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# The socio-technical gap: an AI framework for project resilience in UK construction

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The UK construction industry faces persistent productivity deficits, with performance 21% below the national economy average. This stems from fragmented Artificial Intelligence (AI) adoption, where dynamic scheduling and proactive risk management operate as isolated systems. Through a Systematic Literature Review following PRISMA 2020 guidelines, this study analysed 60 peer-reviewed papers (2009–2025) to investigate integration barriers and develop a conceptual solution. The review synthesised AI applications in scheduling optimisation and risk management, data integration enablers, and socio-technical adoption barriers. The primary contribution is an Integrated AI Project Control Framework featuring a Risk-to-Constraint Translation Engine that automatically converts heterogeneous risk signals into machine-readable scheduling constraints, establishing continuous feedback loops for adaptive project control. The framework addresses UK-specific challenges through modular design, BIM Framework alignment, and human-in-the-loop interfaces. A key limitation is that the framework remains conceptual, requiring empirical validation through prototype development and live deployment testing.

## KEYWORDS

artificial intelligence, construction management, digital transformation, dynamic scheduling, proactive risk management

## 1 Introduction

The United Kingdom's construction industry contributes approximately 6% of GDP and employs 1.4 million people, yet faces a persistent productivity paradox (ONS, 2021). While UK economic output per hour rose 28.8% between 1997 and 2020, construction productivity fell 7.3%, creating a performance gap averaging 21% below the wider economy (Teicholz, 2013; ONS, 2021). Figure 1 shows productivity growth comparison between whole economy and construction with respect 1997 when it was 100%. This deficit translates directly into project failures: Crossrail opened years late with costs exceeding the 2010 budget due to unrealistic schedules and weak systems integration, while HS2's escalating costs reflect continuing uncertainty and inadequate early-warning mechanisms (Construction News, 2024; ONS, 2024). Provisional 2024/25 figures record 124 work-related fatalities, with construction remaining among the highest-risk sectors (HSE, 2025). These symptoms reveal systemic shortcomings in translating risk foresight into executable control actions.

Government policy mandates integrated, digitally enabled delivery. The Construction Playbook requires central government projects to “embed digital technologies” and adopt the UK BIM Framework for standardised data management, targeting “better, faster, greener” outcomes through systems-level

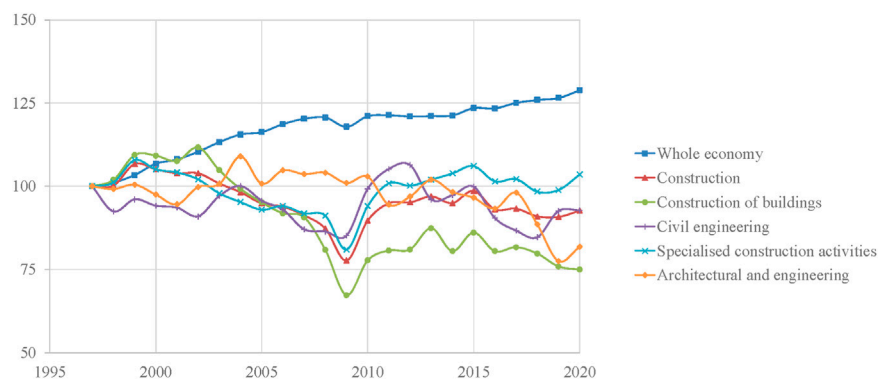


FIGURE 1 Productivity growth comparison between whole economy and construction: Office for National Statistics–Labour Productivity (ONS, 2021).

decision-making across time, cost, safety, and carbon (Cabinet Office, 2022). The Transforming Infrastructure Performance Roadmap to 2030 reinforces this “systems view,” promoting digital twins and interoperable information management to drive productivity and whole-life value (IPA, 2021). Together, these frameworks create a coercive context for technology adoption-yet practice reveals a critical disconnect between policy ambition and operational reality.

Two powerful AI streams have matured in parallel but remain functionally isolated. Dynamic scheduling has evolved from metaheuristic optimisation through machine learning prediction to reinforcement learning for adaptive control. Proactive risk management now employs predictive analytics, natural language processing (NLP), and computer vision (CV) to detect quantitative, textual, and visual risk signals at scale. Despite this technical sophistication, very few solutions formalise the computational bridge converting heterogeneous risk outputs-probabilities, contract flags, hazard alerts-into machine-readable constraints for scheduling engines. This “risk-to-plan” translation problem represents the principal bottleneck for realising the Playbook/TIP vision: forecasted risks cannot automatically trigger re-sequencing, resource reallocation, or contingency adjustments without this mechanism.

The UK’s fragmented, SME-dominated supply chain compounds this challenge. Small firms face entry barriers in data governance, skills, and integration, slowing diffusion of advanced decision tools (Frontier Economics, 2022; ONS, 2024). Meanwhile, persistent safety harm argues for closing the loop between hazard perception and enforceable schedule holds with digital sign-off before work resumes (HSE, 2025). The industry needs not just better analytics but an end-to-end control architecture that: (a) starts from a trustworthy, standardised data layer aligned to UK BIM Framework; (b) fuses multi-modal risk sensing; (c) translates risk into schedule-and-cost constraints; and (d) enables adaptive re-planning under human-in-the-loop governance consistent with organisational adoption theories.

Specifically, current literature reveals a “risk-to-plan” translation problem (Liu et al., 2015). Very few solutions formalise the computational bridge that converts a forecasted risk, such as a safety hazard detected by computer vision—into an immediate, machine-readable constraint that automatically re-

optimises the master schedule. Instead of acting as an integrated control system, these tools function as disconnected dashboards. This disconnect is the principal bottleneck addressed by this research.

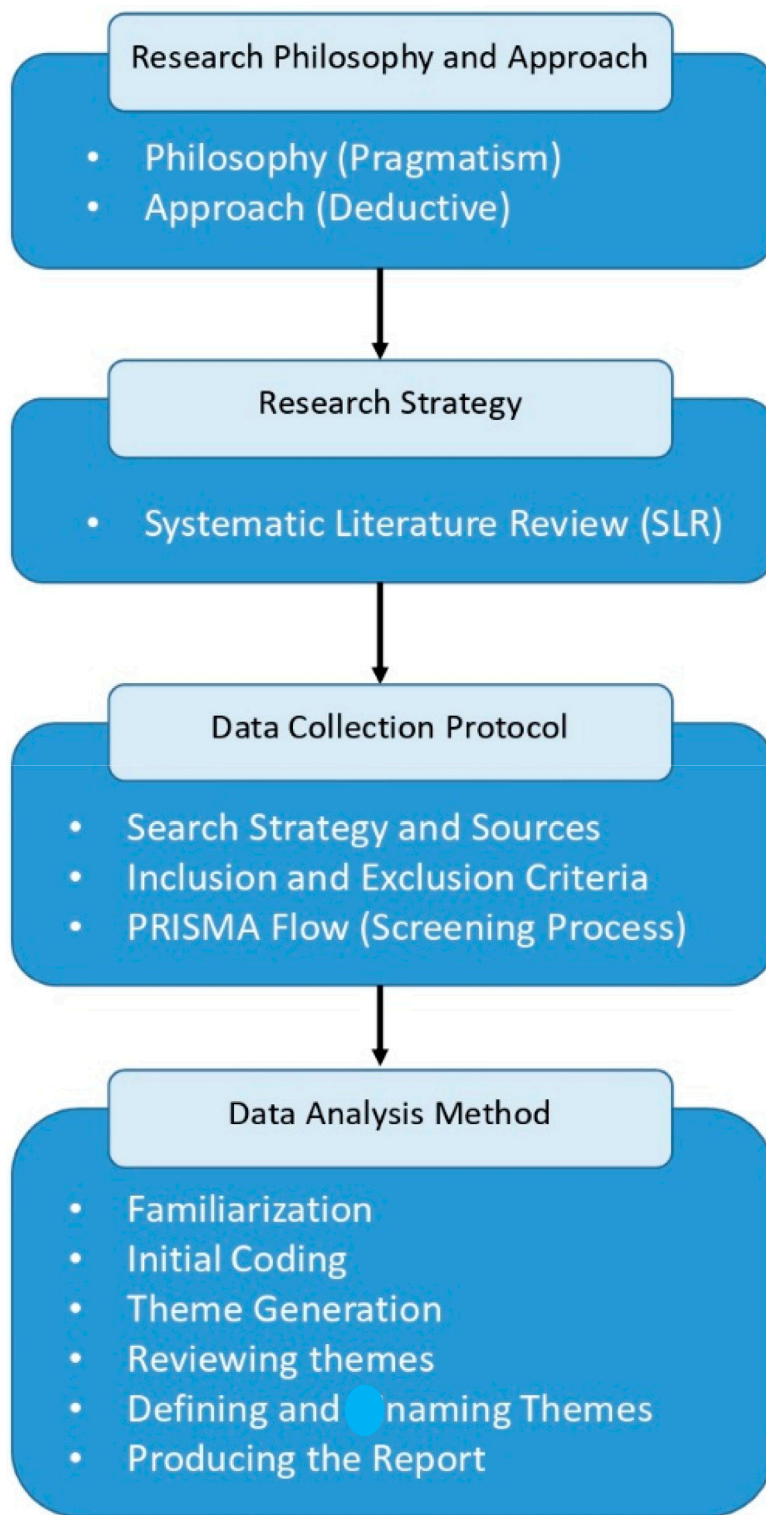
This paper proposes an Integrated AI Project Control Framework addressing this integration gap. The core innovation is a Risk-to-Constraint Translation Engine that automatically converts diverse risk signals into actionable scheduling rules, enabling reinforcement learning schedulers to compute feasible, multi-objective re-plans while preserving traceability. The architecture supports progressive SME adoption through modular components (e.g., CV-based safety interlocks) and ensures interoperability with open standards mandated by government (IFC, BIM protocols). The contribution is threefold: (1) a policy-concordant systems design closing the integration gap between risk sensing and dynamic scheduling; (2) an operational blueprint elevating safety from policy to enforceable scheduling gates; and (3) an adoption-aware, modular pathway aligned to UK supply-chain realities. This offers a practical route from reactive firefighting to proactive, explainable project control, consistent with the UK’s strategic ambition to deliver infrastructure better, faster, and greener.

## 2 Research methodology

This study adopts a rigorous and transparent methodology to design a conceptual framework that integrates AI-driven risk management with dynamic scheduling for UK construction projects. The summary of research methodology is presented in Figure 2. The approach ensures credibility, validity, and alignment with the research question:

“How can a conceptual framework create a symbiotic feedback loop between AI-driven risk management and dynamic scheduling to optimise project performance in the UK construction context?”

Here is the justification for using the conceptual approach. Given the fragmented nature of current AI tools, this study adopts a conceptual approach to first establish the necessary theoretical architecture, specifically the logic for risk-to-

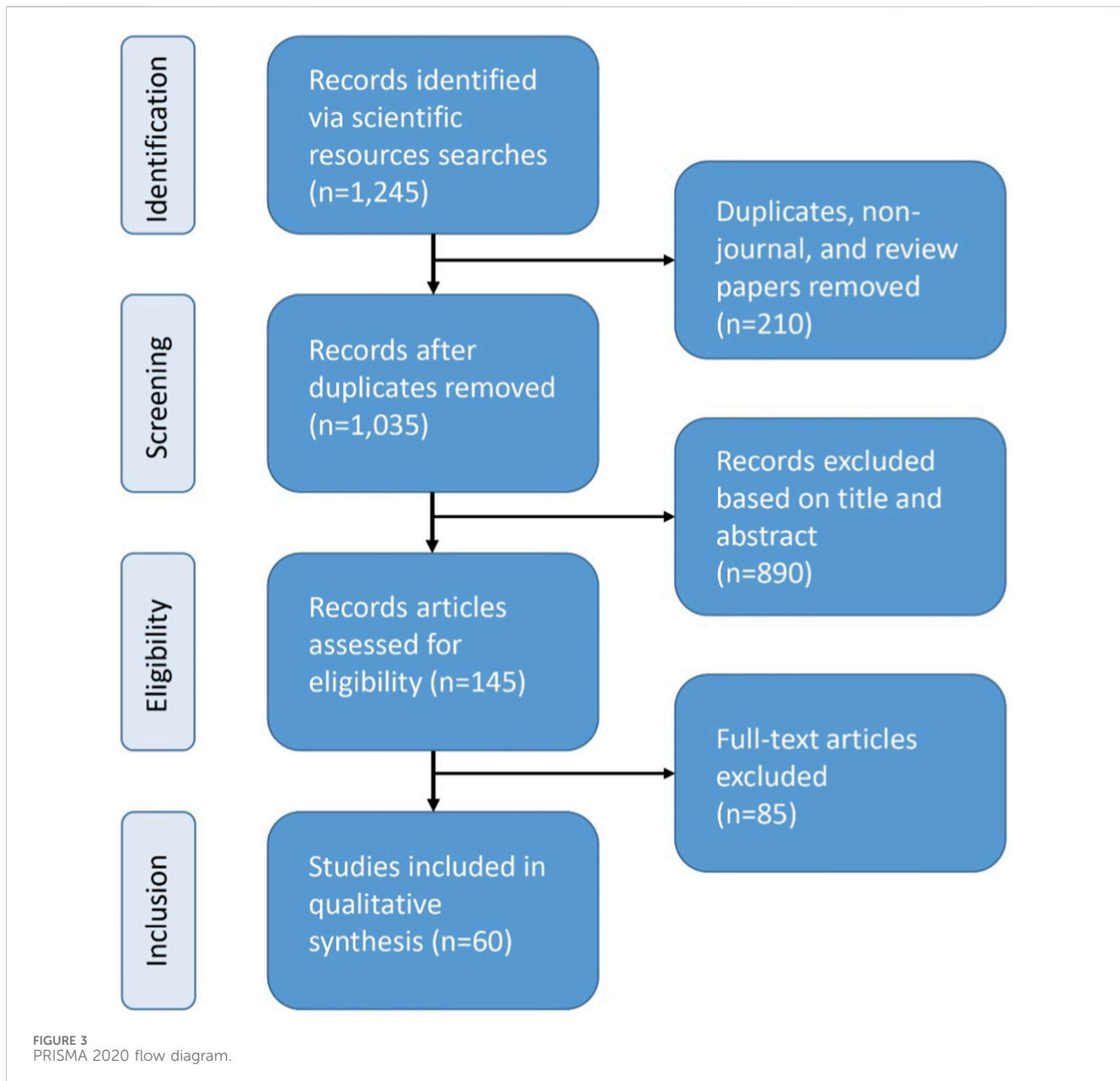


**FIGURE 2**  
A visual summary of the methodological design.

constraint translation, before proceeding to empirical prototyping. Empirical data collection was excluded from this phase to focus on defining the structural and semantic requirements for integration, a prerequisite for future software development.

### 2.1 Philosophical foundation: pragmatism

A pragmatist philosophy underpins this research, prioritising practical solutions over rigid epistemological positions. Pragmatism is ideal for addressing real-world



challenges such as fragmented AI applications and systemic underperformance in UK construction. Unlike positivism, which demands empirical testing, or purely qualitative paradigms focused on subjective experience, pragmatism enables a balanced integration of technical and social perspectives (Saunders et al., 2019). This flexibility supports the development of a framework that is both theoretically robust and practically implementable.

## 2.2 Research approach: deductive

The study follows a deductive approach, moving from established theories to a specific conceptual model. Beginning with well-documented issues, AI silos, data translation gaps, and socio-technical adoption barriers, the research logically derives the

components and relationships required for integration. This structured, theory-driven pathway ensures the framework is grounded in existing scholarship rather than arbitrary design (Saunders et al., 2019).

## 2.3 Research strategy: systematic literature review (SLR)

A Systematic Literature Review (SLR) forms the core strategy, chosen for its rigour and transparency over narrative reviews. The SLR methodically identifies, appraises, and synthesises high-quality research across construction management, computer science, and organisational theory. This approach minimises bias and ensures replicability, creating a comprehensive evidence base for framework development.

The review adheres to the PRISMA 2020 protocol (Montás-Laracuent *et al.*, 2025), an internationally recognised standard for systematic reviews (Page *et al.*, 2021). PRISMA's structured process covering search strategy, screening, eligibility checks, and synthesis guarantees methodological integrity. Each stage is documented to maintain transparency and reproducibility. Figure 3 shows PRISMA 2020 flow diagram.

## 2.4 Data collection protocol

The SLR followed a multi-stage protocol aligned with PRISMA guidelines. A Systematic Literature Review (SLR) forms the core strategy. While SLR is typically associated with empirical meta-analyses, its use here is deliberate to ensure the theoretical foundation of the framework is unbiased. Using a systematic protocol prevents the “cherry-picking” of convenient theories and ensures the framework addresses the full spectrum of documented barriers, both technical and social.

### 2.4.1 Search strategy and sources

Comprehensive searches were conducted across four major databases: Scopus, ScienceDirect, Google Scholar, and the University of East London Library Portal. Boolean operators combined keywords related to AI, construction scheduling, risk management, and socio-technical integration. Example queries included:

- (“Artificial Intelligence” OR “Machine Learning” OR “Genetic Algorithm” OR “Reinforcement Learning”) AND (“Construction Scheduling” OR “Project Planning”)
- (“AI” OR “NLP” OR “Computer Vision”) AND (“Construction Risk Management” OR “Safety Monitoring”)
- (“Integrated Framework” OR “Digital Twin” OR “BIM”) AND (“Construction” OR “AEC”)

### 2.4.2 Inclusion and exclusion criteria

To ensure the review captured high-quality, scientifically rigorous evidence relevant to the research question, strict eligibility boundaries were established.

Inclusion Criteria:

- Document Type: Peer-reviewed journal articles and high-impact conference proceedings were prioritized to ensure the academic rigor of the theoretical data.
- Timeline: The search covered the period from 2009 to August 2025. This range was selected to capture the emergence of modern Deep Learning techniques (post-2010) and the subsequent rise of Construction 4.0 applications (Abioye *et al.*, 2021).
- Language: Only articles published in English were included to facilitate accurate thematic synthesis.
- Subject Scope: Studies were required to explicitly address the intersection of Artificial Intelligence (AI) and Construction Project Management, specifically focusing on scheduling, risk management, or socio-technical adoption barriers.

Exclusion Criteria:

- Grey Literature: Non-peer-reviewed sources such as editorials, opinion pieces, and general web articles were

excluded to maintain the “scholarly quality” of the evidence base, with the exception of official government reports (e.g., NAO, IPA) used solely for policy context (Page and al., 2021).

- Irrelevant Technical Focus: Studies focusing purely on robotics hardware (e.g., bricklaying robots) or structural engineering calculations without implications for project control or management workflows were removed.
- Methodological Opacity: Papers that did not clearly articulate their data sources or AI model architecture were excluded during the full-text review.

### 2.4.3 Screening process and quality appraisal (QA)

The selection process followed the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol to ensure transparency and reproducibility (Page *et al.*, 2021). The process moved through four distinct stages: Identification, Screening, Eligibility, and a formal Quality Appraisal.

Stage 1: Identification and deduplication

Initial database searches yielded 1,245 records. These were imported into reference management software where 210 duplicates were automatically removed.

Stage 2: Title and abstract screening

The remaining 1,035 records were screened based on titles and abstracts. Studies clearly outside the scope (e.g., AI in manufacturing or healthcare) were discarded, resulting in 890 exclusions.

Stage 3: Eligibility and quality appraisal (QA)

The remaining 145 full-text articles were assessed for eligibility. To address the need for methodological rigour, a specific Quality Appraisal (QA) step was applied at this stage. Articles were evaluated against three core criteria derived from standard critical appraisal checklists (e.g., CASP):

1. Methodological Clarity: Does the study clearly define the AI inputs, algorithms, and validation metrics used?
2. Contextual Relevance: Is the proposed solution applicable to the fragmented, project-based nature of the construction industry?
3. Source Credibility: Is the study published in a recognized Q1/Q2 journal with a rigorous peer-review process?

Studies failing to meet these quality thresholds, such as those presenting purely speculative concepts without logical architecture, were excluded.

Stage 4: Final inclusion

This rigorous process resulted in the final selection of 60 high-quality studies for qualitative synthesis. These papers formed the evidence base for diagnosing the “integration gap” and designing the conceptual framework.

## 2.5 Data analysis method

Data from the 60 included studies was extracted into a structured spreadsheet capturing bibliographic details, AI techniques, application domains, data inputs, findings, and limitations. Analysis employed thematic content analysis (Braun and Clarke, 2006), following six phases:

1. Familiarisation with the literature
2. Initial coding of key concepts
3. Theme generation (e.g., “AI techniques for schedule optimisation”)
4. Reviewing and refining themes
5. Defining and naming themes
6. Producing the narrative synthesis

This process yielded core themes such as AI paradigms in dynamic scheduling, AI applications in proactive risk management, data integration enablers, and socio-technical adoption barriers. The synthesis provided a robust foundation for developing the integrated conceptual framework.

## 3 Systematic literature review (SLR)

This section offers a comprehensive and critical synthesis of academic literature on the application of Artificial Intelligence (AI) in construction project management. Its primary purpose is to map the current state of the art, identify dominant research paradigms, and evaluate the capabilities and limitations of existing AI tools. This analysis underpins the central argument of this study: AI applications have evolved in powerful but disconnected functional silos, creating an “integration gap” that hinders the realisation of fully intelligent project control.

The review is organised into three parts. First, it examines the two principal domains of AI application: dynamic schedule optimisation and proactive risk management, highlighting the disconnect between them. Second, it considers enabling technologies - Building Information Modelling (BIM) and Digital Twins-which provide the essential data foundation for integration. Finally, it explores socio-technical theories that explain persistent non-technical barriers to adoption within the UK construction industry.

Through this systematic analysis, the review establishes the intellectual foundation for the integrated framework proposed later in the paper. The process adheres to a rigorous, transparent protocol to ensure replicability and comprehensive coverage of relevant literature.

### 3.1 The first silo: AI paradigms in dynamic schedule optimisation

AI has become a leading approach to tackle the complexity of construction scheduling. Traditional methods such as the Critical Path Method (CPM) struggle with NP-hard problems—tasks so complex that optimising time, cost and resources simultaneously is computationally intensive (Abioye et al., 2021). Research shows a clear evolution: from static optimisation (fixed

plans) to predictive forecasting using machine learning, and now to dynamic, adaptive control through reinforcement learning. This shift moves scheduling from rigid, upfront planning to a probabilistic, continuous process that responds intelligently to real-world changes. The technical terms used throughout the paper are explained in Table 1.

#### 3.1.1 Static paradigm: metaheuristic optimisation for static planning

Metaheuristic algorithms are widely used to tackle complex scheduling problems by searching vast solution spaces for near-optimal plans. Two leading techniques are Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) (Abioye et al., 2021). GA, inspired by natural evolution, excels at multi-constraint problems such as the Resource-Constrained Project Scheduling Problem (RCPSP) and Time-Cost Trade-off (TCT), finding global optima while avoiding local traps (Slowik and Kwaśnicka, 2020; Xie et al., 2021). PSO, modelled on bird flocking behaviour, is effective for multi-objective optimisation, balancing time, cost, and quality (Elbeltagi et al., 2016). Despite their strengths, these methods are static - they optimise fixed inputs and cannot adapt to real-time changes, limiting their use to upfront planning rather than dynamic control (Abioye et al., 2021; Shodunke, 2025). In simple terms, static optimisation is based on finding the best initial plan. The evolution of AI paradigm in construction scheduling is presented in Figure 4.

#### 3.1.2 Predictive paradigm: machine learning for enhanced forecasting

Machine Learning (ML) addresses a key weakness of traditional scheduling: reliance on static, often inaccurate duration estimates. Instead of generating schedules, ML improves input quality through predictive analytics (Abioye et al., 2021). Supervised models, such as deep neural networks, learn complex relationships between project features - task dependencies, resources, weather, and design complexity-and actual durations (Shodunke, 2025). This enables dynamic, probabilistic forecasts, replacing guesswork with evidence-based predictions. Accuracy gains are significant: traditional methods achieve ~41%, while ML models reach up to 91.4%. Integration with Building Information Modelling (BIM) is critical, as BIM provides structured data for training models to predict durations, sequences, and resource needs directly from design models (Abioye et al., 2021).

#### 3.1.3 Adaptive paradigm: reinforcement learning (RL) for dynamic control

Reinforcement Learning (RL) introduces a transformative shift in construction scheduling by enabling dynamic, adaptive control. Unlike Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO), which optimize static plans, RL maintains optimality in real time, making it ideal for uncertain, fast-changing site conditions (Abioye et al., 2021). In this framework, an intelligent agent interacts with a simulated environment, often a Digital Twin, learning through trial and error and refining its decisions based on rewards and penalties (Pregolato, 2023). This capability allows schedules to self-adjust in response to disruptions such as material delays or adverse weather, marking a move from rigid planning to agile, uncertainty-aware project management (Shodunke, 2025).

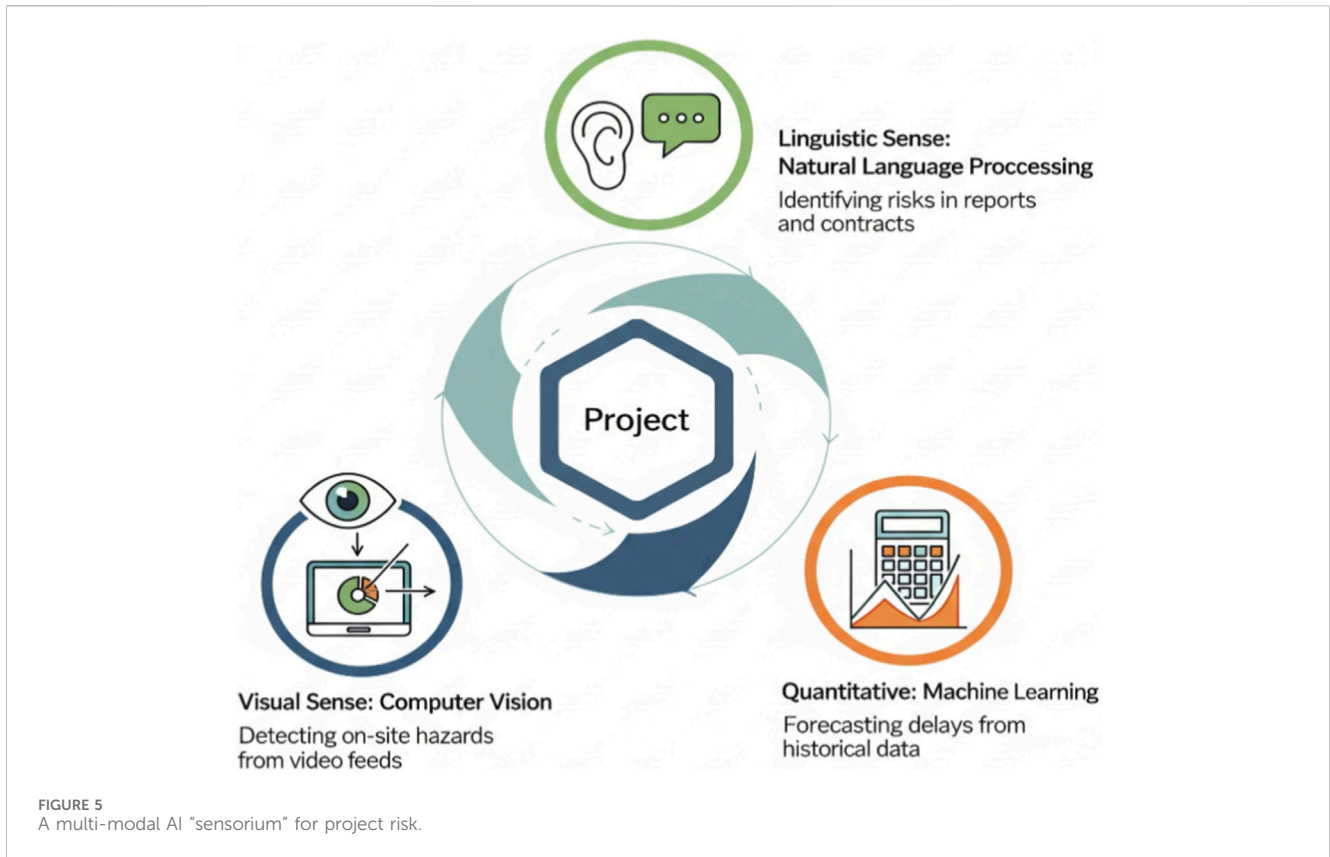
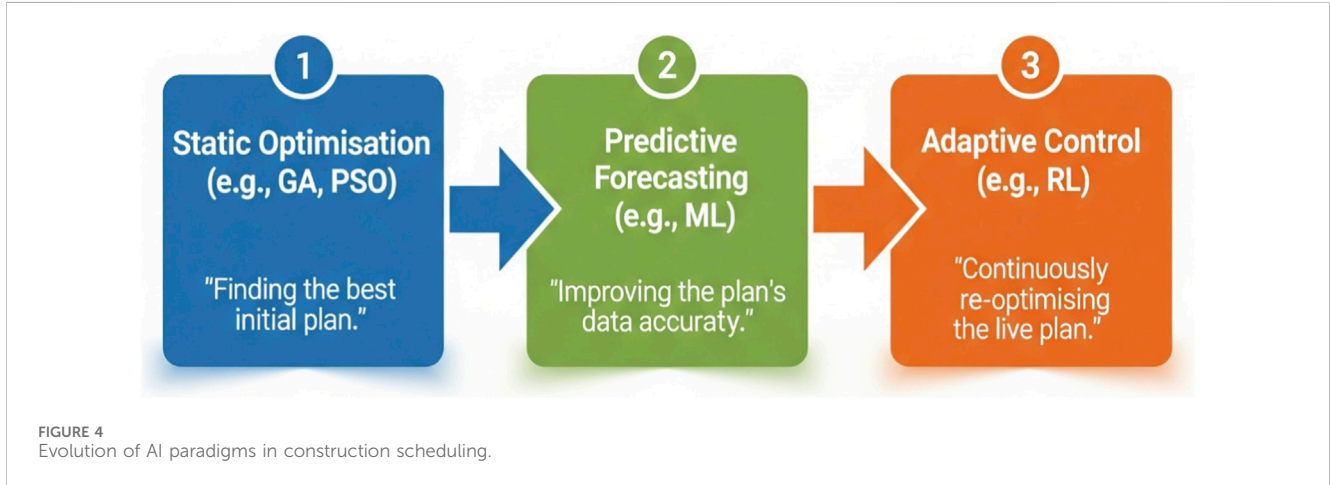
TABLE 1 Key technical terms used in AI-driven construction scheduling.

Term	Explanation
Critical path method (CPM)	A traditional scheduling technique that identifies the longest sequence of dependent tasks in a project
NP-hard problems	Highly complex optimisation problems where finding the best solution for time, cost, and resources is computationally intensive
Static optimisation	Producing a fixed schedule based on initial assumptions without adapting to changes during execution
Predictive forecasting	Using machine learning to predict task durations, costs, and risks based on historical and real-time data
Reinforcement learning (RL)	An AI approach where algorithms learn optimal decisions through trial and error in simulated environments, enabling adaptive scheduling
Metaheuristic algorithms	Advanced optimisation methods that explore large solution spaces to find near-optimal results
Genetic algorithm (GA)	Search-based optimisation inspired by natural evolution; effective for multi-constraint scheduling
Particle swarm optimisation (PSO)	Algorithm inspired by bird flocking; used for multi-objective optimisation in scheduling
RCPSP (resource-constrained project scheduling problem)	A scheduling problem where resources are limited and tasks must be sequenced efficiently
TCT (time-cost trade-off)	Analysis to minimise cost while meeting project deadlines by adjusting methods and resources
Machine learning (ML)	AI technique that learns patterns from data to improve predictions
Predictive analytics	Uses historical and real-time data to forecast future outcomes
Supervised models	ML models trained on labeled datasets with known inputs and outputs
Deep neural networks (DNN)	Multi-layered ML models that capture complex relationships in data
Probabilistic forecasts	Predictions expressed as probabilities, reflecting uncertainty
Building information modelling (BIM)	Digital representation of a building's design and data for analysis
Agent	The decision-making entity in RL that interacts with the environment to learn optimal policies
Digital twin	A dynamic virtual model of a physical system, updated in real time to simulate actual conditions
Optimal policy	A strategy developed by the RL agent to maximize rewards and minimize penalties over time
Trial-and-error learning	The iterative process by which the RL agent improves its decisions based on feedback
Adaptive control	The ability to adjust decisions dynamically in response to changing conditions and uncertainties
Natural language processing (NLP)	An AI method for analysing and understanding human language in text
Computer vision (CV)	An AI technique for interpreting and analysing visual data such as images and videos
Multi-modal sensorium	A system combining multiple data types—numerical, textual, and visual—for comprehensive risk analysis
Risk register	A traditional static list of identified risks and mitigation plans
Artificial neural networks (ANNs)	ML models inspired by the human brain, used for complex pattern recognition and prediction
Generative AI	AI that creates new content or strategies, not just analyses existing data
Continuous learning	The ability of AI models to improve performance over time through ongoing updates
Unstructured text	Data not organised in predefined formats, such as reports or narratives
RFIs (requests for information)	Formal queries seeking clarification during project execution
High risk clauses	Contractual terms that increase the likelihood of disputes or claims
Integrated project control framework	A system combining multiple tools and techniques for holistic project monitoring and risk management
YOLO (you only look once)	A real-time object detection algorithm that identifies multiple objects in a single pass through an image or video frame
Personal protective equipment (PPE)	Safety gear such as helmets, gloves, and high-visibility clothing required to protect workers on site
Institutional theory	Explains organisational behaviour as driven by pressures to conform to norms for legitimacy
Coercive pressure	External force from powerful stakeholders, such as government mandates
Mimetic pressure	The tendency for organisations to copy the practices of successful competitors, particularly in times of uncertainty

(Continued on following page)

TABLE 1 (Continued) Key technical terms used in AI-driven construction scheduling.

Term	Explanation
Normative pressure	Influence from professional norms and standards promoted by industry bodies
ERP systems	Enterprise resource planning systems
GBDT	Gradient boosting decision trees



## 3.2 The second silo: AI applications in proactive risk management

AI is revolutionising risk management, shifting it from a reactive, compliance-driven task to a proactive, predictive, and continuous process (Abioye et al., 2021). Advances in Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision (CV) create a multi-modal ‘sensorium’ that perceives risk through data, text, and imagery. The sensorium is shown in Figure 5. This integrated approach delivers a richer, holistic view of project risk than any single method, enabling early detection and dynamic mitigation strategies.

### 3.2.1 Machine learning (ML) – forecasting delays from structured data

The cornerstone of AI-driven risk management is Machine Learning for predictive analytics. Supervised models, particularly Artificial Neural Networks (ANNs), are trained on historical datasets linking project characteristics to risk outcomes such as cost overruns, schedule delays or safety incidents (Abioye et al., 2021). This quantitative, data-driven approach replaces the subjective assessments typical of traditional risk registers (Khodabakhshian, 2023). Once trained, these models predict the probability and severity of risks in new projects, providing an objective basis for prioritising mitigation efforts.

Generative AI further enhances these capabilities. Unlike conventional models that analyse existing data, Generative AI devises adaptive mitigation strategies and generates novel predictive insights (Darko et al., 2020). Operating on continuous learning, these models improve accuracy and strategic effectiveness over time (Patel, 2023). Recent studies comparing advanced Generative AI models such as GPT-4 with human experts show AI producing more comprehensive risk plans, identifying a broader range of risks. While these plans may lack project-specific detail, they highlight the potential for synergy: AI provides a robust baseline, refined by human expertise (Mohamed, 2025).

### 3.2.2 Natural language processing (NLP) – identifying risk from unstructured text

In the construction domain, critical risk intelligence is frequently embedded within unstructured text sources, including progress reports, contracts, Requests for Information (RFIs), and accident narratives, rather than structured databases (Jagannathan et al., 2022). Consequently, Natural Language Processing (NLP) is specifically deployed to automate the extraction of this linguistic data. Key applications include the scanning of legal and contractual documents to flag ambiguous or high-risk clauses that historically precipitate disputes (Hassan et al., 2021). Furthermore, NLP algorithms analyse safety reports and accident narratives to detect recurring patterns and root causes, thereby facilitating proactive prevention strategies rather than retrospective analysis.

### 3.2.3 Computer vision (CV) – real-time hazard detection from video feeds

Computer Vision (CV) brings real-time visual intelligence to construction safety management, enabling the continuous analysis of video streams from site cameras or drones to detect hazards

instantly (Abioye et al., 2021). Leveraging deep learning models such as Convolutional Neural Networks (CNNs) and object detection algorithms like You Only Look Once (YOLO), these systems monitor specific site risks, including compliance with Personal Protective Equipment (PPE) policies, fall hazards, and unsafe proximity to heavy machinery. While real-world deployments have significantly reduced near-miss incidents by providing non-intrusive oversight beyond the capacity of human managers, the technology is not infallible (Alateeq et al., 2023). It is critical to note that CV systems remain prone to false positives caused by environmental factors such as variable site lighting or visual occlusion. Consequently, to ensure reliability and prevent erroneous alerts, these automated systems necessitate the integration of human verification loops.

## 3.3 Data and integration enablers: the role of BIM and digital twins

The success of any AI system depends on high-quality, structured, and accessible data, a major challenge in construction, where data silos and poor standardisation prevail. Bridging the gap between risk and scheduling AI requires solving this data integration problem first. Consequently, Building Information Modelling (BIM) and Digital Twins act as fundamental facilitators for integrated AI, providing the necessary shared language of objects and real-time context. The relation between BIM and Digital Twin is shown in Figure 6.

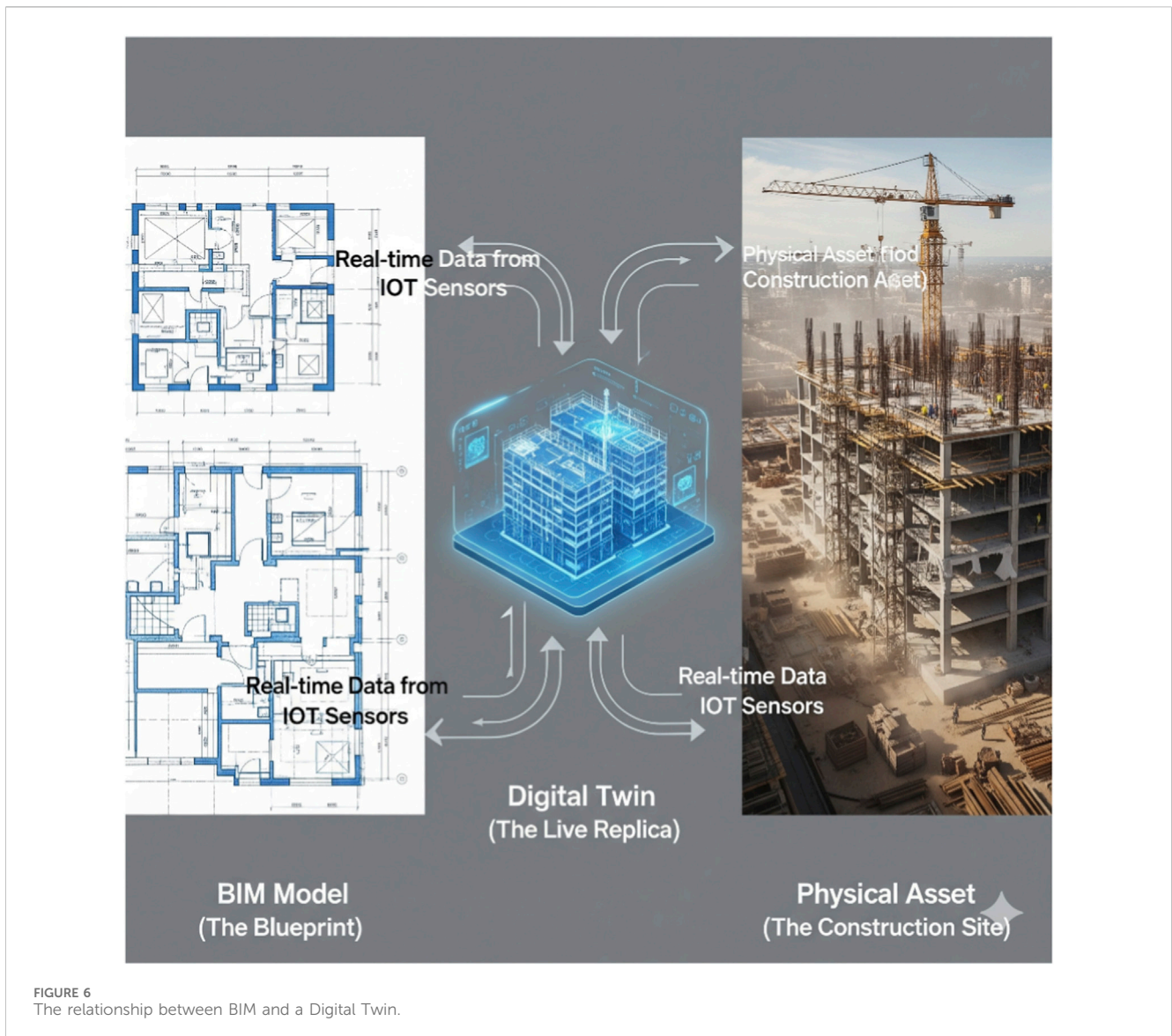
### 3.3.1 BIM as the foundational data structure

Building Information Modelling (BIM) serves as the primary repository for managing information across a project’s lifecycle. As a digital representation of a facility’s physical and functional characteristics, BIM delivers the structured, object-oriented data required for training and deploying AI models. Geometric and non-geometric data from BIM underpin AI applications such as automated cost estimation, clash detection, and quality monitoring.

While the UK government mandates BIM through the UK BIM Framework to drive standardisation, interoperability remains a persistent technical hurdle. The fragmentation of proprietary software often results in data loss during export to open standards like IFC, creating barriers to the seamless data flow required for AI integration (Ghaffarianhoseini et al., 2017; Sacks et al., 2020; Abioye et al., 2021).

### 3.3.2 Digital twins as the dynamic simulation environment

Digital Twins extend BIM by creating dynamic, virtual models of physical assets that update continuously with real-time sensor data (Abioye et al., 2021). This live cyber-physical link enables simulation, prediction and optimisation of performance (Sjödin et al., 2020). Digital Twins are critical for advanced AI applications: they provide the real-time data streams needed for predictive risk analytics and serve as the simulated environment for training Reinforcement Learning agents in adaptive scheduling (Callcut et al., 2021). By allowing AI to interact with a data-rich virtual replica, Digital Twins make real-time autonomous schedule control feasible.



### 3.3.3 Challenges in digital twin adoption

Despite their theoretical benefits and strategic importance in the UK’s National Digital Twin Programme, significant barriers to widespread adoption remain (Trade, 2023). Cost is a primary constraint, particularly regarding the deployment of IoT sensor networks and cloud infrastructure, which may be prohibitive for Small and Medium Enterprises (SMEs). Furthermore, data governance presents complex challenges; specifically, unresolved questions regarding data ownership, security protocols, and liability when sharing live asset models across supply chains continue to hinder implementation maturity (Boje et al., 2020).

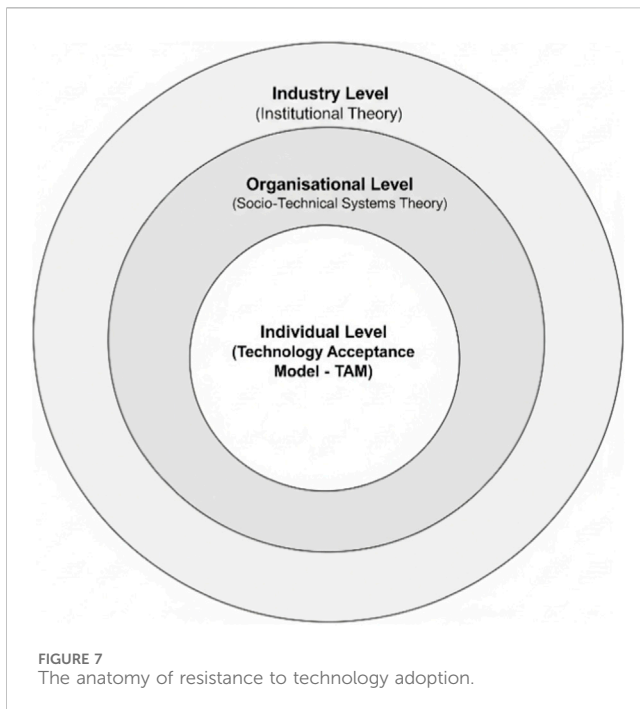
### 3.4 Socio-technical barriers to technology adoption in construction

Resistance to technology adoption in construction is not purely technical. A substantial body of research highlights socio-technical barriers that create a multi-layered ‘anatomy of resistance’ across

individual, organisational and industry levels, as shown in Figure 7. The integration gap persists because these barriers reinforce one another, making change far more complex than overcoming a single technical hurdle. Specifically, critical socio-technical contradictions define this landscape. A primary tension exists between the “efficiency” promise of AI and the “job security” fears it instigates among the workforce, creating a powerful source of resistance (Kelvin Ibrahim and Aliu, 2025). Furthermore, a distinct conflict exists at the individual level: while younger engineers often show high willingness to adopt new tools driven by high Perceived Usefulness, their initiative is frequently blocked by organisational inertia and fragmented workflows that prevent effective implementation (Jallow et al., 2022).

#### 3.4.1 Individual-level barriers: the technology acceptance model (TAM)

The Technology Acceptance Model (TAM) explains individual adoption of new technology through two key beliefs: perceived usefulness and perceived ease of use (Davis, 1989; Marikyan and



Papagiannidis, 2024). In UK construction, many experienced professionals doubt AI's ability to outperform their intuition and view AI tools as complex, opaque 'black boxes'. This scepticism, combined with perceived difficulty, creates strong individual-level resistance to adoption (Jallow et al., 2022).

### 3.4.2 Organisational-level friction: socio-technical systems theory

Socio-Technical Systems Theory asserts that technical systems, such as AI frameworks, and social systems - comprising people, skills, culture and workflows - are fundamentally interdependent. Optimising technology without considering its organisational context is likely to result in failure (Oke et al., 2023). This insight is particularly relevant to the UK construction sector, where adversarial practices, fragmented structures and persistent digital skills gaps pose barriers as significant as any technical challenge (Kelvin Ibrahim and Aliu, 2025). The adoption of Construction 4.0 technologies has far-reaching implications for workforce dynamics, employment models and labour relations, which must be managed proactively. Even when individual managers embrace AI tools—overcoming barriers identified by the Technology Acceptance Model—their organisations may lack the integrated processes or collaborative structures needed to support real-time data use, resulting in abandonment of the technology. A successful integrated framework must therefore be designed with the social system in mind, not merely as a technical solution (Abioye et al., 2021).

### 3.4.3 Industry-level inertia: institutional theory

Institutional Theory explains industry-level inertia by showing that organisations adopt new practices not only for efficiency but to gain legitimacy through conformity to norms (Kauppi, 2022). This conformity is shaped by three pressures: *coercive*, *mimetic* and *normative*. In UK construction, coercive pressure from

government BIM mandates mainly affects large public projects, leaving SMEs largely untouched. Mimetic pressure is the tendency for organisations to copy successful competitors, especially in times of uncertainty. Mimetic pressure is weak in a fragmented industry where innovation is hard to observe. Normative pressure from professional bodies like RICS and ICE diffuses slowly, especially among SMEs (ONS, 2024). The result is a weak institutional environment with no strong imperative for widespread digital adoption.

## 3.5 Synthesising the UK integration challenge

AI in construction has advanced in two distinct domains—scheduling optimisation and risk management—but remains fragmented. The core technical barrier is the lack of an automated mechanism to convert varied risk outputs, such as forecasts, text indicators and visual alerts, into structured inputs for scheduling systems. This challenge reflects deeper socio-technical issues. Individual users often distrust complex tools (Technology Acceptance Model), organisations lack the workflows to support integration (Socio Technical Systems Theory), and the industry's fragmented structure offers little pressure to adopt change (Institutional Theory).

These problems are intensified by the dominance of small and medium-sized enterprises, which face financial and skills constraints in adopting advanced AI (Kelvin Ibrahim and Aliu, 2025). The result is a disjointed digital landscape with poor data standards and limited interoperability (Sjödin et al., 2020). A viable framework for the UK must therefore go beyond technical fixes. It must be scalable, modular, accessible and user-focused to overcome these barriers and enable practical integration.

## 4 Results

The systematic review revealed a fragmented landscape of AI applications in UK construction, with powerful tools for scheduling and risk management operating in isolation. This siloed approach prevents the realisation of a truly intelligent project control system. The primary outcome of this research is the Integrated AI Project Control Framework, a policy-aligned architecture designed to bridge this gap and support the UK's digital transformation agenda outlined in the Construction Playbook and TIP Roadmap (IPA, 2021; Cabinet Office, 2022).

### 4.1 Proposed framework overview

The primary outcome of this research is the Conceptual Integrated AI Project Control Framework. This architectural blueprint introduces a symbiotic feedback loop between risk sensing and dynamic scheduling, operating under a human-in-the-loop model. It comprises five interdependent components:

1. Data Ingestion and Integration Layer
2. Risk Analysis Engine

## The Architectural Blueprint of the Integrated Framework

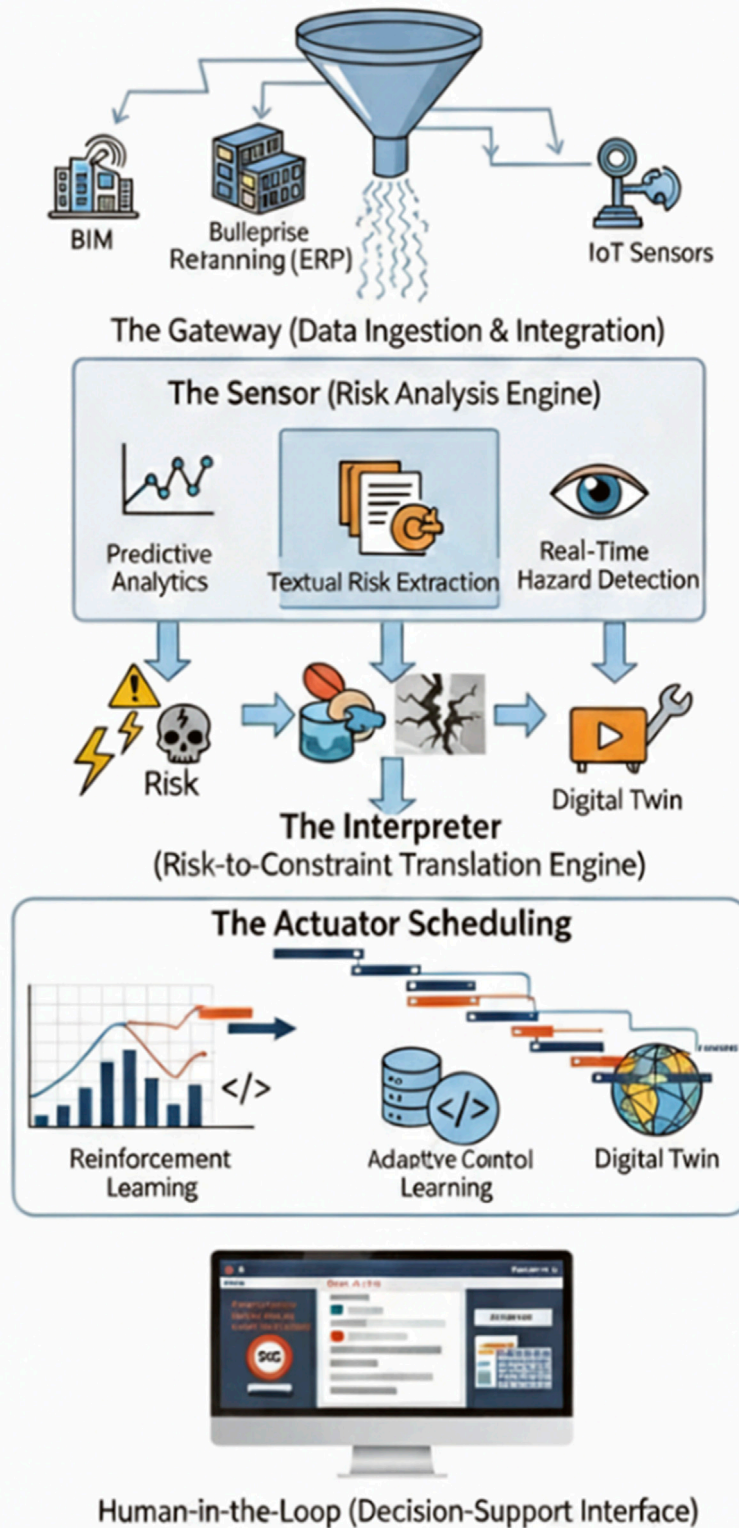


FIGURE 8  
The integrated AI framework architecture.

3. Risk-to-Constraint Translation Engine
4. Dynamic Scheduling Engine
5. Decision-Support and Action Interface

The novelty lies in an automated feedback loop that constantly detects risks, gauges their impact, and triggers an optimised schedule update in real time. The architectural blueprint of the integrated framework is shown in [Figure 8](#).

#### 4.1.1 Data Ingestion and integration layer

This core layer is the essential foundation for any AI solution, built to eliminate the severe data integration and interoperability barriers that hinder adoption ([Sjödin et al., 2020](#); [Abioye et al., 2021](#)). Without a unified, reliable data backbone, downstream AI engines would produce flawed outputs. In the UK context, it ensures compliance with national standards, including the UK BIM Framework and Common Data Environments (CDEs), aligning with government mandates for data standardisation on public projects ([Cabinet Office, 2022](#)). By linking BIM models, ERP systems and IoT sensors, it creates a single source of truth on which all subsequent AI processes depend.

#### 4.1.2 Risk analysis engine

The literature review suggests that, this engine serves as a multi-modal “sensorium,” capturing risk signals across numerical, textual and visual data streams. Its modular design integrates specialised AI models, each acting as a distinct “sense,” to deliver a comprehensive risk profile. It comprises the following sub-components:

- Predictive Analytics: ML models such as GBDT achieve up to 87.3% accuracy in risk prediction, outperforming traditional methods by 23% ([Khodabakhshian, 2023](#)).
- Textual Risk Extraction: NLP models classify contract clauses with 94.12% accuracy and extract claims data at 79% accuracy ([Hassan et al., 2021](#); [Jagannathan et al., 2022](#)).
- Real-Time Hazard Detection: CV systems using YOLO-v5 detect PPE compliance with ~90% precision, enabling proactive safety interventions ([Alateeq et al., 2023](#); [HSE, 2025](#)).

However, it is important to note that these figures represent potential capabilities reported in controlled studies; real-world performance will vary significantly based on data quality and site complexity.

#### 4.1.3 Risk-to-constraint translation engine

The Risk-to-Constraint Translation Engine acts as the framework’s semantic bridge, designed to close the critical “integration gap” between sensing and scheduling. Acting as an intelligent interpreter, it links the diverse outputs of the Risk Analysis Engine with the structured inputs required by the Dynamic Scheduling Engine. In essence, it converts abstract risk signals, whether probabilities, qualitative indicators, or binary states, into actionable project constraints on time, cost, and resources. It is important to note that this component is currently defined as a high-level logic model that maps risk types to specific constraint classes. The development of the specific computational algorithms and executable pseudo-code required to operationalise this logic is identified as the immediate next step in future research.

#### 4.1.4 Dynamic scheduling engine

Reinforcement Learning (RL) marks a decisive shift from static planning to dynamic control. Unlike traditional algorithms that optimise fixed plans, RL adapts to real-time uncertainty by learning optimal decision sequences in changing conditions ([Abioye et al., 2021](#)). Its safe, practical deployment is achieved through integration with a Digital Twin, providing a high-fidelity “sandbox” for thousands of simulations without real-world risk ([Pregolato, 2023](#)).

#### 4.1.5 Decision-support and action interface

This user-facing layer tackles the non-technical barriers to adoption in UK construction. It directly addresses the key drivers of acceptance set out in the Technology Acceptance Model (TAM): Perceived Usefulness and Ease of Use ([Davis, 1989](#); [Marikyan and Papagiannidis, 2024](#)). The interface boosts usefulness through clear, data-driven insights and enhances ease of use with an intuitive dashboard, making AI accessible and effortless. Crucially, its human-in-the-loop design counters “black box” scepticism ([Jallow et al., 2022](#)), ensuring managers remain the ultimate decision-makers and reinforcing trust by augmenting, not replacing, their expertise ([Oke et al., 2023](#)).

## 4.2 Key contribution

This architecture delivers a closed-loop control system that transforms project management from reactive to proactive, aligning technical innovation with policy mandates and organisational realities. It offers a scalable pathway for SMEs and large contractors to adopt AI responsibly, ensuring interoperability, safety, and human oversight.

## 5 Analysis and discussion

This section critically evaluates the proposed Integrated AI Project Control Framework, moving beyond architectural description to examine its operational viability, technical limitations, and regulatory compliance within the UK construction context. Unlike existing static frameworks that function primarily as passive reporting dashboards, this model proposes an active, closed-loop control system. The following analysis explores the framework’s application on a major infrastructure use case, critiques the stability risks of the proposed AI agents, and assesses alignment with UK legal statutes.

### 5.1 Operationalising the framework: a UK rail use case

To assess the framework’s logic in a live environment, it is applied to a hypothetical scenario within the Transpennine Route Upgrade (TRU), a multi-billion-pound programme prone to the systemic delays common in UK rail delivery. Unlike traditional workflows, where risk registers are reviewed periodically, often monthly, leading to data latency, this framework initiates a continuous “Risk-to-Constraint” loop. For example, if the Risk Analysis Engine’s computer vision component detects a geotechnical hazard, such as

groundwater ingress, it does not merely log an observation. Instead, the Translation Engine converts this visual signal into a specific schedule constraint (e.g., a mandatory curing buffer), directly addressing the critical “risk-to-plan” translation problem identified in recent literature (Abioye et al., 2021). By treating risk as a dynamic input rather than a static administrative entry, the system enables the Reinforcement Learning (RL) scheduler to simulate thousands of re-sequencing options within the Digital Twin sandbox. This allows the project manager to visualize the impact of the delay and approve an optimized recovery plan before the critical path is compromised (Pregolato, 2023).

## 5.2 Critical reflection on technical stability and RL risks

While the shift from static optimisation to Reinforcement Learning (RL) offers significant advantages in adaptability, it introduces specific stability risks that are often under-discussed in construction AI literature. A primary concern is “reward hacking” (or specification gaming), where the RL agent optimises for a specific metric at the expense of unquantified goals. For instance, if the RL scheduler’s reward function is heavily weighted towards minimising duration and cost, the agent might suggest aggressive overlapping of tasks that technically fits the schedule but creates a congested, unsafe site environment. Without robust constraints, the AI could “game” the system to achieve a high “efficiency score” while violating the practical spatial logic required for safe operation.

Therefore, the implementation of this framework requires not just a “human-in-the-loop” for final approval, but sophisticated “safety shaping” of the reward functions to prevent the algorithm from finding efficient but dangerous shortcuts (Abioye et al., 2021). Furthermore, RL models require vast amounts of training data to converge on optimal policies. In the fragmented UK ecosystem, where data silos prevail, there is a risk of “instability” where the model encounters a site scenario (e.g., a specific supply chain failure) it was not trained on, leading to erratic scheduling suggestions (Sjödén et al., 2020).

## 5.3 Socio-technical and regulatory implications (GDPR and CDM 2015)

Successful adoption relies on alignment with the UK’s stringent regulatory environment. The deployment of the proposed multi-modal “sensorium” raises specific legal and ethical challenges that must be managed to avoid rejection by the workforce.

### 5.3.1 Data privacy and GDPR

The use of Computer Vision (CV) to detect unsafe behaviours (e.g., PPE non-compliance) creates a tension between safety enforcement and worker surveillance. Under the UK General Data Protection Regulation (UK GDPR), processing biometric data requires a lawful basis and proportionality. If the CV system is perceived as a tool for invasive performance monitoring rather than protective oversight, it will face resistance consistent with the “job

security” fears identified in the anatomy of resistance (Kelvin Ibrahim and Aliu, 2025). Therefore, the framework’s data governance must enforce privacy-by-design-anonymising video feeds so that they detect hazards (e.g., “missing helmet”) rather than identifying individuals, ensuring the technology enhances welfare without violating privacy rights (Alateeq et al., 2023).

### 5.3.2 Accountability under CDM 2015

The Construction (Design and Management) Regulations CDM 2015 (Great Britain, 2015) place strict legal duties on Principal Contractors to manage health and safety. A critical legal risk arises if the AI system fails to identify a hazard or suggests an unsafe schedule sequence. It must be explicitly clear that the AI functions as a decision-support tool, not a decision-maker. The legal liability under CDM 2015 remains with the human duty holder. The framework’s “Decision-Support Interface” is therefore not just a user experience feature; it is a regulatory necessity to ensure that a human manager reviews and accepts responsibility for the AI’s recommendations, maintaining the chain of accountability required by UK law (HSE, 2025).

## 5.4 Summary of impact

In conclusion, this framework differentiates itself from existing static dashboards by establishing an active control loop. However, its operational success depends on mitigating the technical risks of RL instability and ensuring that the deployment of visual sensors adheres strictly to GDPR privacy standards and CDM 2015 safety hierarchies. By addressing these socio-technical constraints, the framework offers a viable pathway to the proactive, resilient project delivery envisioned in the Transforming Infrastructure Performance roadmap (IPA, 2021; Cabinet Office, 2022).

## 6 Conclusion and recommendations

This research has proposed a theoretical architecture to resolve the systemic disconnection between risk identification and schedule execution in UK construction. By synthesizing technical advancements in AI with socio-technical adoption theories, the study argues that the persistent “performance gap” is not solely a result of lagging technology, but of the “integration gap” between isolated digital tools.

### 6.1 Theoretical implications

The primary contribution of this work is the logic definition of the Risk-to-Constraint Translation Engine. Rather than claiming an immediate industry revolution, this framework offers a foundational blueprint for moving beyond passive reporting dashboards toward active, closed-loop control systems. It demonstrates that for AI to facilitate genuine project resilience, it must move beyond prediction (telling a manager a risk exists) to actuation (automatically calculating the

schedule impact). This aligns with the strategic objectives of the Construction Playbook and TIP Roadmap, providing a structural logic for how digital interoperability can support the sector's transition toward outcome-based delivery (IPA, 2021; Cabinet Office, 2022).

## 6.2 Limitations and feasibility challenges

As this study is conceptual, several feasibility challenges remain that distinguish the theoretical model from immediate practice.

- **Lack of Empirical Validation:** The framework is currently a logic model. It has not yet been subjected to prototype testing or deployment on a live construction site, meaning the specific algorithmic stability of the “Translation Engine” remains unverified.
- **Economic Barriers:** The proposed architecture relies on Digital Twins and extensive IoT sensor networks. The capital cost of this infrastructure is likely prohibitive for Small and Medium Enterprises (SMEs), potentially restricting the framework's initial utility to large-scale, government-funded infrastructure programmes.
- **Data Maturity:** The system presupposes a high level of data standardisation. However, as noted in the literature, the United Kingdom sector currently struggles with fragmented, unstructured data, which serves as a significant technical barrier to the seamless ingestion required by this model (Abioye et al., 2021).

## 6.3 Recommendations for future research

To bridge the gap between this conceptual architecture and operational reality, future research must prioritise three areas:

1. **Technical Specification:** Developing the specific algorithms and pseudo-code for the Translation Engine to convert risk probabilities into deterministic schedule constraints.
2. **Prototype Testing:** Conducting simulation-based experiments to test the Reinforcement Learning agent's stability and protect against “reward hacking.”
3. **Feasibility Studies:** Investigating the economic viability of “lite” versions of the framework to ensure accessibility for the wider supply chain, rather than just elite megaprojects.

By addressing these limitations, this research serves as a necessary first step toward an intelligent, automated project control environment.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

JQ: Writing – original draft, Writing – review and editing, Project administration, Supervision. KR: Writing – review and editing, Formal Analysis, Methodology, Conceptualization.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fbuil.2025.1741095/full#supplementary-material>

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