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IMIA Working Group Paper 143 (26) New Risks for Insurers to Consider because of Greater Involvement of AI in Construction

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Executive Summary

Artificial intelligence (AI) is reshaping risk across the construction lifecycle, from pre-feasibility and geotechnical prediction through design, planning, execution, and into operations and maintenance. This paper examines applied AI tools that are already in use or at a realistic near-term stage of adoption, including generative design engines, AI-assisted BIM workflows, AI-enhanced project controls, autonomous and semi-autonomous equipment, computer-vision systems for safety and quality, and digital twins for predictive maintenance. The perspective is global but anchored in the legal and regulatory frameworks of the EU, UK, and US, and is explicitly framed as a snapshot of technology, regulation, and market practice as of May 2026.

The paper has four principal objectives. First, it describes how AI is currently used across construction phases and segments, drawing on real-world examples to map maturity levels, sectoral adoption patterns, and implications for covers such as CAR/EAR, professional indemnity, public liability, and cyber. Second, it maps the evolving risk landscape, showing how AI reconfigures traditional construction risks and introduces technical, cyber-physical, human-factor, and legal/professional exposures with direct relevance for underwriting, PML assessment, and claims causation analysis. Third, it explains the emerging regulatory, legal, and liability implications, emphasizing that most construction organizations are AI deployers and are likely to bear primary responsibility for AI-enabled failures under evolving regimes. Fourth, it translates these developments into practical underwriting, policy wording, claims-handling, and governance responses, including a structured approach to AI-related PML reasoning and the use of tools such as an AI risk maturity ladder and the Project AI Coordinator (PAIC). The paper does not provide legal advice, prescribe a single “correct” governance model, or address speculative long-term AI technologies; it focuses instead on operationally relevant systems and pragmatic practices that support insurability.

AI reconfigures, rather than replaces, construction risk. Traditional hazards such as structural failure, geotechnical uncertainty, unsafe site conditions, workmanship defects, and coordination failures remain, but their causal pathways are altered by digital dependencies, cyber-physical links, and systemic or correlated exposures arising from shared AI platforms and datasets. Liability is expected to fall heavily on deployers who lack robust governance, while insurers must evolve from passive risk carriers to digital risk partners by incorporating AI-specific considerations into underwriting, wording, and claims processes. The recommendations centre on early establishment of AI governance aligned with emerging standards, maintaining human final control over consequential decisions, investing in data quality and traceability, updating contracts and professional practices to address AI explicitly, and building AI-aware insurance and claims capabilities, as preconditions for maintaining manageable risk levels and sustaining the insurability of AI-enabled construction.

Chapter 1: Introduction

Artificial Intelligence (AI) is reshaping how the construction industry conceives, designs, delivers, and operates the built environment. What began as experimental pilots in design offices and isolated automation trials on sites has evolved into a gradual but systemic transformation across the entire construction lifecycle. From early-stage optioneering and geotechnical prediction to digital-twin–enabled operations and predictive maintenance, AI is increasingly embedded in tools and workflows that influence safety, quality, schedule, and cost.

Yet construction differs fundamentally from many other sectors that are rapidly adopting AI. It remains one of the world's highest-risk industries, characterized by fragmented supply chains, heterogeneous project types, complex site conditions, and narrow margins. These characteristics create both an urgent need and a challenging environment for AI. On one hand, AI offers compelling opportunities to reduce accidents, improve productivity, optimize resource use, strengthen documentation, and support decarbonization. On the other hand, AI introduces digital and systemic vulnerabilities: data dependency, model errors, cyber-to-physical failure pathways, and new layers of legal and contractual complexity.

For insurers, reinsurers, brokers, and risk engineers, this evolution has direct implications. Construction risks are no longer solely rooted in physical processes, human error, and conventional software; they also arise from opaque algorithms, interconnected platforms, and cloud-based decision systems. As AI penetrates pre-feasibility assessments, performance-based design, site monitoring, commissioning, and long-term operations, the insurance market must move from being a passive risk carrier to an active partner in digital risk management.

1.1 Purpose and Scope of this Paper

This paper is written for insurers, reinsurers, brokers, risk engineers, and construction professionals seeking to understand how AI is changing the risk profile of construction projects and what that means for underwriting, policy design, and claims handling. It has four main objectives:

1. **Describe how AI is currently used across the construction lifecycle.**
   Drawing on real-world examples and sector-specific applications, Chapters 2 and 3 outlines AI tools and use cases from pre-feasibility through operations and maintenance, and across major construction segments (small civil and refurbishment, high-rise and complex buildings, bridges and large-span structures, tunnelling and underground works, and heavy industrial and energy infrastructure).

2. **Map the evolving risk landscape associated with AI in construction.**
   Chapter 4 explains how AI reconfigures traditional construction risks and introduces new technical, cyber-physical, human-factor, and legal/ professional risks, while also highlighting the opportunities AI creates for improved safety, defect detection, and documentation.

3. **Explain the regulatory, legal, and liability implications.**
   Chapter 6 provides high-level guidance on the emerging regulatory architecture (including the EU AI Act, new product liability regimes, and data protection law) and examines how liability is likely to fall on AI developers, vendors, and especially deployers, most construction firms and their professional advisers.

4. **Translate this into practical underwriting, contractual, and governance responses.** Chapters 5 and 7 set out underwriting considerations, policy wording adaptations, claims-handling implications, and a practical framework for AI governance and risk mitigation, including an AI risk maturity ladder and the role of a Project AI Coordinator (PAIC).

The paper focuses on applied AI, tools already in use or at a realistic near-term adoption stage, rather than speculative long-term technologies. Its perspective is global but anchored in the legal and regulatory frameworks of the EU, UK, and US, given their particular relevance for large construction and insurance markets. It should be however noted that the research behind the paper reflects the state of AI technologies, regulatory frameworks, and market practice as of May 2026. Given the rapid pace of change in AI capabilities and AI-specific regulation (such as the EU AI Act and emerging national frameworks), some details may evolve quickly; the analysis and recommendations should therefore be read as a snapshot rather than a static position.

1.2 Definition of AI

In the context of this paper, Artificial Intelligence (AI) in construction refers to autonomous or semi-autonomous systems that perform cognitive or physical tasks traditionally carried out by humans, with minimal or no human oversight. These systems materially affect construction outcomes across planning, design, execution, and quality control phases, and may also facilitate a seamless transition from construction to operation.
AI systems within scope may make or influence decisions, generate critical project outputs, or control or modify physical operations even where a human remains nominally “in the loop.”

This definition excludes conventional digital tools that merely assist human decision-making or require constant human input. Instead, it focuses on systems that introduce new risk profiles—such as model, data, and governance risks—by reducing or bypassing human control. If a tool learns from data or makes decisions in ways not fully programmed by humans, it is considered AI for the purposes of this paper.

Key Characteristics of AI in this scope include:

- **Autonomy**: The system can act without real-time human intervention.
- **Decision-making capability**: It can evaluate options and select actions based on data or learned patterns.
- **Physical or digital agency**: It can either generate critical project outputs (e.g., designs, schedules, inspections) or manipulate physical systems (e.g., machinery).

1.3 AI in the Construction Lifecycle

AI is now present, albeit unevenly, across all major phases of a project:

- **Pre-feasibility and geotechnical prediction**
  Machine learning models are used to interpret sparse ground investigation data and predict soil properties with high accuracy, improving early risk identification and investigation planning. However, as highlighted in *Chapters 2 and 3*, data scarcity, geological variability, and the need for expert validation mean adoption remains cautious and at an early-to-mid stage.

- **Design and engineering**
  Generative design engines, AI-assisted BIM workflows, and performance-optimization

tools support rapid optioneering and improve structural and environmental performance. LLM-based document intelligence is increasingly used for code checking and compliance. AI acts as a “copilot” in advanced design firms, accelerating workflows but also reshaping professional roles.

- **Planning, scheduling, and project management**
  AI-enhanced project controls systems analyze historical and live data to optimize schedules, resources, and logistics. Tools such as ALICE Technologies and BIM-linked AI engines, described in *Chapters 2 and 3*, can simulate alternative construction sequences and predict potential delays and cost overruns, with significant implications for DSU/ALOP exposures.

- **Construction and site operations**
  Autonomous and semi-autonomous equipment, advanced robotics, and AI-driven site inspection (drones, quadrupedal robots, visual recognition) are moving from pilot to deployment in certain segments, particularly mining, heavy industrial and energy infrastructure, and controlled environments. Real-world examples include autonomous haulage systems, automated drilling, and AI-based crane management on high-rise sites.

- **Safety, quality, and inspection**
  As set out in *Chapters 2, 3, and 4*, computer-vision systems and predictive analytics are used to detect unsafe behaviors, verify PPE compliance, identify defects, and document progress through 360° imaging. These systems can outperform manual monitoring and create high-quality evidence trails for risk management and claims.

- **Commissioning, handover, operations, and maintenance**
  Digital twins and AI-driven predictive maintenance transform O&M from reactive to proactive management. By integrating sensor data, SCADA systems, and BIM models, AI can detect anomalies, forecast failures, and optimize maintenance schedules, extending asset life, and reducing downtime.

Across these stages, AI remains largely an assistive technology rather than a fully autonomous decision-maker. Human judgment and traditional engineering practice continue to provide the primary safeguards, but the balance between human and machine roles is gradually shifting.

1.4 Audience and Perspective

The primary audience for this paper comprises:

- **Insurers and reinsurers**, particularly those underwriting CAR/EAR, professional indemnity, public liability, and cyber covers for construction clients.
- **Brokers and risk engineers**, who must advise clients on how AI adoption affects their risk profiles and insurance needs.
- **Construction firms, designers, and consultants**, who deploy AI in their own operations and are increasingly exposed to AI-related liabilities.
- **Owners, financiers, and regulators**, who need to understand how AI influences project risk, contractual structures, and regulatory compliance.

The paper does not provide legal advice or prescribe a single “correct” governance model. Instead, it aims to:

- clarify how AI changes the nature and distribution of construction risk

- identify where traditional insurance concepts (material damage triggers, PML, serial-loss clauses, professional duty) require adaptation
- propose pragmatic governance and documentation practices that support insurability.

1.5 Structure of the Paper

The remainder of the paper is structured as follows:

- **Chapter 2 – Applications in Construction**:
  Surveys AI applications across the construction lifecycle and sectors, highlighting current maturity levels, real-world examples, and emerging trends.
- **Chapter 3 – Construction Sectors and AI Integration**:
  Expands on sector-specific use cases and technical enablers, providing further granularity on adoption patterns.
- **Chapter 4 – Risk Landscape**:
  Analyses technical, human, cyber-physical, and legal/professional risks introduced or reshaped by AI, as well as the opportunities AI creates for safety, quality, and documentation.
- **Chapter 5 – Underwriting, Policy and Claims Considerations**:
  Translates AI-related risks into underwriting frameworks, policy wording adaptations, PML reasoning, and changes in claims handling and subrogation.
- **Chapter 6 – Regulatory and Legal Aspects of AI in Construction**:
  Outlines the evolving AI regulatory environment, product liability developments, data protection obligations, professional standards, and contractual implications for construction projects using AI.
- **Chapter 7 – Risk Mitigation and Best Practices**:
  Sets out technical, organizational, and contractual controls to manage AI risk, including AI governance structures, data management, sector-specific AI risk plans, privacy and security controls, and the AI risk maturity ladder.
- **Chapter 8 – Conclusions**:
  Synthesizes the findings and offers practical recommendations for insurers and construction stakeholders on how to adapt to AI-driven change.

Chapter 2: AI Applications in Construction

This chapter maps the current and near-term applications of Artificial Intelligence across the full construction project lifecycle. For each major phase, from pre-feasibility and design through site investigation, planning, construction, inspection, safety, commissioning, and operations and maintenance, it describes the AI techniques in use, illustrates them with real-world examples, and notes their current level of maturity. The aim is to give underwriters, claims handlers, and risk engineers a practical understanding of where AI is entering construction workflows and what it does at each stage, providing the foundation for the risk, underwriting, and claims analysis developed in the chapters that follow.

2.1 Pre-Feasibility

AI provides significant value in early project stages, particularly in geotechnical predictive analytics. Traditionally, prefeasibility relied on sparse borehole data, empirical correlations, and engineering judgment, leading to uncertainty in identifying underground risks.

In this context, machine learning (a subset of AI) is the main enabling technique used for geotechnical prediction. Machine learning methods such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees, Random Forests, and Gradient Boosting are applied as data-driven predictive models to process large geospatial and soil datasets. These methods can predict soil properties like shear strength, compression indices, and pressure-meter parameters with high accuracy ($R^2 > 0.9$ in studies).

While these techniques fall under the broader AI domain, they are more accurately statistical learning methods rather than full AI systems with reasoning or autonomous decision-making capabilities. Their role at this stage is primarily predictive analytics and pattern recognition.
These models help engineers detect potential ground hazards earlier, refine investigation plans, and reduce the likelihood of expensive surprises during construction.

However, adoption challenges include:

- Limited dataset size in most real projects.
- Highly variable soil conditions, reducing the applicability of region aggregated datasets.
- Requirement for expert validation before Machine Learning (ML) outputs can be trusted.

In terms of maturity, AI/ML in geotechnical prefeasibility is still at an early to mid-stage and is mainly used in pilot studies rather than full industry practice.
The sector is therefore at a promising but cautious stage, requiring larger curated datasets and hybrid ML–engineering approaches to ensure reliability (Level 2 as per chapter 7.2.3 - AI Risk Maturity Level).

2.2 Design

AI is transforming construction design through automation, generative modelling, and BIM integration. Using generative design engines, designers can rapidly create multiple structural forms, massing options, or layout alternatives based on parameters such as material efficiency, structural forces, daylighting, or energy consumption.

In the design stage, the AI role is to support generative design, optimization, and decision making by helping designers generate and evaluate multiple design alternatives.

Key AI contributions in design include:

- Automated conceptual design and optioneering
- BIM-linked parametric modelling and performance analysis
- LLM-based document intelligence for design code checking and compliance
- Engineering optimization for structural and environmental performance
- Workforce upskilling as design teams adopt AI-assisted tools

Examples from industry:

- MX3D Bridge (Amsterdam) uses generative form-finding and ML-driven real-time monitoring. This project uses AI to optimize the bridge design and monitor its structural performance in real time.
- Archistar automating site feasibility, code checks, and generative massing. It applies AI to quickly assess site constraints, check regulatory compliance and generate design options.
- Foster + Partners' Cyclops AI for real-time solar and daylight analysis. This tool helps designers evaluate daylight and solar performance during the design stage.
- Zaha Hadid Architects exploring text to image concept generation. AI is used to generate early design concepts from text inputs to support creative design explorations.

AI adoption in construction design is currently at an early to mid-stage, with growing use in some projects, particularly among more advanced firms, but not yet widely adopted or standard practice across the industry (Level 3 as per chapter 7.2.3 - AI Risk Maturity Level).

AI is now positioned as a standard copilot in design teams, accelerating workflows and improving quality while reshaping professional roles.

2.3 Site Investigation

AI-driven interpretation of geotechnical investigation data is a rapidly developing field. While AI shows high predictive reliability in lab settings, practical deployment remains limited due to data scarcity.

- Insufficient data volume at project level.
- Geological variability limiting dataset merging.
- Need for expert oversight to validate ML outputs.

AI on-site investigation is promising but currently supplementary and is not a replacement for engineering judgment (Level 1 as per chapter 7.2.3 - AI Risk Maturity Level).

2.4 Planning & Scheduling

AI enhances project planning and scheduling by analyzing historical performance data, live project conditions, weather forecasts, and workforce productivity records.
Key benefits are:

- Optimized schedules and resource allocation.
- Predictive identification of delays and cost overruns.
- Ability to simulate scenarios before construction begins.
- Insight-driven planning to reduce human error.

Tools like Procore, ALICE Technologies, Trimble ProjectSight, and BIM-linked AI engines significantly reduce manual scheduling effort. According to BCG, up to 30% of construction tasks could be automated by 2025, dramatically improving project efficiency. The current AI Risk Maturity Level of global adoption can be rated at Level 2-3 as per chapter 7.2.3.

2.5 Construction & Plant Control

AI adoption during physical construction remains limited but growing, especially in autonomous and semi-autonomous equipment.
Global market forecasts indicate rapid growth of autonomous equipment—projected CAGR of up to 14% through 2030—as contractors seek improved productivity, safety, and resilience against labor shortages.

Real-world examples are as follows.

- Ferrexpo autonomous haul trucks (CAT793D) improving productivity and reducing human risk
- Epiroc automated drilling enabling precision and reduced downtime
- China's 158 km autonomous road resurfacing project using robots and drones
- Liebherr autonomous wheel loaders for repetitive bulk-handling tasks

To achieve full autonomy, five foundational components are essential:

1. Advanced sensors (LiDAR, GPS, IMU).
2. Reliable communications (e.g., MIC 4.0 BUS).
3. Sophisticated AI/ML for perception and decision-making.
4. Compliance with safety standards (ISO 13849, ISO 190144).
5. Integration into digital ecosystems (cloud, digital twins, connected fleets).

Autonomy is progressing fastest in mining and controlled environments, as these types of AI applications require less IT capacity. The autonomous machines work in a defined and consistent environment. Heavy construction machinery like excavators and dumpers affect their surroundings with every step of the process, so it is necessary to quickly recalculate the most effective next step. This involves transferring the new terrain model into the AI model each time. Thus, applications for construction is following gradually as technology matures. The current AI Risk Maturity Level of global adoption can be rated at Level 3 as per chapter 7.2.3.

2.6 Quality & Inspection

AI-driven inspection is increasingly common, enabled by drones, robotics, and advanced imaging systems.

Inspection technologies include:

- UAV/Drones for sitewide imaging and thermal scanning
- Quadrupedal robots (e.g., Boston Dynamics Spot) for indoor and hazardous environments.
- Automated AI visual recognition for defect detection.
- LLM-based multimodal frameworks generating automatic site progress reports (e.g., AutoRepo).

These tools reduce reliance on manual inspection, improve safety, and provide continuous monitoring capability. The next frontier is the automated interpretation of inspection data using multimodal AI. The current AI Risk Maturity Level of global adoption can be rated at Level 3 as per chapter 7.2.3.

2.7 Safety & Compliance

AI significantly improves safety management by reducing injuries and enabling real-time monitoring.

Applications include:

- Wearable sensors tracking worker location, temperature, and fatigue.
- Cameras with AI detection for PPE compliance, unsafe behavior, or hazards.
- Predictive analytics to forecast safety risks based on site conditions.
- VR-based safety training simulations.

Platforms such as Smartvid, viAct, Kwant, and EarthCam's Visual AI provide continuous monitoring and proactive alerts. Studies (Dodge/CPWR 2021) indicate that 28% of contractors believe predictive analytics significantly enhance safety outcomes. The current AI Risk Maturity Level of global adoption can be rated at Level 2 as per chapter 7.2.3.

2.8 Commissioning & Handover

AI, particularly Digital Twin technologies, is reshaping commissioning by integrating real-time data with BIM models to simulate performance and identify issues before handover.

Benefits include:

- Detection of system integration issues.
- Verification of asset readiness and performance.
- Reduced likelihood of latent defects.
- Higher confidence for owners and insurers.

Complex projects (e.g., industrial plants, transit systems) are leading the adoption due to higher risk and system inter-dependency. The current AI Risk Maturity Level of global adoption can be rated at Level 2 as per chapter 7.2.3.

2.9 Operations & Maintenance

O&M is the longest and most costly phase of an asset's life cycle, and AI brings significant advantages through predictive maintenance, IoT sensing, and digital twins. AI transforms maintenance from reactive to predictive, reducing downtime and extending asset life.

Key applications include:

- Condition-monitoring of equipment.
- Predictive failure modeling using neural networks.
- Automatic anomaly detection.
- Maintenance scheduling optimization.
- Explainable AI (XAI) tools like LIME which can improve trust and transparency.

The current AI Risk Maturity Level of global adoption can be rated at Level 1-2 as per chapter 7.2.3.

Chapter 3: Construction Sectors and AI Integration

This chapter examines how AI is being integrated across five principal construction sectors: small civil works and refurbishment, high-rise and complex buildings, bridges and large-span structures, tunnelling and underground works, and heavy industrial and energy infrastructure. For each sector, the discussion covers the principal AI applications currently in deployment or approaching commercial adoption, the technical sensitivities that affect model reliability and risk exposure, and the integration points most relevant to insurers, underwriters, and claims handlers.

3.1 Small Civil Works and Refurbishment

AI adoption within small civil works and refurbishment (SCWR) has transitioned from experimental pilot applications to scalable industrial deployment.
Reality capture platforms such as OpenSpace enable automated 360° documentation and spatial indexing of renovation activities, with demonstrated application in complex airport terminal refurbishment programs where continuous progress verification and stakeholder transparency are required.

Buildots deploys AI-based visual analytics combining helmet-mounted cameras and machine learning algorithms to compare planned versus executed construction sequences. Applications in healthcare infrastructure refurbishments in the United Kingdom demonstrated improved schedule reliability and early detection of execution deviations, reducing coordination conflicts among contractors.

Doxel represents a further evolution toward autonomous construction analytics through integration of LiDAR scanning, robotics, and predictive AI models capable of quantifying productivity variance and cost deviation in real time, thereby enabling proactive corrective actions during mid-scale civil refurbishment works. A documented example is the deployment at a multi-floor medical office complex in San Diego, California.
Digital twin-based governance platforms also demonstrate significant value in asset renewal strategies. Bentley Systems' iTwin platform supported refurbishment planning for the City of Pau, France, enabling simulation of intervention alternatives and optimization of long-term capital investment decisions.

BrainBox AI implemented autonomous HVAC optimization within operational commercial buildings such as 45 Broadway, New York, achieving measurable reductions in energy consumption without intrusive retrofitting. Enterprise-scale platforms including Honeywell Forge and Johnson Controls OpenBlue integrate predictive maintenance, occupancy analytics, and carbon monitoring across commercial and historic building portfolios, demonstrating lifecycle performance improvement aligned with ESG and decarbonization targets.

Four key technical sensitivities affect AI performance and reliability in SCWR deployments. Poor local data leads to misclassification of defects and inaccurate progress tracking arising from regional differences in materials and construction methods. Off-the-shelf models introduce limitations from lack of domain specificity. Limited validation reduces reliability across diverse project conditions. Sparse telemetry hinders post-incident analysis and complicates liability attribution.

In summary, tools such as OpenSpace and Buildots are now deployed on live refurbishment projects, improving schedule reliability and coordination. More advanced systems, including productivity analytics platforms and digital twins, extend this capability to cost and delay

prediction, while autonomous building performance platforms deliver post-construction operational gains. The principal limitation across these applications is data dependency: poor local data quality, generic off-the-shelf models, and limited validation can undermine reliability and complicated post-incident attribution.

3.2 High-Rise and Complex Buildings

Shift Toward Performance-Based Design
Over recent decades, several areas of the construction design industry have shifted from prescriptive code compliance toward performance-based design (PBD), evaluating buildings against explicitly defined performance outcomes across the realistic range of hazard conditions they will experience. This shift originated in the 1990s to improve structural behavior of buildings under seismic loading, and similar frameworks are now advancing across fire, concrete, geotechnical, flood resilience, concrete durability, and façade design.

Although this paradigm shift leads to improved design outcomes, the methodology can require exhaustive parametric numerical modelling, testing hundreds or thousands of possible scenarios, which become impractical with sophisticated models where each evaluation can require hours of computing time. Recently, significant progress has been made in performance-based wind design (PBWD), which is increasingly relevant for complex-shaped high-rise buildings. AI surrogate models, trained on a limited set of simulations and capable of predicting responses in seconds, can substantially compress this computational burden, enabling design teams to explore thousands of geometric or structural configurations that would otherwise be prohibitive to evaluate directly.

At SOM's West Bund Convention Center in Shanghai (2025), over 800 façade configurations were evaluated simultaneously against structural, daylight, sightline, and constructability criteria overnight, compressing months of conventional design development.

Structural Health Monitoring
Tall buildings are now instrumented with hundreds of sensors, survey markers, accelerometers, inclinometers, stress gauges, GPS receivers, wind pressure transducers, generating large volumes of data continuously throughout construction and operation, which are increasingly difficult to process and interpret manually.

Deep learning applied to continuous sensor data streams provides the analytical layer that makes this data actionable in practice. Recent literature documents models trained on historical sensor data that can automatically detect anomalies in the structural response, deviations indicating structural change or abnormal loading, while also identifying the location and severity of changes.

Tower Crane Management
In high-rise construction, tower crane management is a key determinant of project progress. Versatile AI has developed a sensor mounted on the crane hook that, combined with computer vision and machine learning, classifies crane lifts, records cycle times and weights, and reports utilization in real time.

Case studies indicate significant productivity gains from data-driven crane optimization. In a documented deployment on a Turner Construction project in San Diego, the system recorded 2,113 picks over 621 hours and supported the early demobilization of one crane, saving 24 workdays. Separately, Gilbane Building Company reported 90–98% crane utilization during steel erection and façade installation using the same system.

3.3 Bridges and Large-Span Structures

AI is increasingly applied across bridge lifecycles, from design to long-term maintenance. Key applications include topology optimization, structural health monitoring, anomaly detection, and predictive maintenance. The literature highlights rapid adoption alongside persistent challenges in data availability, scalability, and long-term prognostics. Research on large-span structures more broadly reflects a shift toward machine learning and digital twins to manage long service lives under uncertainty.

Topology Optimization and Generative Design
Topology optimization enables efficient structural forms by minimizing material use while meeting performance constraints and is widely recognized as a powerful performance-based design tool. Two examples illustrate its application at scale:

- A 152 m pedestrian bridge designed using the BESO method demonstrates lightweight, efficient load paths.
- A 3D-printed smart bridge incorporating generative design and embedded sensors linked to a digital twin demonstrates integration of structural monitoring at the design stage.

A key challenge is that long bridge service lives limit the validation of AI-generated designs, owing to the absence of long-term performance data.

SHM Anomaly Detection
AI detects structural anomalies using vibration and sensor data, supported by advances in structural health monitoring systems.
Neural networks trained on vibration responses under traffic loading have demonstrated reliable defect detection.
Deep learning approaches, for example, ResNet-152 applied to scalogram representations, achieve high accuracy in anomaly detection.
A notable practical issue is that some anomalies originate from sensor faults rather than structural damage, requiring appropriate filtering before conclusions are drawn.

Predictive Maintenance and Digital Twins
AI supports the forecasting of structural deterioration and maintenance planning, although fully reliable prognostic systems remain limited.
Digital twin frameworks integrating monitoring, prediction, and maintenance decision-making have been documented in the literature.

Real-world applications combining sensor, traffic, and environmental data for ongoing monitoring and decision support are also emerging, including digital twin-based anomaly detection systems.

Cross-Cutting Challenges
- Limited failure data: long service lives and rare failure events constrain machine learning model training.
- Sensor placement and quality: monitoring accuracy depends critically on optimal sensor configuration.
- Model drift: structural changes over time can degrade AI model reliability.

Practical Risk Controls
- Design: combine AI optimization with conventional engineering validation.
- Instrumentation: optimize sensor placement and build in appropriate redundancy.

- Model governance: apply recalibration, drift monitoring, and human oversight using digital twin frameworks.

3.4 Tunnelling and Underground Works

AI applications in underground works and tunnelling span project management, geotechnical interpretation, and construction process optimization, as illustrated by the following examples.

The High Speed 2 (HS2) London–Birmingham railway project faced a significant documentation burden, managing 37,983 requirements across 34 contracts and reviewing approximately 20 assurance packs per month, each requiring detailed verification. Alice Technologies, an AI-based construction simulation platform, enabled project teams to test millions of construction scenarios to optimize labor, materials, and scheduling. By modelling "what if" changes, the project identified more efficient construction strategies, improving productivity without increasing waste or overtime.

AI in Geotechnics and Tunnelling: AI adoption in practice is still emerging, but the research base is extensive, with artificial neural networks (ANNs) being the most widely used approach.

- Soil classification using image-based ANN models, achieving approximately 86% accuracy.
- Cohesion (Cu) estimation using ANN models.
- Settlement prediction: AI models reliably forecast surface and subsurface deformation using geotechnical monitoring data.
- TBM performance prediction: ANN models using geotechnical and machine data can predict outcomes with less than 10% error, supporting design and tunnel alignment decisions.
- Earth pressure and stability: AI enables real-time tunnel boring machine (TBM) pressure control, improving safety and reducing failure risk, with potential for fully automated systems.

Monitoring and Digital Systems: KorrAI uses InSAR satellite monitoring, enhanced with GNSS calibration and ADI filtering, while drone-based InSAR improves local measurement accuracy.

Automation and Safety: Emerging systems are beginning to realize the vision of fully automated underground construction. Prufrock technology pursues the objective of eliminating workers from the underground environment, while ATRIS (Automated Tunnel Robotic Installation System) represents a further step in this direction. Reported performance benefits of such systems include a 70% reduction in underground workers, 40% lower carbon emissions, 40% higher productivity, 30% lower costs, and improved precision through AI and 3D vision integration.

3.5 Heavy Industrial and Energy Infrastructure

AI is increasingly deployed in heavy industrial and energy systems, enabling autonomous decision-making in real-world operational environments.

Mining Sector: AI applications span the full mining value chain, including exploration, planning, and operations. A prominent example is autonomous haulage at Rio Tinto's Yandicoogina and Nammuldi mines in Western Australia, where driverless trucks transport material using sensors, GPS, and centralized fleet management systems.

Mining environments, typically remote and highly structured, are well suited to automation. These systems, often classified as Connected and Autonomous Vehicles (CAVs), combine centralized coordination with local optimization. Since their introduction in 2008, autonomous haulage systems have improved efficiency, reduced operating costs, and enhanced safety across mining operations.

Energy Infrastructure: This consists of distributed, data-intensive assets, making it well suited for AI-driven optimization across multiple functions.

Solar PV construction: AI-enabled robotics automate panel installation. Companies such as Luminous Robotics and ULC Technologies are piloting these systems, though adoption remains at an early stage.

Monitoring and inspection: autonomous drones, including “drone-in-a-box” systems such as DJI Dock, enable remote inspection of energy assets. AI supports fault detection and condition monitoring, with comparable solutions offered by Percepto.

Operations and maintenance (O&M): AI processes SCADA data to enable predictive maintenance, fault detection, and energy forecasting in renewable energy systems. Given that O&M accounts for 25–30% of lifecycle costs, optimization is operationally critical. Condition-based maintenance and machine learning-based forecasting improve reliability and planning. AI is also applied in battery storage systems for operational and market optimization, with platforms offered by Fluence Energy and AutoGrid.

Chapter 4: Risk Landscape

When AI is introduced into construction, risk is no longer confined to purely physical or human factors; it also acquires digital and systems level dimensions. In some configurations, AI can contribute to more correlated or systemic failure modes and, where multiple digital components interact, can complicate the analysis of causation. Like other complex software systems, AI models rely on robust software and data engineering practices, including data quality management, validation, version control, security, and appropriate human oversight.

Because AI models often learn from large, evolving datasets and exhibit nontrivial behavior changes when updated or retrained, weaknesses in these areas can have outsized and less predictable effects on model outputs. AI does not eliminate the traditional risks of construction; rather, it reconfigures them and adds new layers of technical complexity and liability. These dynamics intersect with broader digital risk factors, such as data quality and integrity, to data corruption, model opacity for certain classes of AI systems, uncontrolled software or model changes, dependence on cloud based infrastructure, and digital availability and resilience. While none of these risk categories are unique to AI, AI-enabled workflows can change their impact profile and make their consequences more tightly coupled to construction outcomes. At the same time, when implemented with robust controls, AI creates significant opportunities: to improve safety, enable earlier defect detection, strengthen project documentation, and support better risk assessment by the insurance market.

4.1 Technical and Model Risks

AI models are, at their core, IT systems exposed to many of the same operational, cybersecurity, and governance risks as conventional software. However, because AI models rely on large volumes of data and complex computations, their behavior and outputs are often difficult for humans to anticipate, interpret, or continuously verify. This makes it challenging to assess whether an AI system is still operating correctly over time.

Sensitivity of Model Construction
The construction of an AI model is highly sensitive and requires strong discipline throughout the entire lifecycle. One of the most critical aspects is the integrity of training data, from initial collection through transmission and storage. Data corruption, whether accidental or malicious, can occur at multiple points; if it happens during model development, it may remain undetected and propagate into production, undermining model reliability. Best practice therefore requires end-to-end data security, including encryption during transmission and at rest. Although model building may not appear immediately critical, weaknesses at this stage are particularly dangerous because their effects may only become visible after deployment. Equally important is securing the model development environment. Access to training systems and learning programs should be strictly controlled, for example through multi-factor authentication (MFA), role-based access control, and comprehensive change logging.

Data Quality and Representativeness
AI models, much like statistical models, are fundamentally dependent on data quality, including error detection and correction, consistency checks, and monitoring for missing, corrupted, or biased data. Machine-learning-based models are especially sensitive to the dataset used to define their universe of possibilities. If the dataset is truncated, incomplete, or over-represents specific scenarios, the model may fail to produce accurate outputs for conditions that are insufficiently represented. A key responsibility of the modelling engineer is therefore to define and document a robust data-collection strategy that ensures representativeness across expected operating conditions and edge cases.

Model Testing and Validation
Testing AI models is critically important but inherently complex. Because models are designed to optimize outcomes across numerous fine-grained scenarios, it is rarely sufficient for humans, alone to define all relevant test cases. The modeler must clearly explain and formalize the testing strategy, demonstrate how both normal and extreme scenarios are evaluated, and show how model performance degrades under abnormal or incomplete inputs. Transparent testing methodologies are essential to build confidence in model behavior and to support auditability and regulatory review.

Types of AI Models and Associated Risks
AI models broadly fall into two categories with distinct risk profiles. Physics-based or rule-informed models rely on known physical laws or engineering principles; while such models still require parameter calibration, their behavior is generally more interpretable. A key challenge is ensuring adequate computing capacity to simulate complex scenarios within acceptable timeframes. Data-driven machine learning models are newer and rely on statistical correlations derived from large, representative datasets. They do not require an explicit understanding of underlying physical rules but depend on computational power and data volume. These models are particularly affected by the black-box effect, making it difficult to explain why specific outputs are produced—which in turn complicates validation, trust, and accountability.

Deployment, Updates, and Configuration Control
When AI models are implemented into machines, control systems, software platforms, or when they are updated, it is essential to ensure that deployment is properly secured. Configuration and version controls must be in place to confirm that the correct and approved model release is installed and operating. For safety-critical or business-critical applications, redundancy strategies should be carefully evaluated. These may include dual computers or parallel systems, redundant or diverse sensors, and staggered model updates where one system is updated and monitored before the rollout is extended to others. Such strategies reduce the risk of systemic failure caused by faulty updates or corrupted models.

Digital Twins and System Availability
When digital twins are used to monitor or control physical systems, special attention must be paid to server location and availability. If computational resources are cloud-based and geographically distant, the system becomes exposed to risks related to connectivity, latency, and server outages. Since 100% availability cannot be guaranteed, an explicit analysis should be conducted to assess the consequences of temporary loss of the digital twin, define fallback or degraded-mode operations, and determine acceptable downtime thresholds for the physical system.

4.2 Human Factors, Cyber-Physical Risks, and Process/Integration Risks

Beyond technical and model risks, AI in construction introduces several further risk dimensions with direct insurance relevance. At the human level, overreliance on AI outputs—commonly described as automation bias—combined with skill fade, inadequate supervision, training gaps, and change management failures can undermine the effectiveness of even well-designed systems. At the cyber-physical level, compromised models or sensors, spoofed imagery, and tampered telemetry can translate digital failures into physical harm or construction defects, a pattern consistent with the broader risk of cyber-to-physical loss escalation. At the process and integration level, unclear responsibilities between contractors, engineers, and AI vendors, compounded by version control gaps, documentation shortfalls, and insufficient independent verification and

validation (IV&V), leave responsibility boundaries unclear and complicate coverage allocation.

4.3 Legal and Professional Implications

AI reshapes construction risk not only technically but also legally and professionally. Because AI systems are built on large-scale datasets, often derived from BIM models, engineering drawings, and site monitoring, questions arise over who owns the data, who may lawfully reuse it for training, and who is accountable when AI-driven decisions contribute to loss. Construction data is typically multi-authored and contractually fragmented, so no single party usually has unrestricted rights to reuse it for AI purposes. For a detailed discussion of how specific regimes (such as the EU AI Act and related copyright and data frameworks) address these issues, see Chapter 6.

From a professional perspective, AI does not remove existing duties of care; it changes how they must be exercised in practice. Beyond strictly legal obligations, designers, engineers, and project managers are increasingly expected, as a matter of professional standards and risk management, to:

- understand the capabilities and limitations of the AI tools they use
- maintain meaningful human oversight and avoid uncritical reliance on automated outputs
- adopt processes to validate and document key AI-assisted decisions; and
- communicate, where relevant, how AI tools contributed to their analysis and recommendations.

These expectations are not yet universally codified as distinct legal duties but are increasingly reflected in technical guidance, professional standards, and internal risk management policies.

Looking ahead, some commentators have suggested that, in the longer term, courts and professional bodies may treat certain widely accepted AI-based safety or optimization tools as part of the ordinary standard of care. At present this remains speculative rather than a clearly established legal trend, but it is a relevant scenario for insurers and practitioners to monitor.

Liability boundaries are also becoming more blurred. The same incident may involve:

- potential defects in AI software or data (suggesting product or technology liability)
- inadequate configuration, validation, or supervision by professionals (professional liability)
- and, in some cases, cyber compromise of data or systems (cyber liability).

In practice, responsibility is shaped by a combination of factors, including contractual allocation of risk, regulatory obligations, contributory negligence, and the degree of control exercised over training, deployment, validation, and updates. Parties who determine how AI is configured and used on a project will often carry a significant share of the legal exposure, but they are not the only potential sources of liability.

For insurers, these developments translate into hybrid and systemic risk patterns. AI-enabled failures can:

- turn digital errors (e.g. corrupted BIM or digital twin data) into physical defects and rework
- trigger accidents involving autonomous or AI-assisted equipment

- and generate correlated losses across multiple projects relying on the same AI platforms or data pipelines.

As a result, data and AI governance maturity, i.e., how models are validated, monitored, documented, and overseen, are becoming a central indicator of risk quality. The stronger and more transparent the governance, the easier it is for underwriters and claims teams to assess causation, allocate liability among the parties involved, and evaluate the potential for serial or systemic losses. Chapter 6 explores the underlying regulatory and liability frameworks in detail; while Chapters 5 and 7 translate these implications into underwriting, policy wording, and governance best practices.

4.4 Opportunities

Construction remains one of the world's highest risk industries, with complex work environments, numerous stakeholders, and significant coordination challenges. Traditional safety management and quality assurance practices are labor-intensive and susceptible to human error. Recent advances in AI—particularly deep learning, computer vision, and predictive analytics—have enabled tools that support early hazard detection, automate compliance monitoring, and generate transparent digital records across the entire project lifecycle.

Construction Safety
AI-enabled hazard-detection systems use computer-vision models such as CNNs and YOLO frameworks to identify unsafe conditions in real time, with practical applications spanning automated PPE compliance verification across large job sites, real-time alerts when workers enter high-risk proximity zones, and detection of environmental hazards such as obstructions and edge risks. Automated safety systems outperform manual monitoring by significantly reducing compliance-checking error rates, providing more consistent and objective safety oversight. Predictive modeling further supports teams in forecasting accident-prone areas before incidents occur. Wearable sensors and RFID-AI proximity warning systems enhance worker protection by issuing instant alerts when workers approach machinery or hazardous zones; autonomous equipment further minimizes direct human exposure.

Defect Detection and Quality Control
Machine-learning models analyses historic and real-time project data to identify early indicators of delays, defects, or material inefficiencies; predictive analytics can identify quality-related risks before they manifest in the field. In practice, this encompasses automated flagging of structural misalignments, early detection of missing fireproofing, waterproofing, or critical components, installation-sequence verification using AI-assisted material tracking, and automated quality audits for repetitive construction elements. Computer-vision-enabled 360° imaging systems further support automated detection of incomplete installations, misalignments, or deviations from BIM models, producing structured records that significantly reduce reliance on manual inspections.

Documentation and Progress Verification
AI-driven documentation creates tamper-resistant, time-stamped visual and data records of project progress. Systems combining AI with 360° imaging, BIM, IoT sensors, and AR/VR tools enhance site visibility, streamline communication, and improve audit readiness. In practice, these systems support automated daily site logs using images and sensor data, continuous updates to digital twins reflecting real field conditions, AI-enhanced progress forecasting based on historical and real-time patterns, and fast retrieval of past site conditions for dispute resolution. Natural language processing (NLP) tools also process safety logs, RFIs, and reports to automatically classify issues and surface emerging risks, reducing administrative workload.

Insurance Relevance and Practical Applications
Real-world deployments illustrate the breadth of current applications. A major U.S. contractor deployed Smartvid.io to analyze site photos for PPE non-compliance and unsafe behaviors, with automated alerts enabling early intervention and measurable reductions in high-risk on-site conditions. The OpenSpace platform enables fast whole-floor captures, with AI highlighting incomplete installations and deviations days earlier than traditional walkthroughs. Machine-learning-based predictive models have demonstrated the ability to forecast schedule delays and cost overruns with sufficient lead time for project teams to intervene and stabilize outcomes. Procore's integrated safety analytics platform used AI trend analysis to identify leading indicators of safety issues, strengthening contractor performance through data-driven insights. A further implementation of RFID-AI proximity sensors alerted workers when entering active equipment zones, significantly reducing collisions and near-miss incidents. Where AI controls are robust and verifiable, these capabilities can be recognized in risk selection and pricing.

AI is reshaping the construction lifecycle by improving how safety, quality, and documentation are managed. The technologies highlighted in this chapter—computer vision, predictive machine learning models, wearables, autonomous systems, and documentation platforms—are no longer experimental; they are delivering performance improvements that address long-standing pain points in construction. As adoption accelerates globally, organizations that integrate these tools into their project workflows will gain benefits in risk reduction, operational efficiency, and information reliability.

Chapter 5: Underwriting, Policy and Claims Considerations

The construction industry's shift from static software toward applied AI represents a systemic change in how projects are conceived, managed, and executed. For insurers, this transition means moving beyond the role of pure risk carrier toward that of an active risk management partner — one whose policies must address not only physical damage but also the digital dependencies, non-physical disruptions, and opaque decision processes that AI-driven projects introduce. This chapter translates that risk landscape into practical guidance on risk selection, policy wording, pricing, and claims handling.

5.1 Underwriting Considerations

With the increasing integration of AI into construction planning, execution, and operational processes, the role of insurance is undergoing a fundamental transformation. While policies have traditionally viewed physical damage as the primary cause of business interruptions or delays, digitized and AI-driven construction projects create new systemic dependencies that can lead to significant financial losses even in the absence of physical damage. Insurers must therefore move beyond the role of purely passive risk carriers and, within the constraints of the insurance contract, act as structured risk management counterparts, for example by using underwriting, policy conditions, and advisory services to promote technical, organizational, and data related controls that reduce the likelihood and extent of losses over the policy period.

5.1.1 Understanding AI Risk: Information and Disclosure

The starting point for any underwriting assessment is understanding the AI risk presented by the specific project. Underwriters must determine which AI solutions are being used, how critical they are to project delivery, and how the likelihood and impact of those solutions not performing as intended should be assessed. This requires moving away from static risk assessments toward dynamic, technology-oriented analyses.

Relevant sources of information include a client-provided map of AI usage across the project, any independent AI risk or assurance report prepared by a third party, and evidence of the insured’s alignment with emerging governance standards such as ISO 42001 or the NIST AI Risk Management Framework. At present there is no universally accepted methodology for AI risk assessment, so underwriters should treat such reports as one input among others rather than as a definitive measure of risk maturity. A structured assessment of the policyholder’s AI maturity, ranging from ad hoc use without governance to fully optimized, validated systems, helps to accurately characterize the risk profile. Equally important are due diligence reviews of technology providers, the incorporation of human oversight (“human in the loop”), and verification of data quality, which is essential for both training and operational use.

5.1.2 Delay in Start-Up (DSU) and Advanced Loss of Profits (ALOP)

The shift toward AI-driven construction is particularly consequential in Delay in Start-Up (DSU) and Advanced Loss of Profits (ALoP). Compensation under these covers depends on precise documentation, the integrity of the critical path, and clear evidence of the cause of delays. As soon as essential project functions, such as planning tools, monitoring systems, sensor technology, cloud-based platforms, or automated control are supported by AI or fully digitized, a significant risk of non-physical disruptions arises.

These disruptions include faulty software updates that trigger failures of entire process chains, cloud unavailability, and integration of errors between subsystems. Drifts in sensor technology or algorithms can also materially affect the construction process without any physical damage being present. To address these gaps, insurance coverage must explicitly

account for non-malicious, systemic digital failures and define the circumstances under which their consequences are insurable.

For DSU/ALoP specifically, two scenarios require particular attention: first, delays without any material damage, triggered for example by software errors; and second, material damage caused by AI, software, or data errors, which significantly complicates the assessment of causality. Digital failures can also produce different and potentially longer recovery times than traditional physical damage, a factor that must be reflected in the indemnity period assessment.

5.1.3 Probable Maximum Loss (PML)

Probable Maximum Loss (PML) scenarios for property damage are typically well understood for CAR/EAR projects. The addition of AI models in the design process even where a human remains in the loop introduces new risks that existing PML frameworks do not fully capture. It is suggested that underwriters apply the higher one of the following two PML scenarios. Note that this paper is published in 2026; as additional loss history and data become available, this approach should be adapted accordingly. Please use the decision tree at the end of this section to check if this approach should be followed.

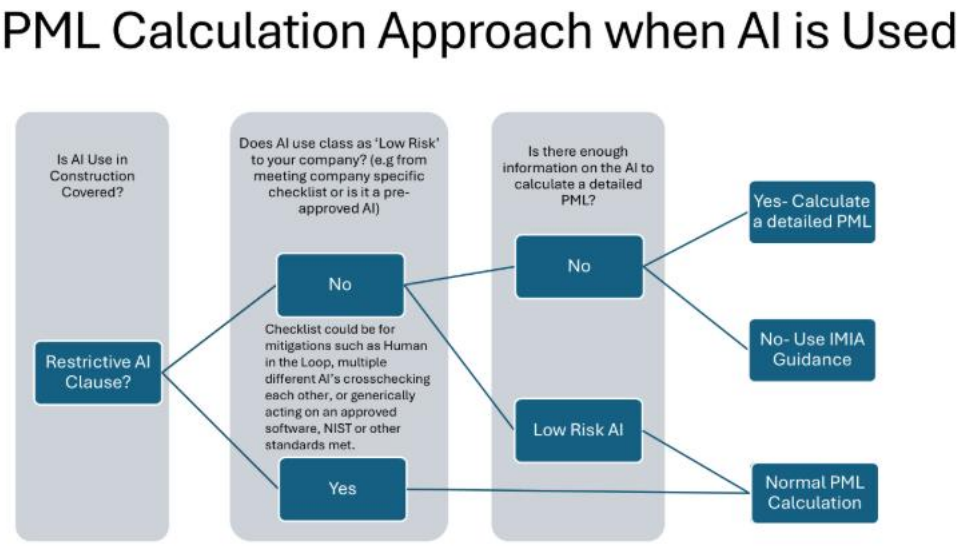
Scenario 1 — PML based on the EU AI Act (worldwide losses): For prohibited AI practices, the applicable threshold is 7% of worldwide annual turnover or EUR 35 million, whichever is higher. This category includes manipulative AI systems, exploitation of vulnerabilities, social scoring by public authorities, and unauthorized biometric identification in public spaces. A lower value is acceptable where the AI in question is used exclusively for high-risk systems such as technical documentation or risk management, in which case the applicable PML is EUR 15 million or 3% of worldwide annual turnover, whichever is higher. This scenario uses the EU AI Act's administrative fine thresholds as an indicative benchmark for potential loss magnitude. It does not imply that the Act applies worldwide; rather, it provides a reference point for estimating systemic exposure where AI practices could trigger significant regulatory, contractual, and reputational consequences. In jurisdictions or portfolios where these thresholds would be disproportionately conservative, underwriters should adjust them to better reflect local legal exposure and market norms. The thresholds are also not intended to suggest that regulatory fines themselves are covered; such fines and penalties are generally excluded under standard policy wordings.

Scenario 2 — PML based on actual insured values of projects under construction in the same phase: 100% of the combined insured values of all projects in the same critical construction phase at the same time is taken as the PML. For example: where five buildings are under construction and three are in the same phase (installation of shear core) while two are in a different phase (foundation works), 100% of the insured values of the three buildings in the shared phase constitutes the PML.

The reasoning behind Scenario 2 reflects a specific characteristic of AI-related design risk. The critical point at which AI-based design errors that have not been caught by human review become irreversible is the installation of the building core. A structural error at this stage may render a building unfixable, requiring demolition, whereas errors in design elements such as facades are typically repairable. Where multiple cores are being installed in parallel, any sub-standard AI-supported design process could affect all buildings simultaneously. This analysis assumes that underwriting clauses exclude liability for design flaws in buildings already operational or handed over, and that LEG 3 coverage does not extend to improvements in design, thereby limiting additional liability exposure.

For Business Interruption and Loss of Profit scenarios, coverage should be tailored to the individual business and policy. However, consistent with the property damage PML

approach, the appropriate starting point is the demolition and rebuilding time of the specific structures in the same critical construction phase that are covered in parallel under the policy.



5.1.4 CAR/EAR and Cyber: Complementary but Distinct

CAR/EAR policies and cyber policies address different dimensions of risk and operate on different coverage triggers. CAR/EAR covers physical loss or damage to the contract works and associated third-party liability arising from the construction project. In many markets, CAR/EAR policies now incorporate cyber exclusions, with the option to buy back cover for cyber-triggered material damage, sometimes on a sub-limited basis. Cyber insurance, on the other hand, typically addresses defined cyber events such as network-security failures, data breaches, and certain non-malicious system failures, including some events not caused by external attacks.

As construction projects become more digitally dependent, AI-related failures may manifest both as physical damage (within the scope of CAR/EAR) and as nonphysical business interruption or data related harms (within the scope of cyber policies, where purchased). Insurers therefore need internal clarity, in product design and portfolio management, about how digital dependencies in construction are treated across their CAR/EAR and cyber books, to avoid unintended risk accumulation.

This distinction has direct implications for coverage design. Where an AI system failure is the result of a cyber event within the scope of a cyber policy, that policy may respond. Where failure arises from non-malicious causes such as model drift, faulty software updates, or sensor degradation and leads to physical loss or damage within the scope of the CAR/EAR wording, the construction policy may respond, while liability for the underlying error may still rest with the deployer or technology vendor as discussed in Chapter 6. Ambiguity at the boundary between the two covers creates the risk of gaps that leave the insured without recourse, and the insurer exposed to dispute.

5.1.5 Liability, Traceability, and Policy Requirements

The involvement of AI systems in planning, monitoring, and operational decisions introduces additional complexity into existing liability frameworks. When a faulty AI output, such as an incorrect calculation, an inadequate recommendation, or an erroneous automated action, contributes to a loss, the key questions include whether responsibility attaches to the professional using the tool, the entity deploying the system, the developer, or, in some cases, the provider of data or infrastructure. The precise characterization of any given failure will depend on the applicable legal regime (e.g. professional liability, product liability, or

operational negligence) and on how AI is treated within that regime, rather than being determined by the wording of the insurance policy itself. Policy wording cannot override these legal allocations of responsibility, but it can clarify how coverage responds to losses that involve a mixture of human and AI-enabled causes, and how the insurer will treat claims where multiple parties may share fault.

A lack of traceability, such as incomplete logs, missing model versions, or insufficiently documented model updates, can significantly complicate the burden of proof in the event of a claim and may limit the prospects for successful recovery against third parties. Clear traceability expectations, whether embedded in policy conditions, underwriting questionnaires, or risk-management guidance, are therefore an important tool for managing AI-related claims complexity.

To ensure the manageability of AI-related risks, policies should in future include specific technical and organizational requirements. These comprise:

- comprehensive documentation obligations covering model versions, data states, decision logs, training data, and sensor and telemetry data
- maintenance, calibration, and updating obligations for all AI and sensor components
- the existence of robust emergency, fallback, and degraded-mode procedures, including manual override options; and
- an explicit guarantee of the insurer's access to technical expertise and data necessary for reconstructing causes of loss and critical paths.

Without this transparency, uncertainty in claims settlement increases significantly, and the insurer’s ability to pursue subrogation against third-party technology vendors is materially diminished.

5.1.6 Policy Wording Adaptations

To ensure that insurance policies adequately address AI-related risk types, adapted wording is necessary across several areas.

Serial-loss and related aggregation clauses are well-established tools in liability and casualty insurance, where a single originating defect or negligent act can generate multiple claims over time. For Construction all Risk policies, which are typically written on a project-by-project basis with separate limits and periods, these mechanisms are less straightforward to apply. Nevertheless, where an insurer covers multiple projects that rely on the same AI platforms or data pipelines, it should consider at portfolio level how a single software error or data poisoning event could generate correlated losses, and whether this is best managed through policy structures outside CAR/EAR (e.g. through liability covers, reinsurance, or internal accumulation controls) rather than through serial loss wording on individual project policies.

In professional indemnity and related liability covers, definitions of “professional services” or equivalent should be reviewed to ensure they explicitly encompass activities related to the selection, configuration, training, and ongoing monitoring of AI models, reflecting the reality that decisions about AI deployment are themselves professional acts that can give rise to liability.

Given the distinct triggers and scopes of construction and cyber policies, insurers should ensure that any interfaces between the two, for example where digital causes lead to physical damage, or vice versa, are clearly understood and, where necessary, explicitly addressed in wording or underwriting guidance, so that AI-related loss scenarios do not create unexpected gaps or overlaps.

AI usage disclosure obligations should be strengthened, for example by requiring the insured at inception to describe the material AI systems deployed on the project and their governance arrangements, and to notify the insurer of any significant changes that could materially alter the risk profile. Given the continuous update cycles typical of AI systems, such obligations will need to be drafted pragmatically, focusing on material changes rather than minor version updates, and may be better framed as information and cooperation duties rather than strict conditions precedent.

5.1.7 Dynamic Premium Models

AI-based construction projects open conceptual opportunities for more dynamic premium models. In principle, real-time data from sensors, IoT devices, and smart construction-site platforms could support risk-adjusted pricing that responds to actual project conditions rather than static assumptions made at inception. In practice, CAR insurance still operates largely on a pooled basis, so any move toward dynamic pricing must be balanced against market norms and portfolio-level considerations. Such models are still at an early stage of development in the CAR/EAR market, and their feasibility is constrained by data quality, contractual simplicity requirements, and the relatively short duration and project-specific nature of many construction policies.

Regardless of whether premiums are static or dynamic, underwriters must ensure that hidden and long-term risks, particularly algorithmic biases or data drift that may only manifest as physical defects years after project completion, are reflected in the overall pricing and capital allocation. Failure to recognize these latent exposures represents a material underwriting risk.

Overall, the increasing use of AI means that insurers are becoming an integral component of digital risk management in construction. Insurability in highly automated projects can only be sustained over the long term if policies define clear technical requirements, documentation obligations, and lines of responsibility.

5.2 Claims Handling Process

The increasing use of AI in construction projects is fundamentally reshaping the landscape of insured losses and the processes required for effective claims handling. Insurers will no longer assess damage solely based on physical evidence and human error; instead, they must evaluate digital causation, hybrid chains of events, and opaque AI-driven decision processes. Large-scale claims analyses already demonstrate that fire and explosion, defective products, and workmanship deficiencies are among the most significant contributors to construction losses, areas in which AI may improve overall quality but can also amplify risks where governance and data integrity are insufficient.
As a result, the claims handling process must evolve on two fronts: adjusters must be capable of investigating losses caused by faults within AI systems, and insurers should simultaneously deploy AI to increase operational efficiency for example through automated First Notice of Loss processing, high-speed document analysis, and fraud detection including the identification of forged or manipulated images. Together, these capabilities will allow claims departments to manage both the increasing complexity and the growing volume of data associated with AI-enabled construction projects.

5.2.1 Fact-Finding in AI-Related Loss Scenarios

The most profound technical change in claims handling occurs during causation analysis. Construction insurance generally covers only material damage, yet many such damages originate from design or execution defects. Historically, those defects could be traced to

human error, faulty calculations, or incorrect use of conventional software. With the introduction of AI-based design tools, this process becomes significantly more complex. AI systems frequently operate as non-transparent “black boxes.” The designers themselves often cannot fully explain the logic behind a model’s decisions. In the event of a loss, this hampers both the identification of the underlying design error and the reconstruction of the original calculation. Because AI tools can be embedded in multiple stages of the design and execution process, an undetected error in a shared model or dataset may propagate through different parts of a project. If the underlying failure mechanism is not clearly identified and corrected, similar AI-assisted calculations or automated decisions may be repeated during rectification or in parallel work streams, causing the same error pattern to recur and giving the appearance of a systemic issue.

For claims handling, this means that adjusters will rely increasingly on independent technical experts to reverse-engineer calculations, verify datasets, analyze model versions, and determine whether the failure lies in the algorithm, the training data, or the user’s application of the system. Digital evidence, e.g., system logs, dataset versions, training histories, model parameters, and sensor records, must be preserved comprehensively from the outset of a loss event, as they form the backbone of the new evidentiary chain.

5.2.2 Attribution and Allocation of Liability

A central challenge for claims professionals is the attribution of fault. Traditional losses typically involve clear distinctions between contractor, designer, and supplier responsibilities. AI introduces a fourth party: the AI software provider. Future claims will present a complex mixture of human negligence, inadequate supervision, flawed data inputs, and potential defects in the underlying algorithm.

To resolve liability, claims handlers must evaluate:

- whether the insured exercised an adequate standard of care in selecting and using the AI system
- whether appropriate human oversight was maintained throughout the relevant decision process
- whether the loss resulted from data corruption, model drift, or a faulty software update and
- whether responsibility for the relevant behavior lies primarily with the entity deploying and configuring the AI system, and only in limited cases whether there is a realistic basis for recourse against the technology vendor, given that probabilistic generative models do not fit neatly within traditional “product defect” concepts.

This requires a new type of forensic investigation, one that combines traditional physical inspection with digital forensics. Prompt histories, algorithm logs, system versions, and digital traceability records will serve as the equivalent of a flight recorder for AI-enabled construction sites. Without such documentation, neither liability attribution nor recourse against third parties is reliably achievable.

5.2.3 Coverage Evaluation and Emerging Loss Patterns

While material damage remains the fundamental trigger in construction all-risk policies, the mechanisms by which such damage arises will increasingly involve digital influences. Losses resulting from AI errors such as incorrect structural calculations or faulty automated control commands are generally covered, provided they produce a physical loss. Pure operational malfunctions without resulting damage continue to fall outside cover but may nonetheless initiate the chain of events that leads to an insured loss.

Defect-related coverage concepts such as LEG 2/DE 3 versus LEG 3/DE 5 become more complex when AI is involved, because the distinction between the defect itself and resulting damage becomes harder to establish. Recourse actions against designers or software vendors will become more frequent but also more difficult, given the challenge of demonstrating a clear and identifiable error within an opaque model. The lack of transparency in AI-derived calculations directly complicates both coverage assessment and downstream recovery.

5.2.4 Subrogation in AI-Related Losses

Subrogation remains a critical mechanism for minimizing the insurer's net loss. For AI-related claims, however, the ability to pursue recourse depends heavily on the completeness of documentation from the first day of the loss event. Missing logs, incomplete datasets, or overwritten system states can eliminate subrogation potential entirely. Early evidence preservation is therefore not merely good practice but a prerequisite for recovery.

At the same time, AI can be deployed proactively by the claims department itself: analytical tools can scan large volumes of project data to identify patterns indicative of responsibility, for example by linking recurring anomalies to a specific software update or to the introduction of a particular digital vendor's system.

5.2.5 New Loss Mechanisms and Their Impact on PML

AI does not replace traditional construction risks but changes the causal pathways through which losses arise, escalate, and are detected. A faulty model update, a degraded sensor, a platform outage, or a system integration failure can simultaneously affect multiple work fronts or even halt an entire project without any preceding physical damage. This shifts accumulation patterns and requires a revised understanding of Probable Maximum Loss. The severity of losses may be determined not only by physical exposures but also by the concentration of critical functions within a single digital ecosystem.

To limit the contribution of AI to a project's PML, manual fallback modes, alternative procedures, and non-digital backup documentation must be available and operable. These mechanisms enable at least partial continuation of work in the event of a systemic digital failure, limiting the scale of DSU and ALoP losses.

5.2.6 Strategic Evolution of the Claims Department

Soon the claims handler's function will operate less as a passive reviewer of physical damage and more as a digital forensic unit. New competencies will be essential for claims teams:

- recognizing AI-specific failure patterns and distinguishing them from conventional defects or negligence scenarios
- validating digital evidence and detecting manipulated or deep-fake documents submitted in support of claims
- assessing the adequacy of human oversight arrangements at the time of the loss; and
- collaborating with specialist AI forensic experts capable of interrogating model behavior and training data.

By deploying AI-driven tools for document analysis, image verification, and causal pattern recognition, claims handlers can focus their effort on strategic decision-making and maximize recovery potential, including recourse actions against third-party technology vendors. This evolution positions the claims department as a central element of the insurer's long-term resilience against the AI-related risks that are rapidly becoming a defining feature of large construction projects.

Chapter 6: Regulatory and Legal Aspects of AI in Construction

This chapter provides high-level guidance on the regulatory, legal, and contractual issues that arise from the use of AI in construction. It is not legal advice. It is intended to help insurers, reinsurers, brokers, risk engineers, and construction professionals understand how existing laws and regulations apply to AI tools across the construction lifecycle — from pre-feasibility and design through to operations and maintenance.

For construction organizations to broaden AI adoption responsibly, legal teams must understand the financial, operational, legal, and reputational implications this entails. The legal landscape is evolving rapidly; regulatory updates, court decisions, and new laws may change the picture described below (correct as of 3 April 2026). Each jurisdiction has its own framework, and differences also arise from whether a country follows a common law or civil law approach.

6.1 Regulatory and Liability Framework

6.1.1 Overview

AI adoption in construction is accelerating across design, planning, commercial management, site operations, and safety — with adoption probably highest at the design and planning stage and lowest in site operations. Testudo Global Inc. puts AI adoption in construction at 26.3% in 2025, up from 7.6% in 2022. It helps to divide the stakeholders in AI tools into three groups:

- Developers: Creators of foundational AI models, such as OpenAI and Anthropic.
- Vendors: Entities that package foundational models into products, such as Microsoft (Copilot) and Salesforce (Einstein Copilot).
- Deployers: Organizations that integrate and use AI systems within their own operations.

These distinctions matter for contractual and risk-allocation purposes. The legal and regulatory framework governing AI in construction is not a single law but a combination of: specific AI regulation (such as the EU AI Act); product liability regimes; data protection law (such as GDPR); tech-neutral regimes covering areas like discrimination, privacy, consumer protection, cybersecurity, and IP; contractual risk allocation; professional negligence standards.

Most construction companies are passive AI deployers rather than developers, a position that carries significant third-party litigation exposure. Recent Canadian case law (Moffatt v. Air Canada, 2024) confirms that deployers are prima facie liable for AI outputs, including hallucinations. This has clear implications for construction firms using AI for design, scheduling, or safety management.

Deployers will generally try to shift liability onto the vendor, and vendors onto the developer, but this may not always succeed. The position of deployers is made harder by the fact that AI developers and vendors routinely cap their own liability in standard contract terms, pushing the financial risk of AI failures onto the deployer.

6.1.2 First-Party and Third-Party Risks

Risks faced by AI deployers in construction fall into two broad categories.

First-party risks (to the deploying organization itself) include AI hallucinations leading to design or planning errors; model drift causing degraded performance over time; training data bias producing inaccurate outputs; over-reliance by professional staff; business interruption from AI platform outages; regulatory fines; and reputational damage from a publicized AI failure.

Third-party risks (to others, for which the deployer may be legally liable) include: bodily injury from autonomous plant or robotics; structural failure from AI-assisted design or inspection errors; property damage from AI scheduling errors; professional negligence claims where AI output was relied on without adequate verification; unlawful processing of workers' personal data via surveillance or wearables; data disclosure through AI outputs; and IP infringement through use of improperly sourced training data.

6.1.3 Specific AI Regulation

Regulators must balance two competing priorities: encouraging innovation and economic growth on one hand and protecting the public from harm on the other. This tension explains the very different approaches taken globally, and the regulatory battle between federal and state levels in the US.

Unlike most regulations, which react to problems after they occur, AI regulation in some regimes (notably the EU and certain US states) is proactive. Because the potential risks of AI could be irreversible or catastrophic, regulators act on the basis of plausible risk rather than proven harm. This is the foundation of the EU AI Act, which classifies AI by risk level: Unacceptable, High, Limited, and Minimal.

EU: The EU AI Act, which partially came into force in August 2024, is the world's first comprehensive AI regulation. For construction, the most significant category is High Risk, which includes AI used in the design or control of critical infrastructure such as transport, water, gas, and energy systems. Deployers of such systems must ensure meaningful human oversight, high-quality training data, detailed technical documentation, and full traceability of AI decision-making.

The application timeline is: obligations on general-purpose AI from August 2025; most obligations, including sanctions and high-risk AI system requirements, from 2 August 2026; and the final deadline for high-risk AI embedded in regulated products is August 2027. Sanctions for prohibited practice scan reach €35 million or 7% of global annual turnover.
USA: There is no federal US AI Act. Instead, individual states have filled the gap. As of late 2025, around 38 states had adopted roughly 100 AI measures. California alone has enacted more than 20 AI measures and accounts for 43% of generative AI litigation. Illinois ranks second, largely due to its Biometric Information Privacy Act (BIPA). Colorado's High-Risk Framework (SB 24-205), effective June 2026, requires deployers to build risk management programs, conduct annual impact assessments, and monitor for algorithmic discrimination.

This proliferation of state measures has triggered a federal response. In December 2025, the federal government pushed back against state regulation, which it regards as anti-innovation. Trump's Executive Orders aim to establish a uniform national approach and direct the Department of Justice to challenge state AI laws deemed inconsistent with federal

policy. Whether this can pre-empt state law without Congress remains constitutionally unresolved.

At the federal level, AI is regulated indirectly through existing agency powers. For example, the SEC has brought enforcement actions where companies misrepresented their AI use ("AI washing") or used algorithms in ways that violated securities law, without regulating AI as such.

UK: Following its AI White Paper in March 2023, the UK decided not to introduce a standalone AI law. Instead, existing regulators (such as the ICO, FCA, and CMA) apply five cross-cutting principles: safety, security and robustness; transparency and explainability; fairness; accountability and governance; and contestability and redress. These currently function as regulatory expectations rather than statutory rules.

The Data (Use and Access) Act 2025 updated data laws to clarify how AI can be used for automated decision-making, creating a somewhat friendlier environment for AI training than the EU. Enforcement depends on the sector: the FCA, for example, holds firms strictly accountable for AI advice under the Consumer Duty, a hallucination by a finance bot is treated as a regulatory breach by the firm.

For construction, the most relevant UK laws are the Data Protection Act 2018, the Health and Safety at Work Act 1974, and the Construction (Design and Management) Regulations 2015.

6.1.4 Product Liability

Product liability is the legal responsibility of a manufacturer or seller for harm caused by a defective product. It was traditionally developed in the context of manufacturers and sellers of physical goods. However, the new EU Product Liability Directive (EU) 2024/2853, adopted in 2024, explicitly includes software and AI systems within the definition of "products."

Construction robotics, autonomous plant, and AI-enabled machinery all fall within this framework. Member States must transpose the Directive by December 2026.
Extending product liability to AI raises difficult conceptual questions. Applying traditional notions of "defectiveness" to generative AI is not straightforward: such systems are inherently probabilistic rather than deterministic and could be said to be imperfect by design. Liability frameworks may therefore need to shift from focusing on predictability to evaluating whether a system operated within its intended design parameters and whether developers took reasonable steps to mitigate foreseeable risks.

In the UK, the Law Commission launched a review of product liability law in September 2025, noting that the current regime under the Consumer Protection Act 1987 "is no longer fit for purpose." The review examines whether definitions need updating to cover AI, and whether the burden of proof for claimants is too onerous given that "AI is opaque even to experts." In the US, there is no product liability law treating AI as a product, though some recent court cases have been argued and won on that basis. For insurers, the practical impact of deeming software and AI systems a "product" is twofold: exposure for AI

developers and vendors is likely to increase substantially, and new laws create uncertainty that prompts more companies to seek insurance cover.

6.1.5 Professional Duty and Standard of Care

Using AI does not change the professional standard of care. Designers, engineers, project managers, and supervisors remain personally responsible for verifying AI-generated recommendations and ensuring that outputs are accurate, safe, and appropriate to the circumstances of the project. When a professional relies on AI in the provision of their advice or service, they are still expected to adhere to the professional standards set out by their respective regulatory body. This means that the individual contracted to provide the service could ultimately be liable where AI produces erroneous outputs that are subsequently relied upon.

Some lawyers believe that where decisions are influenced by automated analysis, the legal question shifts from whether a professional exercised reasonable skill and care to whether reliance on AI-derived outputs was itself reasonable. This is not correct. Under English law, for example, the core test remains, that if the professional did exercise reasonable skill and care.

6.1.6 Data Protection

AI-enabled systems in construction, including video analytics, geolocation tracking, biometric access, wearables, drone surveillance, and digital twins, routinely collect large quantities of personal data. Companies must comply with applicable data protection laws, including GDPR and the UK Data Protection Act 2018.

Key obligations include establishing a lawful basis for processing; providing transparent notice to workers; applying data minimization principles; defining retention limits; and conducting Data Protection Impact Assessments before deploying high-risk surveillance tools. Facial recognition and proximity tracking are likely to constitute processing of sensitive personal data, attracting the highest level of regulatory scrutiny.

The collection of data also creates confidentiality risks, including questions about whether data collection was agreed in advance, how that data may be stored, and whether it can be used to train third-party AI models as well as cybersecurity risks. AI systems often rely on interconnected digital infrastructure, making them potential additional attack vectors, including data breaches and phishing attacks that could result in the disclosure of confidential information.

Standard construction contracts were not drafted with generative design tools or autonomous decision-support systems in mind. This creates real uncertainty about how existing liability provisions apply to AI-generated outputs. Bespoke contractual provisions are increasingly required, covering disclosure of AI use, human oversight and sign-off obligations, liability allocation, IP ownership of AI-generated materials, quality assurance and validation requirements; fallback procedures in the event of system failure; and insurance requirements.

Where AI-driven scheduling tools provide inaccurate forecasts, or BIM-integrated clash

detection misses conflicts, contracts must clearly allocate responsibility. With data flowing into shared systems, ownership of that data, particularly where subcontractors generate most of it, is a growing issue. One approach is for contractors to retain ownership of data produced by their teams, granting owners perpetual licenses for specific uses.
A critical practical concern is the liability cap structure typical of AI vendor agreements. Most AI vendors impose strict and low caps on their own liability, effectively transferring the residual risk to AI deployers. Where a deployer has agreed to such terms without adequate insurance in place, the financial exposure from an AI-related failure may be largely uninsured.

6.2 Insurance Implications

6.2.1 Coverage Gaps and Emerging Products

Traditional insurance lines such as professional indemnity, contractors' all-risks, public liability, and cyber may not provide comprehensive coverage for AI-related exposures. Deployers should not assume that their current insurance programs respond to AI-specific risks without explicit review and written feedback from brokers and insurers.
Hallucination, algorithmic discrimination, model drift, and supply chain compromises create liability through mechanisms these policies were not designed to address.
The insurance industry is responding. Standalone products now address AI-native risks such as performance guarantees, third-party liability arising from AI outputs, IP infringement in training data, regulatory penalties, and AI-driven business interruption. In return, insurers typically require evidence of explicit AI risk management frameworks such as NIST AI RMF or ISO 42001.

6.2.2 Accumulation Risk

The insurance market is beginning to grapple with accumulation risk. The AI ecosystem's reliance on a small number of foundation model providers means a critical flaw in one widely adopted model could trigger claims across thousands of unrelated policyholders simultaneously. Unlike traditional catastrophe scenarios with geographic or sectoral boundaries, AI failures can propagate instantly across industries and borders. Insurers and reinsurers are actively developing frameworks to monitor portfolio-wide exposure to dominant AI platforms, assess whether inherent vulnerabilities such as prompt injection require treatment as systemic perils and calibrate capacity accordingly.

6.2.3 Use of AI Agents

A specific and growing insurance concern is the emergence of AI agents: systems designed to pursue goals specified by users, with access to tools such as memory, computer interfaces, and web browsers. Unlike standard AI tools, agents act more autonomously, making it harder for humans to intervene before a failure causes harm. Current techniques can reduce failure rates but not to the level required in many high-stakes settings.
In construction, AI agents are increasingly being used to manage workflows, monitor budgets, and perform routine tasks. Procore Technologies, for example, unveiled a range of AI agents in 2025 to assist with daily site management, including a log agent, a foreman's personal assistant, and an action item generator for back-office tasks.

6.3 Conclusions

The legal and regulatory landscape governing AI in construction is fragmented, fast-moving, and largely untested in the courts. What is already clear is that liability will fall hardest on AI deployers, and that standard contracts and insurance programs were not designed with AI in mind. As adoption rates in construction continue to rise and as high-risk AI obligations under the EU AI Act come into force on 2 August 2026, the volume and complexity of AI-related claims will grow.

For insurers, the practical response is immediate: review policy wordings for silent AI exposure, require evidence of AI governance frameworks as a condition of cover, and begin monitoring accumulation exposure to dominant foundation model providers. The question is no longer whether AI will create liability and new risks, but whether the construction industry and its insurers can adapt quickly enough to assess and manage them.

Chapter 7: Risk Mitigation and Best Practices

The reliable deployment of AI systems in construction depends on three interdependent conditions: high-quality source and training data, robust governance structures, and clear individual accountability. These conditions hold regardless of the applicable regulatory framework and apply to all parties involved in the construction process, from early planning through handover and operation. In parallel, the insurance industry faces the challenge of developing products capable of covering the evolving risk profiles that AI-driven construction introduces. This chapter sets out the technical, operational, contractual, and insurance-market controls that can reduce exposure and make risk transfer feasible.

7.1 Technical and Operational Controls

7.1.1 AI Organization and Governance

The introduction of AI into construction expands data sources, creates partially automated decision pathways, and generates inter-system dependencies that did not exist in traditional project delivery. Without explicit governance, these changes expose projects to opaque decisions, model drift, and operational failures that are difficult to detect and even harder to defend in a claims or liability context.

Effective mitigation requires a formal governance structure comprising policies, defined roles, risk and incident registers, change-control procedures, and clear acceptance criteria for AI outputs. A practical approach is to align with ISO/IEC 42001 (AI Management System) and the NIST AI Risk Management Framework (Govern–Map–Measure–Manage). These frameworks provide the architecture for accountability: defined owners for data, models, and on-site processes, supported by an AI risk plan that covers potential failure modes, impact, likelihood, controls, IT recovery protocols, and redundancy arrangements.

Governance must also address privacy and security. AI systems in construction routinely process video, photographs, BIM data, sensor streams, plant telemetry, and contractual documentation. This creates exposures to personal data (identifiable individuals, work patterns, vehicle plates, voice recordings) and cyber risks (intrusions, data manipulation, platform outages). Human-in-the-loop principles, modelled on health and safety coordination logic for complex, multi-party environments, should be embedded in the governance structure to preserve human oversight over consequential decisions.

Practical AI Control Checklist (Project Level)

- AI systems inventory
- Responsible people and system owners
- Version control
- Calibration records
- Fallback manual procedures
- Human validation protocols
- Records and traceability

7.1.2 Data Management and Traceability

The most common failure mode in construction-AI is the system operating on disordered, unreliable, or context-mismatched data. A divergence between a BIM model and actual site conditions, for example, can produce recommendations that appear logically sound but are materially incorrect, resulting in wrongly sized orders, infeasible construction sequences, or scheduling conflicts. Models trained or calibrated on non-representative projects (for

instance, road projects applied to tunnel construction) are particularly susceptible to this risk.

Data governance should therefore prioritize data quality, correct program version, representativeness, and real-world fit. It must also manage model–reality lag: the progressive divergence between an AI model's internal state and actual site conditions as a project evolves. ISO/IEC 42001 sets out lifecycle and governance requirements for data and models that provide a suitable reference point.

7.1.3 Sector-Specific AI Risk Plans

AI risk mitigation must be implemented consistently across all project stages to ensure that systems remain controlled, transparent, and aligned with operational and safety requirements. The following summarizes the principal controls applicable to each functional area.

Regulation and compliance: Mandatory human validation is required at key milestones (submission, remediation, approval), supported by version control and requirement checklists designed to prevent "false compliance", situations in which AI-generated outputs appear to satisfy regulatory requirements without genuinely doing so.

Collaboration and contracting: Sensitive decisions, e.g., those with significant cost, time, or liability implications, should require formal approval from the responsible designer or contractor. This preserves accountability and prevents consequential decisions from being made arbitrarily by an automated system.

Design and engineering: Human review remains essential. AI outputs should be constrained by explicit parameters such as applicable design codes, construction sequences, and temporary load conditions. A/B testing of AI recommendations against conventional approaches should be conducted before outputs are translated into site instructions.

Procurement and supply chain management: Systematic cross-checking between AI-predicted demand and actual consumption, measured against executed versus in-progress works, is required to prevent overstocking or material shortages.

Execution: Conservative thresholds should be applied for safety and quality decisions. Human validation is required for all critical alerts and at defined milestones before work items are formally closed.

Technology and robotics: Dual checks on critical components, redundant safety systems, failsafe design, and disciplined maintenance regimes (including cleaning, calibration, and servicing) are required. Human supervision is mandatory for high-value or high-risk decisions.

Capability development: Organizations must implement validation protocols, continuous training programs (including training on AI evolution), competency rotation, and clear responsibility allocation. These measures are designed to prevent overreliance on AI outputs and to guard against false compliance.

7.1.4 Privacy and Security Controls

The range of data processed by AI systems in construction, video feeds from drones, CCTV, and mobile devices; BIM files; sensor streams; plant telemetry; and contract documentation, creates substantial privacy and cybersecurity exposure. Personal data risks include the identification of individuals, the recording of work patterns, the capture of vehicle registration

plates, and the processing of voice data. Cyber risks include platform intrusions, data manipulation, and outages affecting integrated systems.

Mitigation measures should include data minimization (defining what data is collected, for what purpose, for how long, and by whom), encryption of data in transit and at rest, role-based access controls operating on a least-privilege basis, comprehensive audit logs, and robust third-party and cloud-dependency controls covering incident notification and data portability. These measures simultaneously reduce exposure to systemic failure, delay and disruption losses, and legal risks arising from unlawful data processing or extortion following data exfiltration. ENISA's Threat Landscape identifies disruptive availability attacks and malware as persistent EU-level risks that are directly relevant for AI-dependent construction operations.

7.1.5 Human Final Control and the Project AI Coordinator (PAIC)

A central challenge in AI-assisted construction is determining which decisions may be delegated to automated systems, and which must remain under human judgement by reason of their safety, quality, regulatory, or contractual significance. A structured validation procedure transforms AI from an autonomous actor into an auditable assistant: decisions are classified by criticality and by project milestone, and approval points are established for regulatory and documentation matters, safety-critical decisions, quality hold points, and changes to sequence, cost, or program.

Each validation step should specify the inputs and outputs required to demonstrate conformity. Human reviewers should focus on critical items or those that exceed defined thresholds, avoiding the inefficiency of reviewing all AI outputs indiscriminately.
To coordinate this function across a project, the role of Project AI Coordinator (PAIC) should be established. PAIC is the direct analogue of the Health and Safety Coordinator in complex, multi-party construction projects: a technical focal point responsible for setting AI governance rules, approving model changes, and maintaining the incident register from design through to execution. Domain leads (covering AI for Health and Safety, Quality, Planning, Data, and Technology) support PAIC in integrating AI into project decision-making while maintaining clear lines of responsibility.

PAIC also serves a critical function for the insurance market: as the central point of contact for risk analysis, underwriting, and policy renewals, and as the primary source of documentation for claims and loss adjustment, mirroring the role of the H&S coordinator in loss events involving health and safety.

PAIC Responsibilities by Project Phase

Design phase: PAIC identifies intended AI uses (BIM, planning, QA, and related applications) and defines minimum requirements covering data, sensors, connectivity, cybersecurity, and responsibilities. PAIC also prepares the AI Study, which comprises an inventory of AI systems and data sources; a risk register covering technical, operational, legal, and security exposures; and a schedule of preventive measures including validation systems, usage limits, supervision protocols, and physical cross-checks. A governing principle at this stage is the avoidance of unsupervised automation and the assurance of full operational traceability.

Execution phase: PAIC ensures rule harmonization across contractors and subcontractors, including alignment of AI versions, data sources, and approval flows. PAIC approves human-review protocols at critical milestones (concreting, welding, material receipt, and testing), oversees data-quality controls including sensor calibration and drift management, and is responsible for continuous verification and validation of AI systems on site. PAIC also

maintains the AI Site Logbook and coordinates AI-related matters with the Principal Designer and Principal Contractor.

7.2 Contractual and Insurance-Market Mitigations

7.2.1 Key Challenges for Insurers

The adoption of AI applications in the construction industry introduces challenges that require insurers to develop new approaches to risk assessment, claims processing, and product design. The principal challenges are as follows.

1. **Data Foundation:** Limited historical claims data for autonomous systems complicates risk evaluation.
2. **Technology Complexity:** Insurers must assess the reliability of advanced AI systems, sensors, and associated technologies used in autonomous machines.
3. **Risk Profiles:** New risk assessment models are needed to address the novel risk profiles associated with AI applications in construction.
4. **Forensics:** Technical accident and damage analysis for autonomous systems is complex, requiring specialist expertise in root cause analysis and the distribution of liability among manufacturers, software developers, and operators.
5. **Premium Calculation:** Insufficient experience data makes accurate premium calculation difficult for construction projects that deploy AI-driven applications.
6. **Product Design:** Insurers must develop coverage solutions for cyber-physical risks, including hybrid products that combine traditional insurance with protection against cyber and software-related risks.
7. **Data Evaluation:** Analyzing large volumes of data from sensors and log files is essential for understanding risk and loss events. Data must enable classification, filtering, temporal correlation, and traceability to allow events to be reconstructed.
8. **Evidence Preservation:** Ensuring the secure preservation of digital evidence following a loss event is critical for claims processing and liability determination. It must be possible to verify that data has not been corrupted, has been properly preserved since the incident, and that its authenticity can be established.

7.2.2 Practical Underwriting and Insurance Checklist

The following minimum evidence requirements should be applied when underwriting construction projects that deploy AI systems.

- Inventory of AI systems, including system descriptions, providers, and intended uses
- Records of alerts, errors, model changes, and telemetry
- Change management procedures for software and models
- Identification of critical failure points, with assessments of severity, probability of operational stoppage, and potential impact
- Chain of custody procedures for digital evidence
- Assessment of AI maturity (see Section 7.2.3)

7.2.3 AI Risk Maturity Ladder

To support consistent risk assessment and underwriting decisions, an AI risk maturity framework can be used to evaluate the degree to which AI use in a construction project is developed, controlled, and reliable. The framework draws on established AI governance principles from ISO/IEC 42001, the NIST AI Risk Management Framework (2023), and broader AI governance perspectives from the OECD and McKinsey. It is structured as an analytical tool for construction underwriting rather than as a direct transposition of any single existing model. The framework comprises five levels.

Level 1 – Initial/Pilot: AI is used only in small-scale experiments. Documentation is absent or minimal, and controls are very limited. Organizations at this level are still testing ideas and developing practical understanding of how AI operates in a construction context.

Level 2 – Basic/Early Adoption: AI begins to be deployed across some projects, but application is inconsistent. Some procedures are documented, but different teams may use AI differently, and governance controls are still developing.

Level 3 – Managed/Growing Use: AI deployment becomes more structured. Clear rules, defined responsibilities, and regular monitoring are in place. AI is used more consistently across projects, and performance is measured in a structured way.

Level 4 – Proactive/Advanced Adoption: AI is actively managed in real time. Organizations use monitoring tools, automated checks, and performance indicators to ensure AI systems are functioning correctly and safely.

Level 5 – Optimized/Full Maturity: AI is fully embedded in decision-making and project delivery processes. Systems are subject to continuous review, independent validation, and full integration into business and project workflows.

For practical underwriting purposes, these five levels are consolidated into three bands:

Maturity Band	General Conditions	Likely Underwriting Consequence
Low (Levels 1–2)	Experimental or uneven AI use; weak governance; limited traceability; fragile continuity and evidence preservation.	Stricter conditions, additional warranties, higher deductibles, reduced capacity, or required corrective actions before binding.
Medium (Level 3)	Controlled and documented AI use in key areas; adequate governance; identifiable system owners; structured records; partial fallback capability.	Insurable with conditions focused on change management, evidence retention, fallback and manual controls, and human validation.
High (Levels 4–5)	Strong governance; robust logs and telemetry; tested fallback arrangements; claims-ready evidence; formal independent validation; continuous monitoring.	Broader coverage, improved pricing and/or greater capacity, subject to project-specific exposures.

In practical terms, projects with higher maturity levels present more controlled and reliable AI risk profiles, which generally support more favorable insurance terms including broader coverage, greater capacity, and more competitive pricing. Projects at lower maturity levels may require additional risk controls or corrective actions before coverage can be bound or may be subject to more restrictive policy conditions and higher deductibles. Used in conjunction with the AI Control Checklist and the underwriting evidence requirements set out in Section 7.2.2, the maturity ladder provides a structured basis for translating AI governance quality into underwriting decisions on pricing, capacity, and policy conditions.

Chapter 8: Conclusions

AI adoption in construction is no longer a distant prospect; it is an operational reality in design offices, project controls, site inspection, and asset management. At the same time, the industry remains at an early to mid-stage of maturity, with uneven deployment across sectors and geographies and a heavy reliance on human oversight. For insurers, reinsurers, and construction firms, this transitional phase is both an opportunity and a risk.
Drawing on the analysis in Chapters 2 to 7, three overarching themes emerge.

- **AI reconfigures, rather than replaces, construction risk.**
  Traditional hazards such as structural failure, geotechnical uncertainty, site safety incidents, and coordination failures remain, but AI changes the causal pathways and can introduce digital dependencies, cyber-physical escalation, and systemic/serial loss potential.
- **Liability will fall heavily on deployers without robust governance.**
  Construction organizations are predominantly AI deployers. Under emerging regulatory and legal frameworks, they are often prima facie responsible for AI outputs and remain subject to traditional professional duties of reasonable skill and care.
- **Insurers must evolve from passive risk carriers to digital risk partners.**
  Underwriting, policy wording, Risk Consulting and claims processes must explicitly account for AI-driven causation, non-malicious digital failures, evidence requirements, and accumulation across shared AI platforms.

8.1 Reconfigured Risk

AI does not remove the traditional hazards of construction, e.g., structural failure, geotechnical uncertainty, unsafe site conditions, workmanship defects, and coordination failures. Instead, as described in *Chapter 4*, it changes the causal pathways through which these hazards manifest:

- **Digital dependencies** mean that data quality, model validity, and platform availability can now be primary sources of loss. A corrupted BIM model, a faulty software update, or model drift in a safety system can trigger defects or halt works even in the absence of physical damage.
- **Cyber-physical links** connect AI systems, sensors, and autonomous plant directly to physical outcomes, allowing digital failures to escalate rapidly into physical damage and bodily injury.
- **Systemic and correlated exposures** arise when the same AI platform, dataset, or model version is used across multiple projects or assets, raising the prospect of serial losses from a single software defect or misspecification.

These changes demand a broader conception of construction risk—one that incorporates digital causation, hybrid loss chains, and accumulation across projects using shared AI tools.

8.2 Deployers' Liability

The regulatory and legal landscape summarized in *Chapter 6* makes one point clear: most construction organizations are AI deployers, not developers, and will bear the brunt of liability for AI-enabled failures. Under emerging product liability regimes and case law, deployers are often prima facie responsible for AI outputs, including hallucinations and erroneous recommendations. At the same time:

- Professional standards still hinge on **reasonable skill and care**, not blind reliance on automated tools.
- Data protection laws impose strict duties on organizations using AI for surveillance, wearables, and digital twins.
- Standard contracts were not drafted with generative design tools or AI agents in mind, creating uncertainty over who is responsible when AI-based scheduling, inspection, or design support leads to loss.

Where AI vendors cap their liability and retain control over key technical parameters, construction firms and their insurers may find themselves exposed to substantial, and sometimes uninsured, losses.

Against this backdrop, the governance practices proposed in *Chapter7,* including formal AI management systems, clear system ownership, documented validation protocols, and the Project AI Coordinator (PAIC) role, are not optional enhancements; they are emerging prerequisites for defensible decision-making and insurability.

8.3 Insurers as Risk Partners

As set out in *Chapter 5*, AI requires insurers to rethink core assumptions about triggers, PML, coverage boundaries, and claims investigation:

- **Underwriting** must move beyond static questionnaires to structured AI risk assessments, including inventories of AI systems, evidence of governance (ISO/IEC 42001, NIST AI RMF), and evaluation of AI maturity.
- **Risk Engineering** must keep pace with the rapid deployment of AI and provide systematic support to Underwriting through technical reviews, scenario analysis, and ongoing monitoring of controls
- **Policy wording** should address how non-malicious digital failures are treated and, where relevant, clarify interfaces with cyber coverage in AI-related scenarios, while recognition of serial or systemic exposures may be managed at portfolio and reinsurance level rather than solely through CAR/EAR wording.
- **Claims handling** must incorporate digital forensics, model version analysis, and evidence preservation from the outset of a loss to enable causation analysis and subrogation.

Insurers who develop these capabilities can offer differentiated products, such as AI performance covers, DSU/ALOP extensions for systemic digital failure, and dynamic premium models based on real-time data, while maintaining control over accumulation risk.

8.4 Practical Recommendations

For construction firms, designers, and owners:

1. **Establish AI governance early.**
   Implement project-level AI governance, aligned with ISO/IEC 42001 and NIST AI RMF, including an AI systems inventory, defined system owners, and change-control procedures.
2. **Maintain human final control.**
   Classify decisions by safety and contractual criticality and ensure that consequential decisions (design sign-off, sequence changes, safety overrides) remain under documented human review.

3. **Invest in data quality and traceability.**
   Treat BIM, sensor data, inspection imagery, and telemetry as critical assets. Ensure version control, audit trails, and robust evidence preservation to support both operational management and future claims.
4. **Update contracts and professional practices.**
   Introduce AI-specific clauses on disclosure, oversight, liability allocation, IP ownership of AI-generated outputs, and fallback procedures. Embed AI literacy and validation responsibilities within professional standards and internal policies.

For insurers, reinsurers, and brokers:

1. **Integrate AI risk maturity into underwriting.**
   Use a maturity framework such as the AI risk maturity ladder in *Chapter 7* to link governance quality to pricing, capacity, and conditions.
2. **Clarify coverage boundaries and serial-loss exposure.**
   Adapt policy wording to address AI-related non-physical triggers, serial losses from software defects, and the interface between construction and cyber covers.
3. **Build AI-aware claims capabilities.**
   Develop internal or external expertise in AI forensics, digital evidence analysis, and deepfake detection. Require, through policy conditions, the preservation of logs, model versions, and datasets relevant to loss events.
4. **Monitor systemic and accumulation risk.**
   Track exposure to major AI platforms and model providers and treat potential model-wide vulnerabilities as systemic perils when calibrating capacity.

8.5 Looking Ahead

The trajectory of AI in construction is clear: tools will become more powerful, more autonomous, and more deeply integrated into everyday project workflows. Generative design, AI agents, and real-time digital twins will increasingly shape decisions that carry significant safety, financial, and legal consequences.

The central question for the construction and insurance sectors is not whether AI will introduce new risks—it already has—but whether organizations can develop the governance, contractual, and evidentiary disciplines necessary to keep those risks within manageable bounds. Projects that combine robust AI controls with transparent documentation and clear lines of accountability will be better positioned to capture AI's benefits: fewer accidents, earlier defect detection, greater program certainty, and more resilient assets.

Ultimately, the insurability of AI-enabled construction depends on collaboration. Developers, vendors, deployers, and insurers must work together to define standards for safe and responsible AI use, share lessons from early losses, and continually refine both technical controls and insurance products. If this collaboration succeeds, AI can become not only a driver of productivity and quality, but also a catalyst for more accurate, data-driven risk assessment and, in the long run, a safer built environment.

The analysis in this paper reflects conditions as of May 2026. Given the rapid evolution of AI capabilities, regulation (including implementation of the EU AI Act), and court decisions, insurers and construction stakeholders should periodically revisit these conclusions and adjust governance, contractual frameworks, and insurance arrangements as practice and law develop.

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