supports interpretation by translating structured outputs into actionable insights for decision-makers. Third, *insight generation* is enabled through the retrieval of relevant entities, relationships, and precedents from the knowledge store using retrieval augmented generation. The LLM synthesizes this information and communicates actionable insights to the project team.

**Lean Action:** The insight generated by the LLM is used to come up with Lean interventions through the Lean Construction Practice component. For instance, a strategic *Muda* walk is directed specifically at finishing trades in areas identified to be prone to defective work rather than a general site inspection. A *Poka-yoke* intervention is introduced: a mandatory hold point requiring supervisor sign-off on preceding trade completion before finishing trades commence on any level, directly informed by the pattern the LLM identified. These targeted actions operationalise the framework's core logic, that LLM-generated intelligence should guide specific, evidence-informed Lean responses rather than generic quality checks, and the outcomes feed back into the defect record corpus, progressively enriching the knowledge base over subsequent projects and closing the continuous improvement cycle.

## DISCUSSION

This framework extends the work of Cisterna et al.'s (2022) which identifies the synergy between AI and lean construction for continuous improvement in two aspects. First, it specifies LLM operating on unstructured defect text, rather than treating AI generically. This matters because the challenge of unstructured, sparse defect records is the principal barrier to cross-project learning identified in the literature (Fan, 2022; Matthews et al., 2022), and LLMs are distinctively suited to address it in ways that other AI modalities are not. Second, the present framework embeds LLM analysis within an explicit operational cycle linking data capture to Lean action, providing a more concrete account of how AI and Lean interact in practice, beyond establishing that they are philosophically compatible.

The framework also challenges two prevailing assumptions in the literature and offers explicit propositions for future testing. The first assumption it challenges is that technology adoption alone improves defect outcomes: the framework proposes instead that AI capability produces quality improvement when structured by Lean principles that govern how outputs are acted upon, not merely generated. The second assumption challenged is that defect records are primarily compliance artefacts: the framework reframes them as the primary input to an organisational learning system, proposing that their analytical value is proportional to the quality and completeness of capture. Two testable propositions follow.

- Proposition 1: organisations that embed LLM-supported defect analysis within an explicit Lean action cycle will demonstrate greater reduction in recurring defect types across projects than those deploying LLM analysis in isolation.
- Proposition 2: The effectiveness of LLM pattern recognition in defect management is contingent on a minimum threshold of record completeness - specifically, the inclusion of contextual fields beyond description alone.

This first proposition is grounded in evidence that technology adoption alone does not improve defect outcomes (London et al. 2021); the critical variable is whether AI-generated outputs are structured into specific Lean action mechanisms that change site behaviour rather than simply informing it. These propositions provide a basis for the empirical programme that the framework is designed to precede.

## CONCLUSION

This study proposes the Lean AI-Driven Defect Management Framework as a conceptual response to persistent limitations in construction defect management by integrating Lean Construction principles with the analytical capabilities of Large Language Models. The framework reframes defect management from a reactive, compliance-driven activity into a proactive, learning-oriented process grounded in the Lean principle of Respect for People, positioning artificial intelligence as an enabling tool that supports human decision-making and reduces non-value-adding administrative effort. Through a cyclical operational engine that integrates defect management processes, AI capabilities, and Lean practices, the framework transforms raw defect data into actionable knowledge, supports the optimisation of the whole, and enables proactive quality assurance and right-first-time delivery. As a conceptual study, the framework requires empirical validation through case studies or pilot implementations, alongside further research into data quality, ethical considerations, and human-AI interaction to ensure effective and human-centred adoption in construction practice. Three specific future research directions are identified. First, the propositions advanced here should be tested through controlled studies comparing LLM-integrated Lean workflows against conventional defect management, with recurring defect rate as the primary outcome variable. Second, research into minimum data quality thresholds for reliable LLM performance is needed, including whether retrieval-augmented generation can compensate for sparse records.

## REFERENCES

- Amdal, H., and F. Drevland. 2024. "Lean Construction Principles in Practice: Continuous Improvement in the Norwegian Construction Industry." *IOP Conference Series: Earth and Environmental Science*, 1389 (1): 012036. <https://doi.org/10.1088/1755-1315/1389/1/012036>.
- Aravindh, M. D., G. Nakkeeran, L. Krishnaraj, and N. Arivusudar. 2022. "Evaluation and optimization of lean waste in construction industry." *Asian Journal of Civil Engineering*, 23 (5): 741–752. Springer Science and Business Media Deutschland GmbH. <https://doi.org/10.1007/s42107-022-00453-9>.

- Argyris, C., and D. A. Schön. 1978. *Organizational learning : a theory of action perspective*. Addison-Wesley Pub. Co.
- Aziz, R. F., and S. M. Hafez. 2013. "Applying lean thinking in construction and performance improvement." *Alexandria Engineering Journal*, 52 (4): 679–695. Elsevier B.V. <https://doi.org/10.1016/j.aej.2013.04.008>.
- Ballard, G. 2021. "2020 Current Process Benchmark for the Last Planner(R) System of Project Planning and Control." UC Berkeley. <https://doi.org/10.34942/P2F593>.
- Barbosa, A. da S., and D. B. Costa. 2021. "Productivity Monitoring of Construction Activities Using Digital Technologies: A Literature Review." In: *Proc 29th Annu. Conf. Int. Group Lean Constr. IGLC*, 707–716. Lima, Peru.
- Bazzan, J., M. Echeveste, C. T. Formoso, and J. D. S. Kowalski. 2024. "A data-driven customer complaint management model for residential building companies." *Architectural Engineering and Design Management*. Taylor and Francis Ltd. <https://doi.org/10.1080/17452007.2024.2306847>.
- Bølviken, T., J. Rooke, and L. Koskela. 2014. "THE WASTES OF PRODUCTION IN CONSTRUCTION – A TFV BASED TAXONOMY."
- Brissi, S. G., and L. Debs. 2019. "Lean, automation and modularization in construction." In: *Annu Conf Int Group Lean Constr IGLC*, 711–722. The International Group for Lean Construction.
- Caldas, C. H., and L. Soibelman. 2002. "AUTOMATED CLASSIFICATION METHODS: SUPPORTING THE IMPLEMENTATION OF PULL TECHNIQUES FOR INFORMATION FLOW MANAGEMENT."
- Cisterna, D., S. Lauble, S. Haghsheno, and J. Wolber. 2022. "Synergies Between Lean Construction and Artificial Intelligence: AI Driven Continuous Improvement Process." 199–210. Edmonton, Canada.
- Cusumano, L., N. Olsson, M. Granath, R. Jockwer, and R. Rempling. 2025. "Clustering techniques and keyword extraction with large language models for knowledge discovery in building defects data." *Construction Innovation*, 25 (7): 76–97. <https://doi.org/10.1108/CI-04-2024-0123>.
- Fan, C.-L. 2022. "Data mining model for predicting the quality level and classification of construction projects." *Journal of Intelligent and Fuzzy Systems*, 42 (1): 139–153. IOS Press BV. <https://doi.org/10.3233/JIFS-219182>.
- Get It Right Initiative. 2016. "Call to Action | Get It Right Initiative." Accessed October 2, 2024. <https://getitright.uk.com/reports/call-to-action>.
- González, V. A., F. Hamzeh, and L. F. Alarcón. 2022. *Lean Construction 4.0: Driving a Digital Revolution of Production Management in the AEC Industry*. 1st ed. London: Routledge.
- Hamzeh, F., V. A. González, L. F. Alarcon, and S. Khalife. 2021. "Lean Construction 4.0: Exploring the Challenges of Development in the AEC Industry." In: *Proc 29th Annu. Conf. Int. Group Lean Constr. IGLC*, 207–216. Lima, Peru.
- Hopkin, T., S.-L. Lu, M. Sexton, and P. Rogers. 2019. "Learning from defects in the UK housing sector using action research: A case study of a housing association." *Engineering, Construction and Architectural Management*, 26 (8): 1608–1624. <https://doi.org/10.1108/ECAM-04-2018-0146>.
- Jeon, K., and G. Lee. 2025. "Hybrid large language model approach for prompt and sensitive defect management: A comparative analysis of hybrid, non-hybrid, and GraphRAG approaches." *Advanced Engineering Informatics*, 64: 103076. <https://doi.org/10.1016/j.aei.2024.103076>.
- Korb, S. 2016. "'Respect for People' and Lean Construction: Has the Boat Been Missed?" In: *24th Annu. Conf. Int. Group Lean Constr*. Boston, Massachusetts, USA.

- Lee, D.-Y., H.-L. Chi, J. Wang, X. Wang, and C.-S. Park. 2016. "A linked data system framework for sharing construction defect information using ontologies and BIM environments." *Automation in Construction*, 68: 102–113. Elsevier B.V. <https://doi.org/10.1016/j.autcon.2016.05.003>.
- London, K., Z. Pablo, and N. Gu. 2021. "Explanatory defect causation model linking digital innovation, human error and quality improvement in residential construction." *Automation in Construction*, 123: 103505. <https://doi.org/10.1016/j.autcon.2020.103505>.
- Love, P. E. D., J. Matthews, L. A. Ika, P. Teo, W. Fang, and J. Morrison. 2023. "From Quality-I to Quality-II: cultivating an error culture to support lean thinking and rework mitigation in infrastructure projects." *Production Planning and Control*, 34 (9): 812–829. Taylor and Francis Ltd. <https://doi.org/10.1080/09537287.2021.1964882>.
- Lundkvist, R., J. H. Meiling, and M. Sandberg. 2014. "A proactive plan-do-check-act approach to defect management based on a Swedish construction project." *Construction Management and Economics*, 32 (11): 1051–1065. Routledge. <https://doi.org/10.1080/01446193.2014.966733>.
- Luo, H., L. Lin, K. Chen, M. F. Antwi-Afari, and L. Chen. 2022. "Digital technology for quality management in construction: A review and future research directions." *Developments in the Built Environment*, 12: 100087. <https://doi.org/10.1016/j.dibe.2022.100087>.
- Matthews, J., P. E. D. Love, L. A. Ika, and W. Fang. 2022. "Error aversion or management? Exploring the impact of culture at the sharp-end of production in a mega-project." *Developments in the Built Environment*, 10: 100074. <https://doi.org/10.1016/j.dibe.2022.100074>.
- Matthews, J., P. E. D. Love, S. Porter, and W. Fang. 2023. "Curating a domain ontology for rework in construction: challenges and learnings from practice." *Production Planning and Control*. Taylor and Francis Ltd. <https://doi.org/10.1080/09537287.2023.2223566>.
- McHugh, K., B. Dave, and L. Koskela. 2022. *On The Role of Lean in Digital Construction*. Structural Integrity, 226.
- Naveed, H., A. U. Khan, S. Qiu, M. Saqib, S. Anwar, M. Usman, N. Akhtar, N. Barnes, and A. Mian. 2024. "A Comprehensive Overview of Large Language Models." arXiv.
- Perera, S., S. Davis, and M. Marosszeky. 2011. "Interventions in Effecting Change Towards Lean for Australian Building Contractors: Defect Management as a Case of Reference." In: *19th Annu. Conf. Int. Group Lean Constr.*, edited by J. Rooke and B. Dave. Lima, Peru.
- Sadi, M. K., F. Nateghi, F. Mohammadi, and A. Abdullah. 2014. "Mobile application for building defect management system." *Indian Journal of Science and Technology*, 7 (2): 174–179.
- Snyder, H. 2019. "Literature review as a research methodology: An overview and guidelines." *Journal of Business Research*, 104: 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>.
- Tommelein, I. D. 2008. "'Poka yoke' or quality by mistake proofing design and construction systems." In: *Proc IGLC Annu Conf Int Group Lean Constr*, 195–205.