Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 6, 2026

RISK MANAGEMENT IN CONSTRUCTION PROJECTS USING BIM AND ARTIFICIAL INTELLIGENCE: A COMPARATIVE STUDY OF DEVELOPED AND DEVELOPING CONTEXTS

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DOI: https://doi.org/10.5281/zenodo.20958614

Keywords
Building Information Modelling (BIM); Artificial Intelligence; Construction Risk Management; Construction 4.0; Digital Twin; Machine Learning; Developing Countries; Pakistan.

Article History
Received: 24 April 2026
Accepted: 06 June 2026
Published: 21 June 2026

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Abstract
The construction sector continues to rank highly among the sectors in the world economy, which are highly risky and poorly digitalized. There is always a persistent threat of cost overrun, time delays, design defects, and safety hazards. BIM and artificial intelligence have become two key pillars of Construction 4.0 as means to take data-driven and proactive as well as predictive actions in risk management. This paper gives an overview and comparison of BIM and AI for construction risk management in both developed and developing countries, focusing particularly on Pakistan. The analysis is based on a systematic review of fifty research papers and reliable reports in peer-reviewed journals from 2018 to 2026 on the subject. The paper makes a comparative assessment of technology adoption, benefits, challenges, and enablers in both matured markets such as the United Kingdom, the US, Germany, and Australia and emerging markets like Pakistan, India, Nigeria, and Southeast Asia. The findings illustrate a clear divergence wherein the adoption of BIM is above 70% in the UK after being mandated by the government in 2016, yet in Pakistan, there is 63% awareness with only 17% usage and use of AI in construction risk management is still at a primitive stage in both contexts, but more advanced in developed countries. The findings illustrate the fact that the constraint in developing countries is mostly institutional, including the lack of any mandate, fragmented standards, training pipeline and awareness, as opposed to technical issues. Based on the findings, the paper suggests an integrated multi-layered BIM-AI risk management framework that could be adapted in rich and scarce resource contexts consisting of Data Integration, AI Analytics Engine, Digital Twin Simulation and Decision Support Layer with continuous feedback mechanism. Insights from case studies reveal that integrated application will result in significant reduction in design mistakes, rework and schedule slippages, while also improving hazard identification.

1. INTRODUCTION
1.1 Background
The building sector is the bedrock of economic development in countries all around the world; indeed, it accounts for a sizable portion of the total global gross domestic product, employs about 7% of the world's workforce, and is responsible for annual spending of USD 10 trillion worth of goods and services [48]. This notwithstanding, the sector is generally regarded as having poor

efficiency and digital immaturity. In the same vein, according to the McKinsey Global Institute, construction productivity growth has been just 1% per year for two decades, while the global economy and manufacturing productivity have grown at 2.8% and 3.6%, respectively. In this respect, there is an annual forgone potential value creation worth approximately USD 1.6 trillion [48]. One of the most significant features of poor performance in the sector is its vulnerability to risks. According to studies carried out on megaprojects, an approximate 86% of big infrastructure projects have cost overruns averaging 28%; this has been called the "iron law of megaprojects" [44, 45].

In this context, Building Information Modeling (BIM) and Artificial Intelligence (AI) have emerged as key players in the Construction 4.0 paradigm – the construction-oriented version of Industry 4.0 [41, 42]. Building Information Modeling creates a common, parametric, multi-dimensional digital representation of a facility and allows for clash detection, estimation of quantities, 4D scheduling and 5D cost management, which helps transfer risk management from corrective to preventive approach [1, 2]. Artificial Intelligence, comprising such technologies as machine learning, deep learning, computer vision and natural language processing, takes this approach further by supporting predictive analysis, automatic hazard identification and decision-making [6, 8]. BIM and AI integration, often facilitated by the use of digital twins and IoT solutions, is becoming more and more recognized as an effective way of managing risks during the lifecycle of a facility [3, 13, 16].

1.2 Problem Statement

Despite the fast-paced development of technical literature on BIM and AI for risk management, the gains are not evenly shared. While developed economies have institutionalized the use of BIM through policies and standards, which have seen high levels of adoption and reduced risks, developing countries are still struggling with huge adoption gaps [27, 33]. For example, in the case of Pakistan, the awareness about BIM is relatively high at about 63% while its usage is only around 17% [33]. Similarly, the use of AI for risk management in construction is less reported in developing countries, posing an evidentiary gap. Notably, there is very little integration of both BIM and AI in a single risk management framework that takes into account the different infrastructures, funding, regulatory systems, and manpower available in developed and developing economies.

1.3 Research Objectives

Objectives of this paper include (i) conducting a comprehensive review of literature related to BIM and AI in the context of risk management in construction sector from 2018 to 2026; (ii) comparative analysis of the adoption, advantages, disadvantages, and enablers in the context of developed countries as well as developing countries, with particular focus on Pakistan; (iii) development of an integrated, flexible BIM and AI based risk management model applicable to both resource abundant and resource scarce environments; and (iv) formulating actionable policy and practice guidelines and roadmap for Construction 4.0.

1.4 Significance of the Study

The importance of this research can be discussed in three ways. Theoretical contribution lies in the development of a comprehensive approach to BIM-AI risk management, which fills the identified gap between technology-based approaches and the context of the developing country. Practical contribution is in providing the construction industry in Pakistan and countries alike with practical steps to adopt BIM-AI for risk management on the basis of adoption rates. Finally, it contributes strategically to the overall digital transformation of the construction sector in the developing countries.

1.5 Structure of the Paper

The remainder of the paper is organised as follows. Section 2 reviews the literature on BIM, AI and their integration for risk management, and identifies research gaps. Section 3 describes the systematic review and comparative methodology. Section 4 contrasts traditional and BIM-AI risk management approaches. Section 5 presents the comparative analysis of developed and developing contexts. Section 6 introduces the proposed framework. Section 7 discusses case-based insights. Section 8 synthesises results and discussion, and Section 9 concludes with recommendations and future research directions.

2. Literature Review

2.1 BIM in Construction Risk Management

BIM has been extensively examined as an enabler of construction risk management. The seminal review by Zou, Kiviniemi and Jones synthesised the application of BIM and BIM-related technologies to risk management, concluding that visualisation, clash detection and information integration directly mitigate design, coordination and safety risks while highlighting that organisational and process barriers constrain realisation of benefits [1]. Azhar characterised BIM as a paradigm offering significant benefits in coordination and error reduction but also introducing new legal and data-ownership risks [2]. Subsequent systematic reviews have mapped BIM applications across the project lifecycle, finding that the technology is most frequently deployed for risk identification and analysis during design and pre-construction, with comparatively fewer applications in operational-phase risk control [4, 5].

Empirically, BIM-enabled clash detection and 4D/5D modelling have been associated with reductions in design errors, requests for information, change orders and rework. Synthesised case-study evidence indicates design-error reductions in the order of 50-60%, clash reductions of approximately 40%, and rework-cost reductions of 40-50%, although these magnitudes are case-specific and should be interpreted as indicative rather than universal [4, 5]. Clash-detection return-on-investment studies have reported coordination savings of an order of magnitude relative to virtual-design-and-construction labour costs on individual projects [1]. BIM has also been investigated specifically for construction safety in developing countries, where automated hazard analysis and design-for-safety workflows show promise but remain underutilised [40].

2.2 AI in Construction Risk Management

Artificial intelligence has attracted intense research attention as a means of moving construction risk management from descriptive to predictive and prescriptive paradigms. Pan and Zhang provide a critical review of AI roles in construction engineering and management, identifying machine learning, knowledge-based systems, computer vision and optimisation as dominant techniques and forecasting growing integration with BIM and digital twins [6]. Scientometric analyses confirm rapid growth in AI-in-construction research, with risk, safety and cost prediction among the most active themes [7]. Recent systematic and bibliometric reviews dedicated to AI in construction risk management consolidate this evidence, reporting that supervised machine-learning models dominate cost- and schedule-overrun prediction, while deep learning and computer vision dominate safety applications [9, 10].

In cost and schedule risk, artificial neural networks and ensemble methods have demonstrated strong predictive performance; for example, a neural-network model optimised with metaheuristic search achieved approximately 92% accuracy in predicting cost and time overruns on a dataset of construction projects [12]. In safety risk, computer-vision systems based on object-detection architectures enable real-time detection of personal-protective-equipment non-compliance, unsafe proximity and hazardous behaviour [21, 23, 24]. Machine-learning classifiers have been applied to derive safety leading indicators and to assess scaffolding safety with high accuracy [25, 26]. Natural language processing has been used to mine accident and near-miss reports for latent risk patterns [10]. Collectively, these studies establish AI as a credible instrument for anticipatory risk management, while also noting persistent challenges of data quality, interpretability and generalisation.

2.3 Integration of BIM and AI
Integration of BIM and AI is the research frontier. Sacks et al. provide a conceptual framework wherein BIM provides structured data that is consumed by AI for predictive and generative insights, aided by digital twins increasingly [3]. Systematic reviews on machine learning and BIM find the applications in design automation, clash detection, energy and cost estimations and risk analyses [13]. Digital twin studies extend the BIM-AI integration to the operation phase and use BIM geometry along with the sensors and AI to facilitate continuous monitoring and early warnings, as evidenced in construction safety of tunnels and data mining-integrated project management [16-20]. BIM-AI integration, however, raises some concerns about interoperability, data standardisation and organisational readiness being the major ones, along with the paucity of validations in actual projects especially in developing countries [14, 15].

2.4 Gaps in the Literature
Three main gaps arise from this review. The first gap is the scarcity of studies that discuss the integration of BIM and AI in an actual risk management framework, even though there are numerous technical studies about the two approaches separately. The second gap is the presence of empirical research data mostly collected from developed nations while systematic comparison with developing nations such as Pakistan is very uncommon, especially for AI. The third gap lies in the lack of consideration of the feasibility factors that determine the applicability of the risk management frameworks in resource-limited situations.

3. Methodology
3.1 Research Design
The review utilizes a systematic review approach, along with structured comparative analysis and a framework proposal with a design-science approach. The systematic review is conducted using the concepts of transparency, replicability, and structured synthesis according to existing reporting guidelines adapted for the purpose of conducting a systematic review by a single author. The aim was not an exhaustive listing but rather a rigorous synthesis of high-quality information suitable for comparison and framework creation.

3.2 Data Sources and Search Strategy
Sources were selected from reputable scholarly databases and indexes like Scopus, Web of Science, ScienceDirect, ASCE Library, MDPI and Taylor & Francis, with additional grey literature sources from NBS National BIM Reports, McKinsey, Dodge Data and Analytics, Royal Institution of Chartered Surveyors and International Labour Organization. Search keywords were related to the concept areas of the study such as "BIM", "Building Information Modeling", "Artificial Intelligence", "machine learning", "digital twin", "risk management in construction", "safety", "cost overrun", "adoption", "Pakistan", "India", "Nigeria" and "developing countries". The focus of the search was on papers published between 2018 and 2026, although earlier papers of enduring significance were also considered.

3.3 Inclusion and Exclusion Criteria
The inclusion criteria involved studies that were published in peer reviewed journals, conference papers and institutional papers; those which discussed Building Information Modelling, Artificial Intelligence or their integration with regard to construction risks, safety, cost or time frame; and those which provided some form of evidence in relation to adoption, benefits, barriers or frameworks. The exclusion criteria included studies that did not have any methodological rigour, studies which were promotional or vendor driven without verifiable data, and those which covered other domains of interest. The grey literature was included when it provided authoritative industry figures which could not be found through peer reviewed publications.

3.4 Comparative Analysis Framework
The comparative analysis followed a structured approach of applying the same dimensions to both developed and developing contexts: the level of technology adoption, regulation and policy environment, financial capability, human

resources and skill levels, maturity of data and infrastructural capabilities and organizational culture. The developed countries included the UK, the US, Germany and Australia, while the developing countries comprised of Pakistan, India, Nigeria and some selected Southeast Asian economies. For each dimension, the evidence was collected, compiled and analyzed to observe any systematic biases and the implications for framework design. Statistical assertions have been classified into two categories: well-justified if supported by research papers or surveys and indicative if coming out of individual case studies or secondary estimation.

3.5 Analysis Methods

Synthesis proceeded through thematic and comparative analysis. Evidence was coded against the conceptual domains of risk identification, analysis, mitigation and monitoring, and against the comparative dimensions described above. Quantitative indicators of adoption and performance were extracted where available and normalised for comparability, with explicit acknowledgement that adoption metrics differ in definition across surveys. The proposed framework was developed iteratively by mapping recurrent functional requirements identified in the literature onto a layered architecture, and was qualitatively assessed for adaptability to resource-constrained contexts. Table 1 summarises the comparative dimensions and indicators applied in the analysis.

Table 1. Comparative dimensions and indicators applied in the analysis.

Dimension	Indicators examined	Primary evidence basis
Technology adoption	BIM awareness and usage rates; AI deployment maturity	NBS reports; peer-reviewed adoption surveys
Regulatory environment	Mandates; standards (e.g., ISO 19650); procurement policy	Government strategies; institutional sources
Financial capacity	Hardware, software and training cost burden; ROI evidence	Industry reports; case studies
Skills and human capital	Availability of trained professionals; curricula; CPD	Barrier studies; regional surveys
Data and infrastructure	Data quality; interoperability; common data environments	Integration reviews; barrier studies
Organisational culture	Collaboration; resistance to change; data-sharing norms	Qualitative and survey studies

4. Risk Management in Construction: Traditional versus BIM-AI Approaches

4.1 Common Risks in Construction Projects

Construction projects are exposed to a heterogeneous portfolio of risks that recur across geographies and project types. Cost overruns and schedule delays are the most pervasive, driven by estimation error, scope change, design rework, procurement volatility and coordination failure [44, 45]. Design and coordination errors, frequently arising from uncoordinated discipline-specific drawings, propagate downstream into rework and disputes [1, 2]. Safety risk is acute: the International Labour Organization estimates that at least 108,000 workers are killed on construction sites annually, representing approximately 30% of all occupational fatal injuries, and that construction workers are three to four times more likely than other workers to die from accidents, with risks in the developing world estimated to be three to six times greater still [47]. Additional categories include financial and contractual risk, environmental and regulatory risk, and operational risk during the asset lifecycle. Figure 1 conceptualises how an integrated BIM-AI approach addresses these categories across the risk-management cycle.

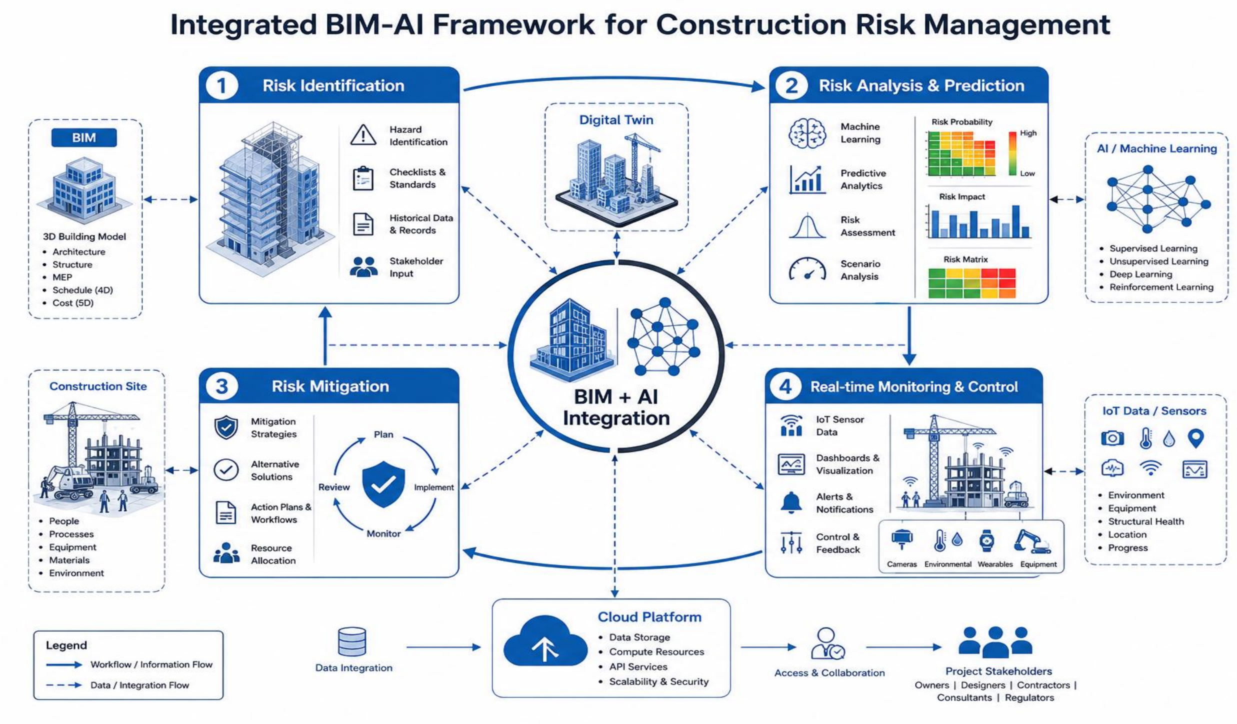

Figure 1. Conceptual Framework of BIM and AI Integration for Risk Management

4.2 Traditional Risk Management Methods

Traditional Construction Risk Management consists of manual, documentation-based, and experience-driven practices. Traditional risk management usually involves checklists, brainstorming sessions, and expert opinion for risk identification; qualitative probability-impact matrices, and sometimes Monte Carlo simulation for risk analysis; and static risk register that undergoes periodic reviews for risk mitigation. Such practices are inherently reactive and fragmented, as they are highly dependent on individual expertise, prone to individual biases and optimistic bias, and have a hard time accommodating complex data flows characteristic of modern construction projects [44]. Most importantly, traditional practices tend to identify a great number of risks only after they occur, limiting options for correcting the situation. The fact of systemic cost and schedule overruns persisting in construction even after decades of development of traditional practices testifies to the limitations of this approach [45].

4.3 Benefits of BIM-AI Approaches

The BIM-AI approach reframes risk management based on shared data, automation and predictions. BIM consolidates information about projects into a single digital model which helps to conduct automatic clash detections, constructibility analysis, schedule modeling in 4D and cost planning in 5D, thus making it possible to detect and solve risks before the construction phase begins [1, 2]. AI further builds on these capabilities with predictive analytics that can forecast schedule and cost overruns, computer vision that observes building sites for potential dangers, and natural language processing that draws insights from unstructured data [6, 21, 23]. Digital twin integration helps to maintain continuous monitoring with sensors throughout the project lifecycle [16, 19]. The result is a change in paradigm from corrective action to preventive measures, with proven benefits in terms of decreased errors, reduced rework, more accurate schedules and hazard identification. This comparison is summarized in Table 2 and illustrated by Figure 2 below.

Table 2. Comparison of traditional and BIM-AI approaches across the risk-management cycle.

Risk-management stage	Traditional approach	BIM-AI integrated approach
Identification	Checklists, workshops, expert judgement; document-based	Automated clash detection, constructability analysis, AI pattern recognition
Analysis	Qualitative probability-impact matrices; limited quantification	Predictive ML models for cost/schedule; data-driven prioritization
Mitigation	Static risk registers; periodic manual review	Scenario simulation, design-for-safety, optimisation-based strategies
Monitoring	Manual inspection; periodic reporting	Real-time sensor and computer-vision monitoring; digital-twin early warning
Knowledge reuse	Tacit, individual, project-bound	Continuous feedback loops; model retraining; organisational learning

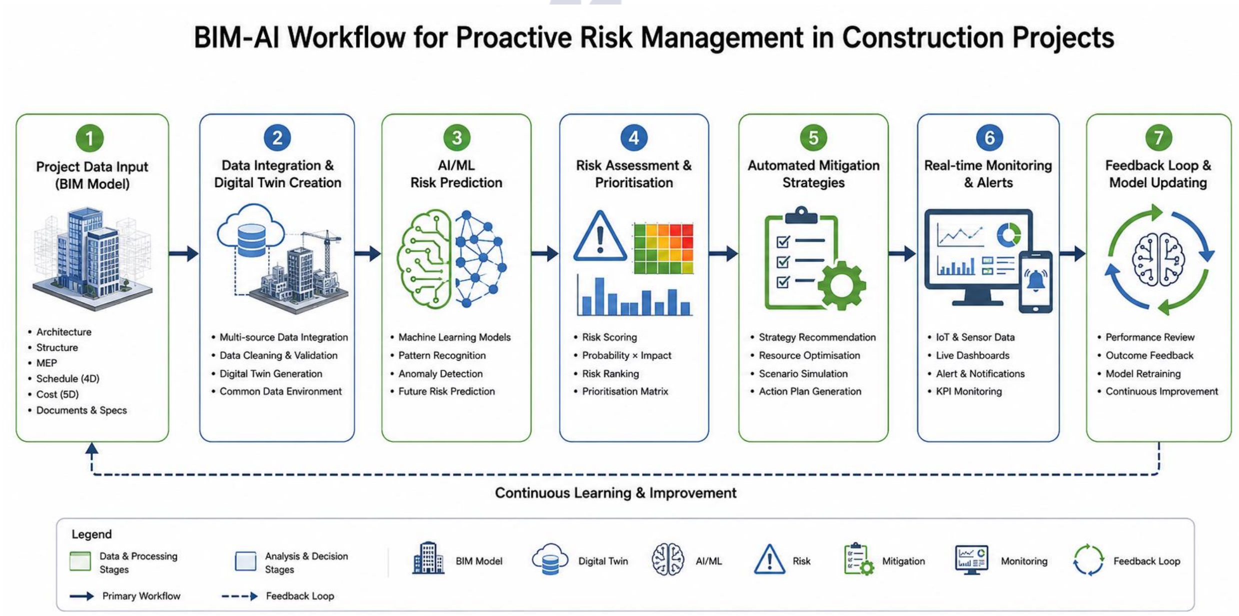

Figure 2. BIM and AI Workflow for Construction Risk Management

Table 3. Key AI techniques and their applications in construction risk management.

AI technique	Representative algorithms	Primary risk-management application
Machine learning	ANN, SVM, Random Forest, XGBoost	Cost- and schedule-overrun prediction; risk classification [9, 12]
Deep learning	CNN, RNN/LSTM	Defect and crack detection; structural health monitoring [11]
Computer vision	YOLO, SSD, R-FCN	PPE compliance, hazard and intrusion detection [21, 23, 24]
Natural language processing	Text mining, transformers	Accident-report mining; contract and compliance analysis [10]
Optimisation and reasoning	Genetic algorithms, rule-based systems	Resource trade-off; automated code compliance [6]
Digital twin analytics	Hybrid ML + IoT fusion	Real-time monitoring; lifecycle early warning [16, 19, 20]

5. Comparative Analysis: Developed versus Developing Contexts

5.1 Adoption Levels

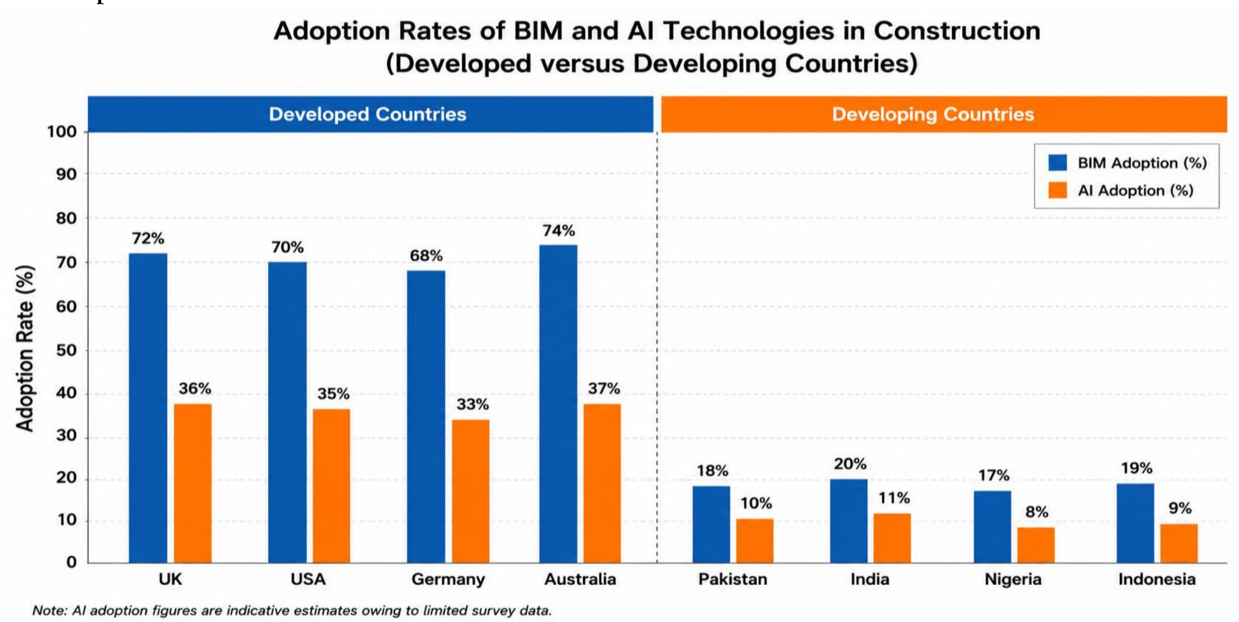

Figure 3. Comparative Adoption of BIM and AI in Developed versus Developing Countries

The adoption of BIM, by association, AI technologies shows sharp differences between developed countries and developing economies. In the UK, the National BIM Report series has highlighted an increase in adoption from less than 10% in 2011 to 54% in 2016 and around 70% by 2019 to reach 73% in 2020, largely thanks to the governmental requirement of BIM Level 2 on centrally procured projects since April 2016 [27]. In the USA, the industry surveys show that the adoption is already mature and engaging BIM users who reported ROIs of over 25% and reductions in rework [28, 29]. In Germany, the progressive use of BIM is required on federal transport and infrastructure projects since the end of 2020 following a nationally staged strategy [27].

In Pakistan, there is an adoption of around 63% and utilisation of 17%, while the adoption rate in India is estimated to be in the range of 10-18% [33, 36, 50] and Nigeria, similarly low due to the lack of legislative enablement [37]. The comparison is shown in Figure 3 and summarised in Table 4.

Table 4. Representative BIM adoption indicators across selected developed and developing economies.

Country	Context	Reported BIM status	Principal driver / constraint
United Kingdom	Developed	~70-73% adoption (2019-2020)	Government BIM Level 2 mandate (2016)
United States	Developed	High engagement; strong ROI reported	Client demand; mature VDC practice
Germany	Developed	Staged mandate from end-2020	Federal infrastructure roadmap
Australia	Developed	Established adoption in major firms	Industry-led; partial public support
Pakistan	Developing	~63% awareness; ~17% usage	No mandate; cost and skills barriers
India	Developing	~10-18% adoption	Cost barriers; fragmented supply chain
Nigeria	Developing	Low adoption	Absence of enabling legislation; cost

5.2 Success Factors in Developed Contexts

The level of maturity of developed markets is less a consequence of technology being available everywhere in the world than of institutional frameworks that make it possible. The key has been government intervention: the UK's 2016 mandate made sure there was client demand for the services and normalized BIM usage, while Germany's incremental approach to mandating its infrastructure has been doing the same [27]. Standardization, through the ISO 19650 standards, has helped in reducing confusion and enabling interoperability. A good educational framework, with universities' degree programs and ongoing education programs, has provided the needed labor force. A more collaborative procurement process, such as Integrated Project Delivery, has helped in sharing information and sharing risks. Successful ROI, as seen in surveys of the industry, has encouraged further adoption voluntarily [28, 29].

5.3 Barriers in Developing Contexts

The developing nations face an array of interlinked challenges. First, financial problems: costs of purchasing hardware and software licenses, updates, training, etc., are too high for many small- and medium-size companies that prevail in such environments [33, 36, 37]. Second, the problem of inadequate human capital is very acute; there is a shortage of qualified specialists and poor introduction of both BIM and AI in engineering education programs. Third, regulatory problems are crucial; the lack of mandatory rules makes the key incentive of developed-market success missing [33, 37]. Finally, although awareness increases, it does not always lead to utilization, as demonstrated by the Pakistani example [33]. Cultural reluctance to change, non-transparent data exchange processes and conflict-oriented agreements make teamwork more difficult, while poor data quality and interoperability hinder the very bases of AI functioning. As for Pakistan, the research based on the methods of interpretive structural modeling shows that the lack of specialists, high costs of implementation, refusal to share information and security issues are the main barriers [33]. Figures 4 and 5 demonstrate residual risk profiles of the two paradigms and barrier intensity, respectively; Table 5 provides a summary of the barrier-enabler dichotomy.

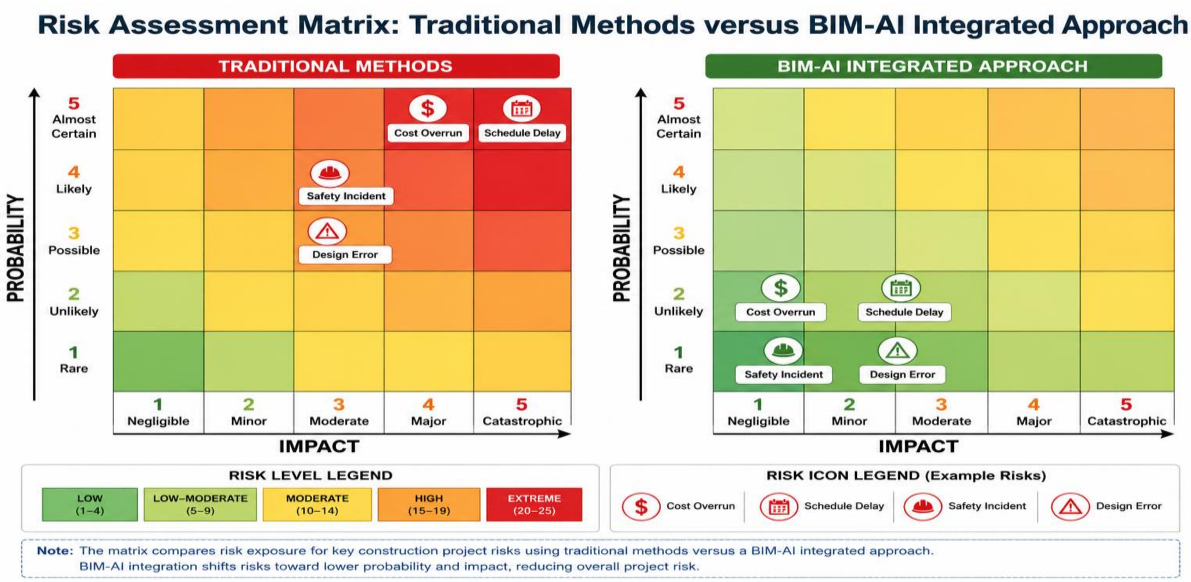

Figure 4. Risk Matrix for Traditional versus BIM-AI Approaches

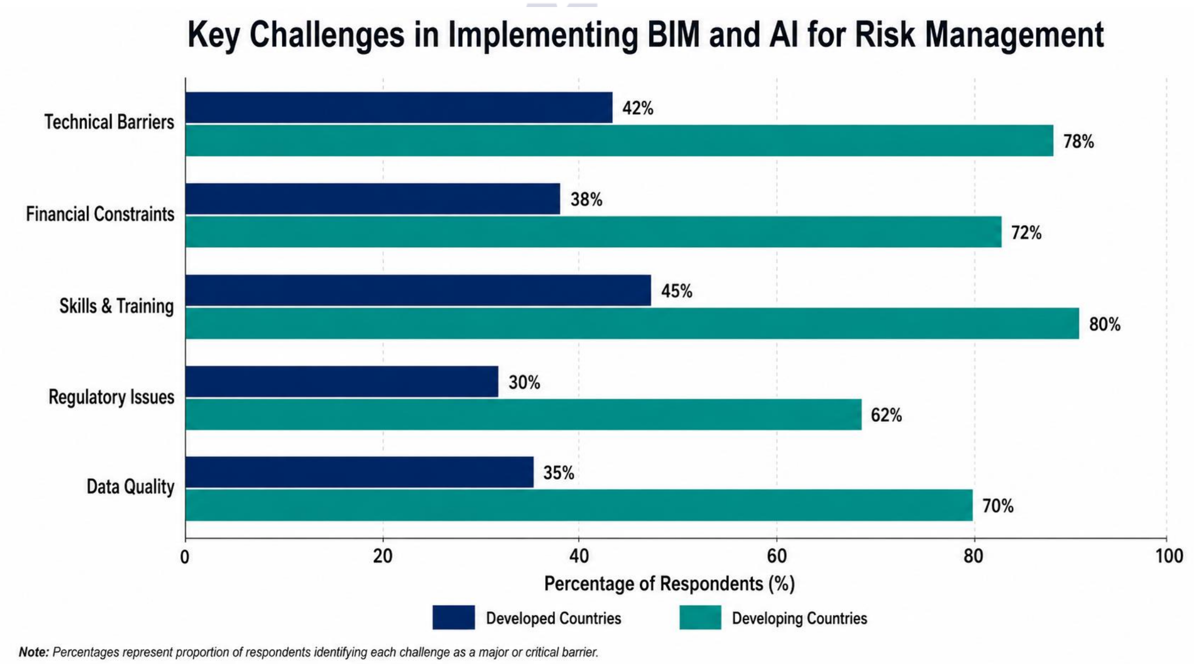

Figure 5. Comparative Challenges and Barriers in BIM-AI Implementation

Table 5. Barrier-enabler dichotomy between developing and developed contexts.

Dimension	Developing-context barrier	Developed-context enabler
Financial	High hardware, software and training cost burden	R&D budgets; demonstrated ROI
Skills	Shortage of trained staff; limited curricula	University programmes; CPD pipelines
Regulatory	Absence of government mandate	UK 2016 and Germany 2020 mandates; ISO 19650
Awareness	Awareness not translated into usage	Sustained client demand; standard practice
Cultural	Resistance to change; fragmented data sharing	Collaborative and integrated delivery culture
Data	Poor data quality; interoperability gaps	Common data environments; mature standards

5.4 The Pakistani Context in Focus

Pakistan is a model of a developing country yet it holds its own unique advantages. Construction forms about 2.5% of the GDP of Pakistan and accounts for a large number of jobs in the economy and it has been growing rapidly, at rates higher than 9% in some cases, due to demands of housing as well as the China-Pakistan Economic Corridor [33]. The construction industry with its pipeline of big public and infrastructure projects is an obvious means of imposing digitization through policy mandates, like the one used in the case of the UK. However, the 17% penetration rate amid 63% awareness shows that latent demand has not been exploited [33]. The main barriers are institutional and financial and not technological. The proposed framework and roadmap in the ensuing sections are tailored to such a situation.

6. Proposed Framework

6.1 Rationale and Design Principles

This proposed framework addresses the gaps discussed in Section 2 through a multi-layered framework incorporating BIM and AI. The design of this framework is governed by four principles. The first principle is modularity, which means that each layer of the framework can be rolled out incrementally to cater for organisations operating under conditions of scarce resources. Secondly, interoperability – the proposed framework builds on the basis of open standards such as the Industry Foundation Classes and the information management standard ISO 19650 to address issues of poor quality and integration of data, which have been identified as common challenges in the developing world. Thirdly, scalability – by virtue of being cloud-based, the cost of setting up computing infrastructure is mitigated, as costs are operational rather than capital.

6.2 Framework Architecture

This architecture consists of four interconnected layers, shown in Figure 6 below. The bottom-most Data Sources layer combines building information models, IoT sensor data flows, and project history in a unified data space, providing the structure that is the basis for any analytics. The next AI Analytics Engine layer performs cost and schedule prediction using machine learning, detects defects and hazards with the help of deep learning and computer vision, and uses natural language processing to analyse unstructured records – thus creating risk intelligence from data. The third Digital Twin and Simulation layer combines data and model geometry to allow scenario testing and early warning of potential issues during the whole lifecycle of the project. The top-most Decision Support layer provides prioritised risks and actionable insights through dashboards and generates alerts automatically; in case of certain risks, mitigation can be done automatically as well. Continuous feedback loop connects decision outcomes to data and analytics layers for model training. Table 6 describes components, functionalities and enablers of each layer.

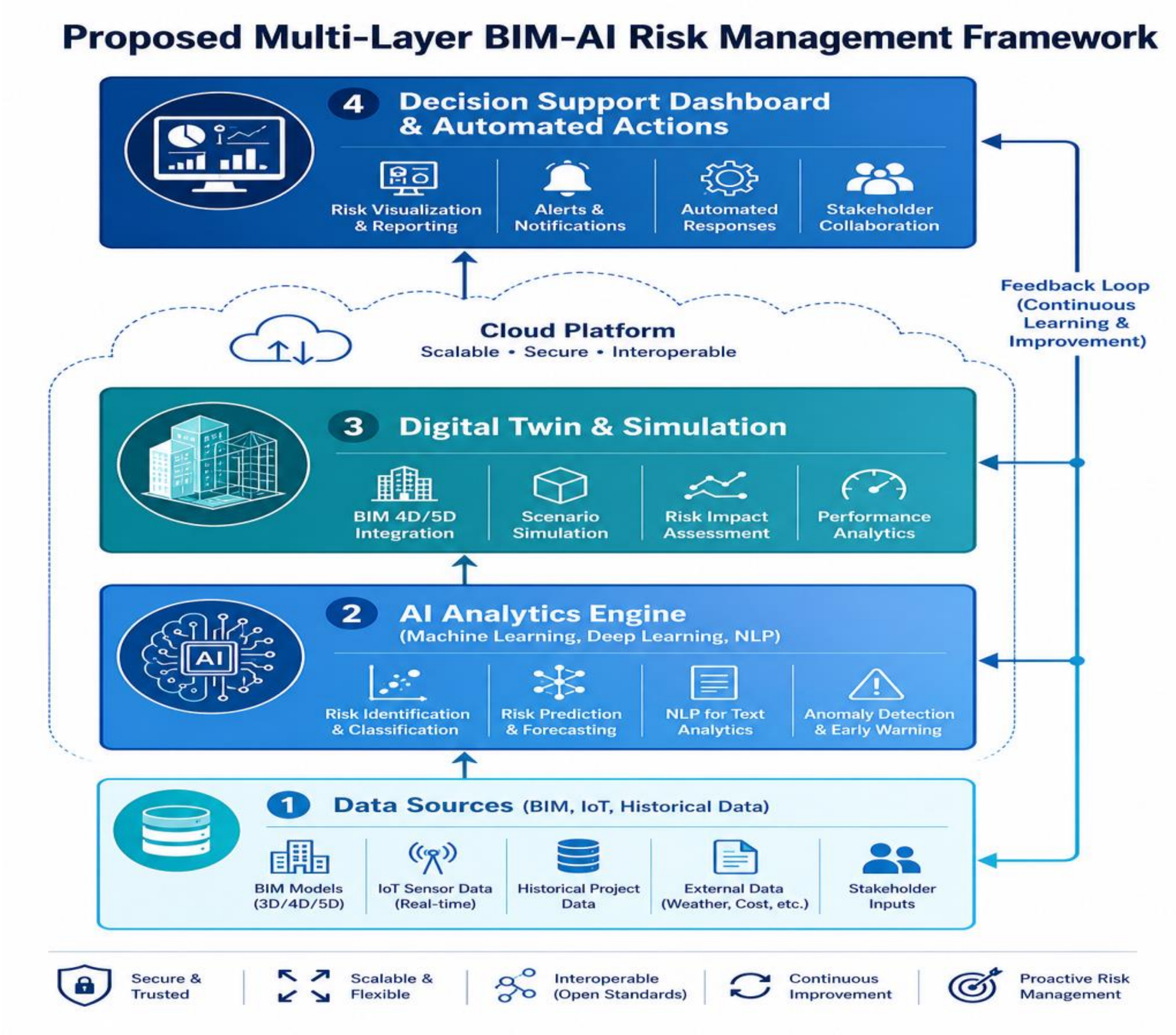

Figure 6. Proposed Multi-Layer BIM-AI Risk Management Framework Architecture

Table 6. Components, functions and enabling technologies of the proposed framework.

Layer	Core function	Enabling technologies	Risk-management contribution
Data Sources	Integrate and standardise project data	BIM (IFC), IoT sensors, CDE, ISO 19650	Reliable foundation for identification
AI Analytics Engine	Convert data into risk intelligence	ML, deep learning, CV, NLP	Predictive analysis and prioritisation
Digital Twin & Simulation	Model, simulate and forecast scenarios	Digital twin, 4D/5D simulation	Proactive mitigation; early warning
Decision Support	Visualise, alert and act	Dashboards, alerts, automation	Real-time monitoring and control
Feedback Loop	Capture outcomes and retrain	MLOps, model versioning	Continuous learning and improvement

6.3 Contextual Adaptation

Unique to the framework is the fact that it supports two modes of operation. In developed countries, the entire framework can be adopted taking advantage of well-developed data, competencies, and infrastructure to deploy digital twins and automation for mitigation. In developing countries like Pakistan, however, a sequential and light-weight framework is recommended whereby organizations start with data sources and a limited analytics layer utilizing cloud computing technology and open source software to limit expenditure. High impact and less complex applications including clash avoidance and cost overrun prediction are deployed prior to adopting digital twin monitoring. The framework implementation roadmap in section 9 illustrates the adaptation strategy.

7. Case Studies and Discussion

As an illustration of how the methodology would be applied, along with some potential benefits, three scenarios based on cases have been provided below. The first two are based on actual project experiences found in literature, while the third one is a hypothetical yet evidence-based scenario developed for the Pakistani context. The quantitative values used herein have been either based on or aligned with the values reported in literature case studies, and are therefore representative in nature.

7.1 Case Study 1: BIM-Enabled Clash Detection on a Complex Building Project (Developed Context)

The literature on clash-detection studies for complex building projects requiring intensive coordination in mature markets reveals significant benefits. According to one ROI study, a virtual design and construction coordination process that cost around USD 200,000 in man-hours brought in savings from rework exceeding USD 2.2 million, plus savings in time, yielding total benefits amounting to more than USD 2.5 million with a benefit-cost ratio nearing ten-to-one [1]. The rationale behind it is simple – through conflict resolution in the virtual world involving structural, mechanical, electrical and plumbing systems, the project was saved from expensive rework, changes in orders, and delays.

7.2 Case Study 2: AI-Based Cost and Schedule Overrun Prediction (Cross-Context)

Overrun prediction using machine learning techniques has been tested with real-life data from construction projects. A neural network optimized by using meta-heuristics on data from construction projects attained about 92% accuracy in predicting cost and schedule overruns with a coefficient of determination greater than 0.9 in cost prediction

[12]. Deployed early in a project, such a model enables management to identify high-risk projects before commitment and to allocate contingency and mitigation resources proportionately. Because the principal input is structured historical project data, this application is comparatively transferable to developing contexts, provided that organisations establish disciplined data-collection practices. It therefore represents a high-priority, lower-barrier entry point for AI-enabled risk management in emerging markets.

7.3 Case Study 3: Integrated BIM-AI Safety Monitoring on a CPEC-Type Infrastructure Project (Pakistani Context)

Consider a large infrastructure project of the type proliferating under the China-Pakistan Economic Corridor, where safety risk is elevated and historically under-managed. An integrated deployment combining a BIM model with computer-vision monitoring, consistent with documented systems that fuse BIM and computer vision for workforce safety, would enable automated detection of personal-protective-equipment non-compliance and unsafe worker proximity to hazards, with alerts routed to site supervisors [23, 40]. Drawing on reported performance of comparable computer-vision safety systems, such a deployment could plausibly improve hazard-detection coverage and reduce recordable safety incidents relative to manual inspection, while BIM-based design-for-safety review would eliminate selected hazards at source [21, 40]. This scenario demonstrates how the proposed framework, even in partial form, could address the disproportionate safety burden borne by developing-country construction workers, where fatality risk is estimated at three to six times that of developed markets [47].

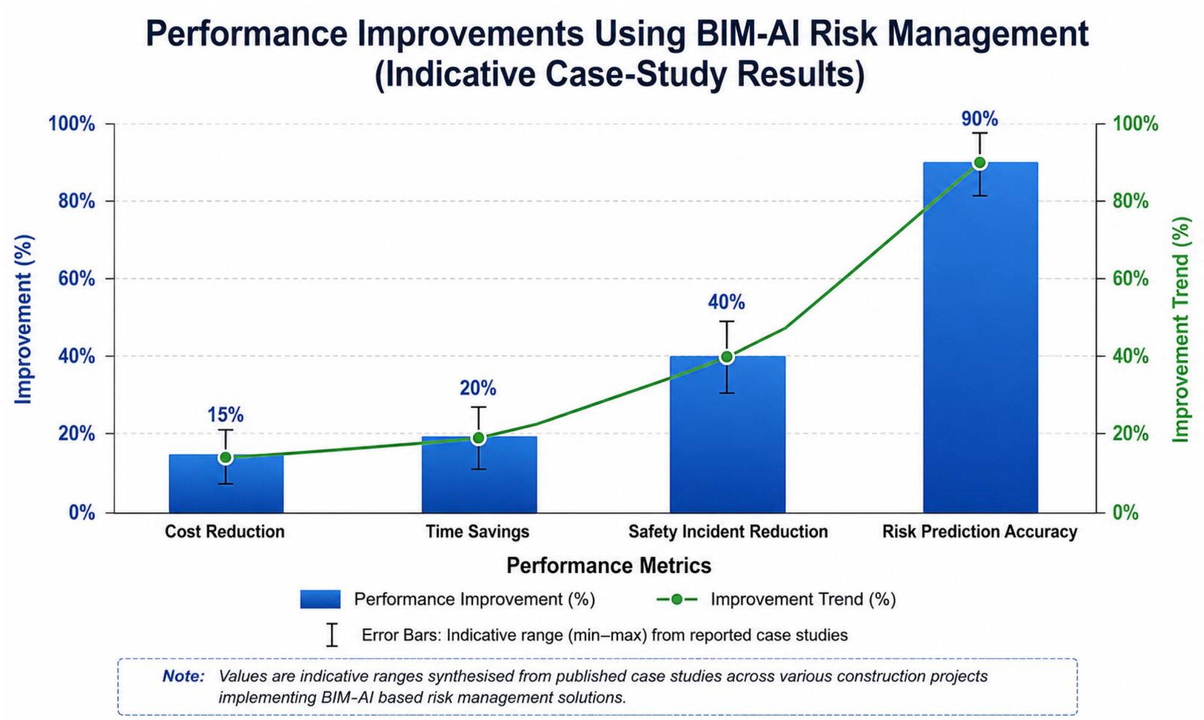

Figure 7. Performance Benefits from Case Studies

Table 7. Indicative performance metrics synthesised from case-based evidence.

Case	Primary technology	Indicative benefit	Evidence tier
1. Clash detection (developed)	BIM coordination	~10x ROI; multimillion rework savings	Indicative (single project) [1]
2. Overrun prediction (cross-context)	ML / ANN	~92% prediction accuracy	Well-supported (peer-reviewed) [12]
3. Safety monitoring (Pakistan scenario)	BIM + computer vision	Improved hazard detection; fewer incidents	Indicative scenario [21, 23, 40]
Synthesised ranges	BIM + AI	~15% cost, ~20% time, ~40% safety	Indicative (aggregated case studies)

8. Results and Discussion

8.1 Principal Findings

Three key insights emerge from the synthesis. The first one is that the technical potential of BIM and AI technologies in construction risk management has been conclusively proven by now, as BIM ensures design coordination risk reduction, while AI provides valid predictive performance in cost, schedule and safety management, along with integration of digital twins improving the efficiency of all these tools [1, 6, 12, 16]. The second insight is that the realization of the potential is profoundly uneven and determined more by institutional factors than by the availability of the respective technologies. Comparison of the 70% adoption rate driven by mandate in the UK and the mere 17% utilization rate in Pakistan despite 63% awareness rate makes this point clear [27, 33]. Finally, the third insight is that the limitations in the developing countries are primarily institutional and financial rather than technical.

8.2 Benefits and Opportunities

These benefits have been reported in the literature and demonstrated by cases and are significant and multifaceted. These consist of fewer design mistakes and redesigns, better schedule predictability, increased cost predictability, and better safety due to early hazard identification [1, 12, 21]. The scope for such an improvement for developing countries becomes greater when one considers the scale of inadequacy: where there is more risk exposure and poorer safety performance, there will be greater incremental benefits than those which can be obtained in the optimally functioning developed countries. The existence of many major public and corridor-connected infrastructure projects in Pakistan makes it possible to leverage procurement to bring about a change similar to the UK.

8.3 Limitations and Challenges of Implementation

Several shortcomings limit the above claims. Many of the quantitative figures associated with benefit calculations come from case studies for individual projects, making them suggestive and not generalizable; amounts depend on project types and baseline maturity and measurements. Data on adoption rates are inherently defined by their own definitions, since awareness, adoption, and regular usage are measured differently between different surveys, making comparisons difficult. Data on adoption of AI technology in construction and particularly in developing countries is very limited, which represents an actual gap in this field that cannot be filled completely by this research. Challenges associated with implementation of the suggested framework are not minor, including such aspects as data quality and compatibility, model explainability and reliability, cybersecurity issues, and lack of skilled workers, especially where the amount of possible benefit is highest. Finally, construction safety data in developing countries is known to be unreliable due to lack of proper recording systems [47].

8.4 Methodological Limitations

As a single-author systematic review, this study is subject to the usual limitations of selection and interpretation, mitigated but not eliminated by transparent criteria and evidence tiering. The reliance on certain industry reports, though clearly distinguished from peer-reviewed sources, introduces a degree of grey-literature dependence in the adoption statistics. The proposed framework, while grounded in recurrent functional requirements identified across the literature, has not yet been empirically validated in a live project, and its contextual adaptation for Pakistan remains a proposition awaiting field testing. These limitations define the agenda for future research set out in the concluding section.

9. Conclusion and Recommendations

9.1 Summary of Contributions

This paper has reviewed and analyzed the use of BIM and AI in construction risk management in both developed and developing countries, with a particular focus on Pakistan. This paper has shown that the effectiveness of the two technologies in terms of technical performance is proven, that their advantages do not accrue equally, and that the critical determinants of their use in developing countries are institutional and financial rather than technical. The most significant original contribution of this paper is the development of an integrated BIM and AI risk management framework which is designed to be used in both resource-abundant and resource-limited situations. By doing so, this paper contributes to the conversation on the equal adoption of Construction 4.0 and the use of digital risk management as a mechanism for transforming the construction industry in developing countries like Pakistan.

9.2 Policy and Practical Recommendations

Four suggestions can be made based on the discussion above. First, governments within developing countries must enforce BIM regulations within large-scale public and infrastructure projects starting with corridor-related and value-related works, similar to the procurement trigger that reshaped the developed countries [27, 33]. Second, standardized practices according to the ISO 19650 information management series must be established. Third, there must be constant investment in the development of human resources in terms of integration of BIM and AI into engineering courses as well as professional development programs. Fourth, the public sector must fund demonstration projects and cloud-based toolkits that decrease the capital constraint on small and medium-sized enterprises and transform awareness into action. Figure 8 shows an implementation plan following these suggestions within Pakistan's context.

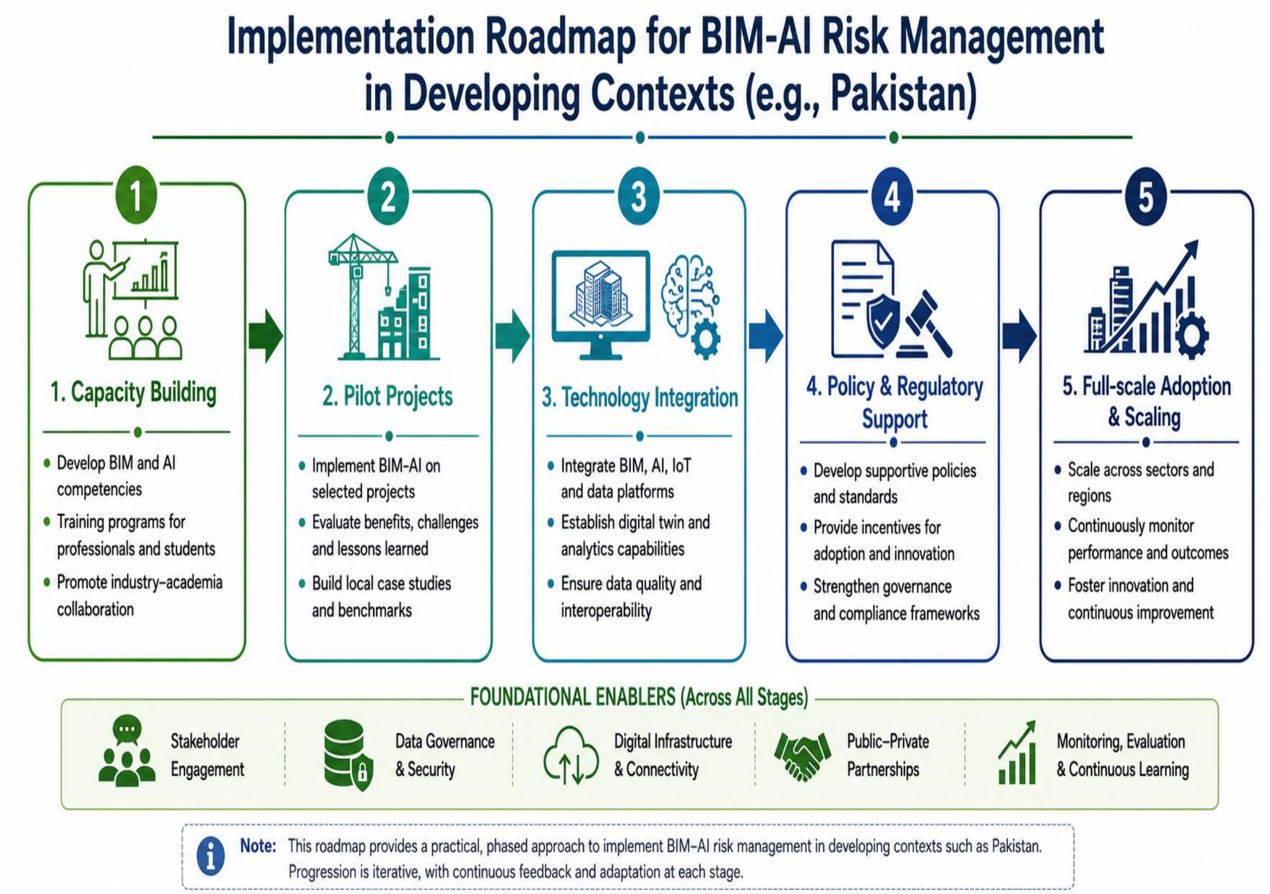

Figure 8. Roadmap for BIM-AI Implementation in Developing Countries

9.3 Future Research Directions

Three research areas can be identified. First, validation of the framework in real-life projects, especially those from developing countries, through empirical work will help in transforming the idea into evidence while also quantifying the benefit associated with the specific context. Second, primary data collection regarding the adoption of AI in construction, which is an evidence-scarce field, will help fill a void that could properly be filled through institutions like the one the author works at. Third, research into low-cost and interoperable BIM-AI applications for small and medium firms will directly help solve the cost and capability issue in developing nations.

9.4 Concluding Remark

The findings of this research indicate that there are tools for transforming risk management in the construction industry which are proven to work and are readily available. The challenge of developing economies lies in policy making and not technology as the economies have all it takes to implement the tools to transform their respective construction industries through digitization. This will be achieved through the exploitation of the massive infrastructure projects in the country such as Pakistan.

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