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Research Article

Data Governance and Quality in AI Systems and Projects in Middle East Construction Sector

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Abstract

The integration of artificial intelligence (AI) into construction projects across the Middle East, particularly in Gulf Cooperation Council (GCC) countries, presents unprecedented opportunities for enhanced project delivery, predictive analytics, and digital transformation. However, the success of AI-driven construction initiatives fundamentally depends on robust data governance frameworks and high-quality data ecosystems. This comprehensive review examines the intersection of data governance, data quality management, and AI deployment in Middle East construction, with specific focus on the United Arab Emirates (UAE), Saudi Arabia, Qatar, and Oman. Through systematic analysis of 91 scholarly sources and regional case studies including NEOM, Dubai Roads and Transport Authority (RTA), and Building Information Modeling (BIM) adoption initiatives, this article identifies critical success factors, persistent challenges, and emerging frameworks that shape AI-enabled construction outcomes. Key findings reveal that technology and infrastructure factors most strongly influence AI success, followed by governance and human enablers, with data quality and scalable infrastructure serving as critical mediators. The article synthesizes evidence on prominent governance frameworks including the Cognitive Project Management AI (CPMAI) model, AI-driven data mesh architectures, DAMA-DMBOK AI-assisted governance, and regional regulatory instruments from the Saudi Data and Artificial Intelligence Authority (SDAIA) and Dubai Government Accelerators (DGA). Persistent challenges include fragmented and non-standardized data across project phases, ownership and intellectual property ambiguities on collaborative platforms, data scarcity for supervised learning models, and insufficient lifecycle governance mechanisms. The article proposes evidence-based policy recommendations including mandated lifecycle data-quality metrics in public procurement, adoption of domain data contracts and mesh patterns, promotion of automated governance tooling, strengthened workforce training programs, and clear sovereignty and residency rules for cross-border projects. This research contributes to the emerging body of knowledge on trustworthy AI in construction by providing a comprehensive framework that integrates technical,

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organizational, and regulatory dimensions of data governance tailored to the unique socio-technical context of Middle East construction ecosystems.

Keywords: Data governance, data quality, artificial intelligence, construction management, Middle East, GCC, BIM, digital twins, CPMAI, data mesh, SDAIA, Saudi Arabia, UAE, NEOM, Dubai RTA

Introduction

The construction sector in the Middle East, particularly across Gulf Cooperation Council (GCC) nations including the United Arab Emirates, Saudi Arabia, Qatar, and Oman, is undergoing a profound digital transformation driven by ambitious national visions, megaproject developments, and the strategic integration of artificial intelligence technologies. Projects such as Saudi Arabia's NEOM smart city, Dubai's extensive infrastructure modernization initiatives, and Qatar's preparations for major international events have catalyzed unprecedented investment in AI-enabled construction management systems, Building Information Modeling (BIM) platforms, digital twins, and intelligent project delivery frameworks. These technological advances promise substantial improvements in project efficiency, cost optimization, safety management, sustainability outcomes, and decision-making quality.

However, the realization of AI's transformative potential in construction fundamentally depends on two critical enablers that remain insufficiently addressed in both academic literature and industry practice: robust data governance frameworks and high-quality data ecosystems. Data governance encompasses the policies, procedures, standards, and organizational structures that ensure data assets are managed effectively throughout their lifecycle, while data quality refers to the fitness of data for its intended uses, measured through dimensions such as accuracy, completeness, consistency, timeliness, and provenance. In AI systems, where algorithmic performance is directly constrained by the quality and governance of training and operational data, these factors become not merely supportive infrastructure but fundamental determinants of system trustworthiness, reliability, and value creation.

The Middle East construction context presents unique challenges and opportunities for data governance and quality management in AI systems. The region's construction ecosystem is characterized by rapid technological adoption, substantial public and private investment, diverse international stakeholder participation, complex regulatory environments that blend modern governance frameworks with traditional legal systems, and ambitious timelines for large-scale projects. These factors create both accelerated demand for AI-driven solutions and heightened risks associated with inadequate data practices. Fragmented data across project phases and stakeholders, unclear ownership and intellectual property arrangements on collaborative platforms, insufficient standardization of metadata and schemas, limited workforce capacity in data management disciplines, and evolving regulatory frameworks all contribute to a challenging environment for establishing trustworthy AI systems.

Recent empirical evidence from Saudi construction projects demonstrates that technology and infrastructure factors most strongly influence AI success outcomes, with governance and human factors serving as critical mediating variables (Alnaser et al., 2025). This finding underscores the centrality of data infrastructure and governance mechanisms in determining whether AI investments deliver their promised benefits. Similarly, case studies from Dubai's Roads and Transport Authority and UAE BIM implementations reveal that operational gains from AI and digital technologies are contingent upon coordinated data governance, standardized protocols, and clear contractual arrangements for data access and quality (Shi et al., 2025), (Shafiq, 2021).

The academic and practitioner communities have begun to develop specialized frameworks for data governance in AI-driven construction contexts. The Cognitive Project Management AI (CPMAI) model, adapted for Saudi Vision 2030 initiatives, integrates data-quality governance into each phase of the AI lifecycle to improve key performance indicator (KPI) reliability and auditability in cloud ecosystems (Kayani, 2025). AI-driven data mesh architectures propose decentralized domain-oriented data management with standardized ingestion, knowledge graphs, and large language model integration for infrastructure projects (Mishra et al., 2024). The Data Management Association's Data Management Body of Knowledge (DAMA-DMBOK) framework has been extended to incorporate AI-assisted governance functions including automated metadata discovery, rule generation, and policy enforcement (Kumari, 2024). These emerging frameworks represent important theoretical and practical advances, yet their adoption remains limited and their effectiveness in Middle East construction contexts requires further empirical validation.

This article addresses a critical gap in the literature by providing a comprehensive, evidence-based analysis of data governance and quality challenges, frameworks, and solutions specifically tailored to AI systems in Middle East construction. Drawing on systematic analysis of 91 scholarly sources, regional case studies, and policy documents, the article synthesizes current knowledge on governance frameworks, identifies persistent data quality challenges, examines AI applications and their data requirements, analyzes regional initiatives and case studies, and proposes actionable policy recommendations grounded in empirical evidence. The research questions guiding this investigation are: (1) What data governance frameworks are most applicable to AI-driven construction projects in the Middle East context? (2) What are the primary data quality challenges impeding AI adoption and effectiveness in regional construction projects? (3) How do regional initiatives and case studies illuminate the practical implementation of data governance and quality management? (4) What policy interventions and regulatory mechanisms can most effectively promote trustworthy AI through improved data governance in Middle East construction?

The article is structured to provide both theoretical depth and practical applicability. Following this introduction, Section 2 reviews relevant literature on data governance, AI in construction, and regional digital transformation initiatives. Section 3 establishes the theoretical framework integrating data governance, quality management, and AI system trustworthiness. Section 4 examines specific governance frameworks applicable to AI-driven construction, including CPMAI, data mesh, DAMA-DMBOK, and intelligent governance systems. Section 5 analyzes data quality challenges specific to Middle East construction contexts. Section 6 surveys AI applications in regional construction and their data dependencies. Section 7 presents detailed case studies from Dubai, Saudi Arabia, and other GCC nations. Section 8 synthesizes policy recommendations and analyzes the evolving regulatory landscape. Section 9 concludes with implications for research, practice, and policy.

This research contributes to the emerging body of knowledge on trustworthy AI in construction by providing the first comprehensive framework that integrates technical, organizational, and regulatory dimensions of data governance tailored specifically to the Middle East construction ecosystem. The findings have direct implications for construction firms, technology vendors, project owners, regulatory authorities, and academic researchers seeking to understand and improve the data foundations of AI-enabled construction transformation in the region.

Literature Review

The literature on data governance and quality in AI-driven construction systems spans multiple disciplinary domains including construction management, information systems, data science, AI ethics, and regional studies. This review synthesizes relevant scholarship across these domains to establish the knowledge foundation for the present investigation.

Data Governance in Construction and Engineering Contexts

Data governance in construction has evolved from traditional document management and quality assurance practices to encompass complex digital ecosystems involving BIM platforms, cloud collaboration environments, Internet of Things (IoT) sensor networks, and AI-driven analytics systems. Alreshidi et al. (2018) identified critical requirements for cloud-based BIM governance solutions to facilitate team collaboration in construction projects, emphasizing the need for clear data ownership models, access control mechanisms, version management protocols, and audit trails. Their requirements engineering approach revealed that governance challenges in collaborative BIM environments stem from the tension between openness required for effective collaboration and control needed for data integrity, security, and intellectual property protection.

The transition from centralized to distributed data architectures in construction projects introduces additional governance complexities. Traditional project management information systems (PMIS) operated on centralized databases with clear custodianship, whereas contemporary AI-enabled construction ecosystems involve multiple data sources, diverse stakeholder access patterns, heterogeneous data formats, and dynamic data flows across organizational boundaries. This architectural shift necessitates governance frameworks that can accommodate decentralization while maintaining data quality, security, and compliance standards.

AI Applications in Construction Management

The application of AI technologies in construction management has expanded rapidly over the past decade, encompassing predictive analytics for cost and schedule forecasting, computer vision for safety monitoring and quality inspection, generative design for optimization, natural language processing for contract analysis, and digital twins for simulation and decision support. Savaş (2025) provides a comprehensive review of AI trends, challenges, and future directions in construction project management, identifying data availability and quality as primary barriers to AI adoption alongside workforce skills gaps, organizational resistance, and regulatory uncertainties.

Digital twins represent a particularly data-intensive AI application that integrates real-time sensor data, BIM models, historical project data, and simulation algorithms to create dynamic virtual representations of physical construction assets. Abdulqader et al. (2025) conducted a PRISMA systematic review of digital twin, BIM, and IoT contributions and barriers in construction project management, revealing that data integration challenges, interoperability issues, and lack of standardized data exchange protocols constitute major impediments to digital twin effectiveness. The review emphasizes that successful digital twin implementations require not only advanced AI algorithms but also robust data governance frameworks that ensure data quality, provenance, and lifecycle management.

BIM Adoption and Data Standardization in the Middle East

Building Information Modeling adoption in Middle East construction has been characterized by uneven progress, with significant variations across countries, project types, and organizational contexts. Abdalla et al. (2023) conducted a comparative analysis of BIM patterns and trends in the UAE relative to developed countries, finding that UAE BIM adoption remains fragmentary across lifecycle stages, driven primarily by international firms but lacking unified national standards and full-lifecycle integration. The study identified that BIM use is concentrated in design and construction phases, with limited adoption in operations and maintenance, resulting in data discontinuities that impair the development of comprehensive digital twins and AI-driven asset management systems.

In Saudi Arabia, BIM adoption has been promoted as a key enabler of sustainability and operational efficiency aligned with Vision 2030 objectives. Alasmari et al. (2023) investigated BIM adoption for sustainability enhancement in Saudi construction projects, revealing growing awareness of BIM benefits but persistent barriers including skills gaps, limited training opportunities, cultural factors affecting collaboration, and design-phase focus that neglects lifecycle data management. The study found that while 68% of respondents recognized BIM's sustainability benefits, only 42% had implemented BIM in their projects, indicating a substantial implementation gap.

Across the broader GCC region, Umar (2021) identified 39 distinct challenges to BIM implementation through systematic review and survey research, categorizing barriers into organizational factors (lack of top management support, resistance to change, unclear return on investment), technical factors (interoperability issues, software costs, inadequate IT infrastructure), legal factors (unclear intellectual property rights, lack of BIM-specific contracts, liability concerns), and environmental factors (insufficient government mandates, limited industry standards, shortage of skilled professionals). These multifaceted barriers directly impact data governance and quality by preventing the establishment of standardized data practices, clear custodianship arrangements, and consistent metadata schemas across projects.

Data Quality Challenges in AI Systems

Data quality challenges in AI systems have been extensively documented in the computer science and information systems literature, with particular attention to issues of bias, representativeness, labeling accuracy, and provenance. In construction contexts, these generic AI data quality challenges are compounded by domain-specific factors including the heterogeneity of construction data sources (sensors, BIM models, project documents, financial systems, supply chain data), the temporal dynamics of construction projects where data requirements evolve across phases, the involvement of multiple organizations with different data practices and systems, and the physical-digital integration challenges inherent in cyber-physical construction systems.

Mahmood et al. (2023) examined how AI can leverage PMIS and data-driven decision making in project management, identifying data quality as a critical mediating factor between AI capability and decision quality. Their framework emphasizes that AI algorithms, regardless of sophistication, cannot compensate for poor data quality, and that investments in data governance and quality management are prerequisites for effective AI-driven decision support. The study proposes integrating data quality assessment mechanisms into PMIS architectures to provide real-time feedback on data fitness for AI applications.

Regional Governance Frameworks and Regulatory Initiatives

The regulatory landscape for AI governance in the Middle East is evolving rapidly, with several GCC countries establishing national AI strategies, ethics principles, and regulatory authorities. Trigui et al. (2024) explored AI governance in the Middle East and North Africa (MENA) region, identifying significant gaps, efforts, and initiatives across countries. The study found that while several nations have articulated AI strategies and established coordinating bodies, implementation mechanisms remain underdeveloped, with particular weaknesses in monitoring frameworks, incident reporting systems, and enforcement mechanisms. The authors emphasize the need for harmonized regional approaches to AI governance that balance innovation promotion with risk mitigation.

In Saudi Arabia, the Saudi Data and Artificial Intelligence Authority (SDAIA) has emerged as the primary regulatory body for AI governance, issuing AI ethics principles and developing policy frameworks aligned with Vision 2030 objectives. Alboaneen et al. (2025) introduced Siyasat, an AI-powered governance tool designed to generate and improve AI policies according to Saudi AI ethics principles using retrieval-augmented generation (RAG) approaches. This tool represents an innovative application of AI to governance itself, demonstrating how automated policy generation can accelerate compliance with national ethics frameworks. The tool achieved strong consistency metrics (BERTScore of 0.890 and Self-BLEU of 0.871), indicating high-quality policy generation aligned with SDAIA principles.

The UAE has similarly established governance frameworks through entities such as the Dubai Government Accelerators (DGA) and the UAE Artificial Intelligence Office, which promote AI adoption while establishing ethical guidelines and regulatory sandboxes for testing AI applications. Gorian et al. (2024) examined digital ethics of AI in Saudi Arabia and the UAE, highlighting the unique integration of Islamic ethics and privacy principles into AI governance frameworks. The study emphasizes that Middle East AI governance frameworks differ from Western approaches by incorporating Shariah-based concepts of privacy, data protection, and ethical AI use, requiring governance models that harmonize technological advancement with Islamic legal and ethical principles.

Emerging Governance Frameworks for AI in Construction

Several specialized governance frameworks have been proposed to address the unique requirements of AI systems in construction contexts. Kayani (2025) developed a cognitive project management framework for AI deployment and data quality governance in cloud ecosystems, specifically tailored to Saudi Vision 2030 initiatives. The CPMAI model integrates data-quality indices into each phase of the AI lifecycle—from data collection and preparation through model development, deployment, and monitoring—to ensure KPI reliability, traceability, and policy alignment. The framework emphasizes lifecycle-aligned governance where data quality metrics are continuously assessed and reported, enabling proactive identification of data degradation that could compromise AI system performance.

Mishra et al. (2024) proposed an AI-driven data mesh architecture for infrastructure construction and public procurement, advocating for decentralized domain-oriented data ownership combined with standardized data contracts, federated governance, and self-serve data infrastructure. The data mesh paradigm addresses scalability limitations of centralized data governance by distributing data ownership to domain teams (e.g., design, procurement, construction, operations) while maintaining interoperability through standardized schemas and APIs. The architecture incorporates knowledge graphs and large language models to enable semantic search, automated data integration, and intelligent decision support across distributed data domains.

Kumari (2024) provided a technical overview of intelligent data governance frameworks that leverage AI and machine learning to automate governance functions including metadata discovery, data quality profiling, policy enforcement, and compliance monitoring. The framework maps AI capabilities to DAMA-DMBOK governance functions, demonstrating how natural language processing can automate metadata extraction from unstructured documents, machine learning can detect data quality anomalies, and explainable AI can support audit and compliance requirements. The study emphasizes that while AI can enhance governance efficiency, human oversight remains essential for ethical decision-making and context-dependent policy interpretation.

Abudaqqa et al. (2025) examined AI for IT governance in Saudi Arabia within COBIT 2019 and ISO/IEC 38500 frameworks, identifying opportunities, challenges, and future directions. The study proposes adapting established IT governance frameworks to incorporate AI-specific considerations including algorithmic transparency, bias mitigation, data provenance, and continuous monitoring. The authors recommend developing national taxonomies for AI risks, establishing incident reporting mechanisms, and creating regulatory sandboxes to test governance approaches before mandating them across sectors.

2.7 Critical Success Factors for AI in Construction

Empirical research on critical success factors (CSFs) for AI adoption in construction has identified data quality and governance as central enablers alongside technological infrastructure, organizational readiness, and workforce capabilities. Alnaser et al. (2025) conducted a PLS-SEM study of 120 construction professionals in Saudi Arabia to explore CSFs for AI-integrated digital twins and their impact on project deliverables. The study found that technology and infrastructure factors had the strongest direct effects on project outcomes (time, cost, quality, resource utilization, risk management), followed by governance factors and human factors. Importantly, the study revealed that data quality and scalable infrastructure serve as critical mediators between AI capability and project performance, indicating that investments in data governance yield returns through improved AI effectiveness rather than direct project impacts.

The hierarchical nature of these CSFs suggests that data governance interventions should be prioritized alongside infrastructure investments, as governance frameworks enable effective utilization of technological capabilities. The study recommends that organizations seeking to implement AI-integrated digital twins should invest in data quality assessment mechanisms, establish clear data ownership and stewardship roles, implement metadata standards, and develop workforce competencies in data management alongside AI and digital twin technologies.

Gaps in Current Literature

Despite growing scholarly attention to AI in construction and data governance, several critical gaps remain in the literature. First, most existing research treats data governance as a generic organizational function rather than examining the specific governance requirements of AI systems in construction contexts, where data flows across organizational boundaries, integrates physical and digital systems, and must support real-time decision-making under uncertainty. Second, empirical research on data quality challenges in Middle East construction is limited, with most studies focusing on BIM adoption barriers rather than the specific data quality dimensions that affect AI system performance. Third, the literature lacks comprehensive frameworks that integrate technical data governance mechanisms (metadata standards, data contracts, quality metrics) with organizational governance structures (roles, responsibilities, decision rights) and regulatory compliance requirements specific to Middle East contexts. Fourth, case study research on successful data governance implementations in regional construction projects remains scarce, limiting the availability of practical guidance for practitioners. This article addresses these gaps by synthesizing evidence across disciplinary boundaries, analyzing regional case studies, and proposing an integrated framework for data governance in AI-driven Middle East construction.

Theoretical Framework

This section establishes the theoretical foundation for understanding data governance and quality in AI-driven construction systems, integrating concepts from data management, AI system engineering, organizational theory, and construction management. The framework positions data governance as a socio-technical system that mediates between organizational objectives, technological capabilities, and regulatory requirements to enable trustworthy AI in construction contexts.

Data Governance as a Socio-Technical System

Data governance in AI-driven construction cannot be understood purely as a technical problem of data management or purely as an organizational problem of policy and procedure. Rather, it constitutes a socio-technical system where technical artifacts (data platforms, metadata repositories, quality monitoring tools), organizational structures (governance committees, data stewardship roles, decision rights), social practices (collaboration norms, data sharing behaviors, quality culture), and regulatory constraints (privacy laws, sovereignty requirements, industry standards) interact to shape data outcomes. This socio-technical perspective, grounded in information systems research, emphasizes that effective governance requires alignment across these dimensions rather than optimization of any single component.

In construction contexts, the socio-technical nature of data governance is particularly salient due to the temporary multi-organization (TMO) structure of construction projects, where diverse firms collaborate intensively for limited durations before disbanding. This organizational form creates governance challenges including ambiguous data ownership across organizational boundaries, limited incentives for long-term data quality investments, heterogeneous data practices and systems across participating organizations, and knowledge loss when projects conclude and teams disperse. Effective data governance frameworks for construction must therefore address not only technical interoperability but also organizational coordination mechanisms, contractual arrangements for data rights and responsibilities, and incentive structures that promote data quality contributions from all participants.

Data Quality Dimensions and AI System Performance

Data quality is a multidimensional construct encompassing various attributes that determine data fitness for specific uses. The data quality literature identifies core dimensions including accuracy (correctness of data values), completeness (presence of all required data elements), consistency (uniformity of data representations across sources and time), timeliness (currency and availability when needed), validity (conformance to defined formats and constraints), and provenance (documentation of data origins and transformations). In AI systems, these quality dimensions directly impact algorithmic performance through multiple mechanisms.

For supervised learning models, training data accuracy and representativeness determine the model's ability to generalize to new situations. Incomplete or biased training data leads to models that perform poorly on underrepresented scenarios, a particularly critical concern in construction safety applications where rare but high-consequence events must be detected reliably. For predictive analytics in cost and schedule forecasting, data completeness and consistency across historical projects determine the model's ability to identify relevant patterns and make accurate predictions. For digital twins that integrate real-time sensor data with BIM models, data timeliness and provenance are critical to maintaining synchronization between physical and virtual representations.

The relationship between data quality and AI performance is not linear but exhibits threshold effects where minimum quality levels must be achieved before AI systems provide value, and diminishing returns where incremental quality improvements yield progressively smaller performance gains. This non-linearity has important implications for governance prioritization, suggesting that initial governance investments should focus on addressing critical quality deficits that prevent AI system functionality, while subsequent investments should target quality improvements that enable advanced AI capabilities.

Governance Frameworks and Lifecycle Integration

Effective data governance for AI systems requires integration across the AI lifecycle, from problem definition and data collection through model development, deployment, monitoring, and retirement. The CPMAI framework, adapted for construction contexts, provides a structured approach to lifecycle-aligned governance by embedding data quality assessment and governance checkpoints at each lifecycle phase (Kayani, 2025). This lifecycle perspective ensures that data governance is not treated as a one-time activity during data preparation but as a continuous process that adapts to evolving data requirements, detects quality degradation, and maintains alignment with organizational policies and regulatory requirements.

The lifecycle integration of governance addresses several critical challenges in AI-driven construction. During the data collection phase, governance mechanisms ensure that data is captured with appropriate metadata, provenance documentation, and quality indicators. During model development, governance processes verify that training data is representative, unbiased, and compliant with privacy and sovereignty requirements. During deployment, governance monitors data drift and quality degradation that could compromise model performance. During operations, governance ensures that data used for decision-making meets quality standards and that decisions are auditable and explainable. This comprehensive lifecycle approach contrasts with ad-hoc governance practices that address data issues reactively rather than proactively.

Decentralized Governance and Data Mesh Architectures

Traditional centralized data governance models, where a single team or platform manages all organizational data, face scalability limitations in complex construction ecosystems involving multiple organizations, diverse data types, and distributed decision-making. The data mesh paradigm, proposed by Mishra et al. (2024) for infrastructure construction, advocates for decentralized domain-oriented data ownership combined with federated governance and self-serve data infrastructure. In this model, domain teams (e.g., design, procurement, construction, operations) own and govern their data products, while a federated governance function establishes interoperability standards, data contracts, and cross-domain policies.

The data mesh approach addresses several governance challenges specific to construction. First, it aligns data ownership with domain expertise, ensuring that teams with the best understanding of data semantics and quality requirements are responsible for data governance. Second, it enables scalability by distributing governance responsibilities rather than creating bottlenecks in centralized teams. Third, it promotes data quality by making domain teams accountable for the usability of their data products by downstream consumers. Fourth, it facilitates innovation by enabling domain teams to adopt new technologies and practices without requiring centralized approval, while maintaining interoperability through standardized contracts.

However, the data mesh paradigm also introduces coordination challenges including the need for clear domain boundaries, standardized data contracts that balance flexibility and consistency, federated governance mechanisms that can resolve cross-domain conflicts, and cultural change to establish domain data ownership mindsets. Successful implementation requires not only technical infrastructure but also organizational design, incentive alignment, and capability development across domain teams.

AI-Assisted Governance and Intelligent Automation

An emerging trend in data governance is the application of AI technologies to governance functions themselves, creating intelligent data governance systems that automate routine tasks, detect anomalies, and provide decision support for governance activities. Kumari (2024) outlines how machine learning can automate metadata discovery from unstructured documents, natural language processing can extract data lineage from code and documentation, anomaly detection algorithms can identify data quality issues, and explainable AI can support compliance auditing and policy interpretation.

In construction contexts, AI-assisted governance can address several persistent challenges. Automated metadata extraction can populate data catalogs from BIM models, project documents, and sensor configurations, reducing manual effort and improving metadata completeness. Machine learning-based quality profiling can continuously monitor data streams from IoT sensors and construction management systems, detecting anomalies and triggering alerts when quality thresholds are breached. Natural language processing can analyze contracts and specifications to extract data requirements and governance obligations, ensuring that data practices align with contractual commitments. Knowledge graphs can integrate heterogeneous data sources and enable semantic search and reasoning across project data, supporting intelligent decision-making.

However, AI-assisted governance also introduces new challenges including the need for explainability and auditability of automated governance decisions, the risk of algorithmic bias in governance processes, the requirement for human oversight of AI-generated governance recommendations, and the potential for over-reliance on automation that reduces human governance expertise. Effective implementation requires careful design of human-AI collaboration patterns where AI augments rather than replaces human judgment in governance activities.

Regulatory Compliance and Trustworthy AI

Data governance in AI systems must address not only organizational objectives and technical requirements but also regulatory compliance and broader societal expectations for trustworthy AI. In Middle East contexts, regulatory requirements include data sovereignty and localization rules that mandate local storage and processing of certain data types, privacy and data protection regulations that restrict data collection and use, AI ethics principles established by national authorities such as SDAIA, and sector-specific regulations for construction safety, quality, and environmental protection.

The concept of trustworthy AI, articulated in various national and international frameworks, encompasses multiple dimensions including technical robustness and safety, privacy and data governance, transparency and explainability, fairness and non-discrimination, accountability and auditability, and societal and environmental wellbeing. Data governance serves as a foundational enabler of trustworthy AI by ensuring that data used in AI systems is collected ethically, managed securely, used transparently, and maintained with appropriate quality and provenance documentation.

In construction contexts, trustworthy AI has particular importance due to the safety-critical nature of construction activities, the long-term societal impacts of built infrastructure, the involvement of public funds in many projects, and the potential for AI systems to affect employment and workforce dynamics. Data governance frameworks must therefore incorporate mechanisms for ethical data collection that respects worker privacy and dignity, transparent data use that enables stakeholder understanding of AI-driven decisions, accountable data management that supports auditing and dispute resolution, and inclusive data practices that ensure AI systems serve diverse populations and use cases.

Integrated Framework for Data Governance in AI-Driven Construction

Building on the theoretical concepts outlined above, this article proposes an integrated framework for data governance in AI-driven construction that encompasses four interrelated dimensions:

Technical Dimension

Data architecture, metadata standards, quality metrics, integration mechanisms, and governance tooling that enable effective data management across heterogeneous sources and systems.

Organizational Dimension

Governance structures, roles and responsibilities, decision rights, policies and procedures, and incentive mechanisms that coordinate data practices across project participants and organizational boundaries.

Lifecycle Dimension

Integration of governance activities across AI system lifecycle phases, from problem definition and data collection through model development, deployment, monitoring, and retirement, ensuring continuous governance rather than episodic interventions.

Regulatory Dimension

Compliance mechanisms for data sovereignty, privacy, AI ethics, and sector-specific regulations, along with alignment with national AI strategies and international standards.

This integrated framework recognizes that effective data governance requires simultaneous attention to all four dimensions, as weaknesses in any dimension can undermine overall governance effectiveness. The framework guides the subsequent analysis of specific governance models, data quality challenges, AI applications, case studies, and policy recommendations, providing a coherent structure for understanding the complex interplay of factors that determine data governance outcomes in Middle East construction contexts.

Data Governance Frameworks in AI-Driven Construction

This section examines specific data governance frameworks that have been proposed or implemented for AI-driven construction projects, with particular attention to their applicability in Middle East contexts. The frameworks reviewed include the Cognitive Project Management AI (CPMAI) model, AI-driven data mesh architectures, DAMA-DMBOK AI-assisted governance, and intelligent data governance systems. Each framework is analyzed in terms of its core components, governance mechanisms, implementation requirements, and empirical evidence of effectiveness.

CPMAI × Data Governance Model

The Cognitive Project Management AI (CPMAI) framework, developed by Kayani (2025) for Saudi Vision 2030 initiatives, represents a comprehensive approach to integrating data quality governance into AI-enabled project management in cloud ecosystems. The framework addresses the critical challenge of maintaining KPI reliability and traceability in AI-driven construction projects by embedding data quality assessment and governance mechanisms at each phase of the AI lifecycle.

The CPMAI model consists of several core components. First, it establishes a data quality index that measures multiple dimensions including completeness (percentage of required data elements present), accuracy (correctness of data values verified through validation rules), timeliness (currency of data relative to decision requirements), consistency (uniformity of data representations across sources), and lineage (documentation of data origins and transformations). These quality dimensions are operationalized through specific metrics that can be automatically calculated and monitored throughout the project lifecycle (Kayani, 2025).

Second, the framework defines lifecycle-aligned governance processes that integrate data quality assessment into each AI development phase. During the problem definition phase, governance processes identify data requirements, assess data availability, and establish quality targets. During data collection and preparation, governance mechanisms verify data provenance, apply quality validation rules, and document data transformations. During model development, governance processes ensure training data representativeness, detect bias, and maintain experiment traceability. During deployment, governance monitors data drift and quality degradation. During operations, governance ensures decision auditability and maintains alignment with organizational policies and regulatory requirements (Kayani, 2025).

Third, the CPMAI framework incorporates policy alignment mechanisms that link data governance practices to national AI strategies and ethics principles, specifically SDAIA and DGA standards in the Saudi context. This policy alignment ensures that data practices in construction projects support broader national objectives for trustworthy AI, data sovereignty, and digital transformation. The framework includes templates for data governance policies, procedures for policy compliance verification, and reporting mechanisms that demonstrate alignment with national standards (Kayani, 2025).

Empirical evidence from Saudi construction projects implementing the CPMAI framework demonstrates improved KPI reliability, enhanced traceability of AI-driven decisions, and better alignment with Vision 2030 objectives. The framework's emphasis on lifecycle integration addresses a critical gap in traditional project management approaches that treat data governance as a separate activity rather than an integral component of AI system development and operations. However, implementation challenges include the need for organizational change management to establish new governance roles and processes, technical infrastructure to support automated quality monitoring, and workforce capability development in data governance disciplines (Kayani, 2025).

AI-Driven Data Mesh Architecture

The data mesh paradigm, adapted by Mishra et al. (2024) for infrastructure construction and public procurement, represents a fundamental shift from centralized to decentralized data governance architectures. The framework addresses scalability limitations of traditional centralized data platforms by distributing data ownership to domain teams while maintaining interoperability through standardized data contracts and federated governance mechanisms.

The data mesh architecture for construction consists of four foundational principles. First, domain-oriented data ownership assigns responsibility for data products to the teams with the deepest domain expertise. In construction contexts, this means design teams own design data products, procurement teams own supplier and contract data products, construction teams own execution and progress data products, and operations teams own asset performance data products. Each domain team is responsible for the quality, documentation, and accessibility of their data products, creating clear accountability for data governance (Mishra et al., 2024).

Second, data as a product thinking treats data not as a byproduct of operational systems but as a first-class product with defined consumers, quality standards, and service level agreements. Domain teams develop data products that meet the needs of downstream consumers, including AI systems that require training data, analytics platforms that require integrated datasets, and decision-makers who require timely and accurate information. Data products are documented with metadata, quality metrics, and usage guidelines, enabling consumers to assess fitness for purpose (Mishra et al., 2024).

Third, self-serve data infrastructure provides domain teams with tools and platforms to create, publish, and maintain their data products without requiring centralized IT support for routine activities. The infrastructure includes standardized data ingestion pipelines, automated quality profiling, metadata catalogs, and access control mechanisms. This self-serve capability enables domain teams to respond quickly to changing data requirements while maintaining governance standards (Mishra et al., 2024).

Fourth, federated computational governance establishes cross-domain standards, policies, and decision-making mechanisms that ensure interoperability and compliance while preserving domain autonomy. Federated governance defines data contracts that specify schemas, quality requirements, and service levels for data products. It establishes global policies for data security, privacy, and sovereignty that apply across all domains. It provides mechanisms for resolving cross-domain conflicts and coordinating changes that affect multiple domains (Mishra et al., 2024).

The data mesh architecture incorporates advanced AI capabilities including knowledge graphs that integrate heterogeneous data sources and enable semantic reasoning, large language models that provide natural language interfaces to data products, and AI agents that automate data integration and decision support tasks. These AI capabilities enhance the usability and value of distributed data products while maintaining governance through standardized interfaces and contracts (Mishra et al., 2024).

Implementation of data mesh architectures in construction projects requires significant organizational and technical changes. Organizations must establish domain data ownership roles, develop data product management capabilities, implement self-serve infrastructure platforms, and create federated governance bodies. Cultural change is required to shift from centralized control to distributed accountability, from data hoarding to data sharing, and from IT-driven to domain-driven data management. Despite these challenges, the data mesh paradigm offers substantial benefits for large-scale construction projects with diverse stakeholders and complex data ecosystems (Mishra et al., 2024).

DAMA-DMBOK AI-Assisted Governance

The Data Management Association's Data Management Body of Knowledge (DAMA-DMBOK) provides a comprehensive framework for data governance encompassing multiple knowledge areas including data governance, data architecture, data modeling, data storage, data security, data integration, metadata management, data quality, and master data management. Kumari (2024) extended the DAMA-DMBOK framework to incorporate AI-assisted governance capabilities that automate routine governance tasks and provide intelligent decision support for governance activities.

The AI-assisted DAMA-DMBOK framework maps AI technologies to specific governance functions. For metadata management, natural language processing and machine learning algorithms automatically extract metadata from BIM models, project documents, sensor configurations, and software code, populating metadata repositories with minimal manual effort. Automated metadata extraction addresses a persistent challenge in construction projects where metadata documentation is often incomplete or outdated due to the manual effort required (Kumari, 2024).

For data quality management, machine learning-based profiling algorithms continuously monitor data streams from construction management systems, IoT sensors, and BIM platforms, detecting anomalies, identifying missing values, and flagging inconsistencies. Automated quality profiling enables proactive identification of data quality issues before they impact AI system performance or decision-making. The framework includes configurable quality rules that can be adapted to specific project requirements and data types (Kumari, 2024).

For data security and privacy, AI-powered access control systems use behavioral analytics to detect anomalous access patterns that may indicate security breaches or policy violations. Natural language processing analyzes data content to identify sensitive information that requires protection, automatically applying appropriate security controls. These AI-assisted security mechanisms enhance governance effectiveness while reducing the manual effort required for security monitoring (Kumari, 2024).

For policy enforcement, AI systems automatically verify compliance with data governance policies by analyzing data practices, access patterns, and data transformations. When policy violations are detected, the system generates alerts and recommends corrective actions. Explainable AI techniques provide transparency into policy enforcement decisions, enabling human governance staff to understand and validate automated recommendations (Kumari, 2024).

The AI-assisted DAMA-DMBOK framework emphasizes that AI augments rather than replaces human governance expertise. While AI can automate routine tasks, detect patterns, and provide recommendations, human judgment remains essential for context-dependent policy interpretation, ethical decision-making, and stakeholder engagement. The framework defines clear human-AI collaboration patterns where AI handles high-volume routine tasks while humans focus on strategic governance decisions, policy development, and exception handling (Kumari, 2024).

Implementation of AI-assisted governance requires investment in AI infrastructure, development of AI models tailored to construction data types and governance requirements, integration with existing governance processes and systems, and training of governance staff in AI capabilities and limitations. Organizations must also address ethical considerations including algorithmic transparency, bias mitigation, and accountability for AI-driven governance decisions (Kumari, 2024).

Intelligent Data Governance Systems

Intelligent data governance systems, reviewed by Kumari (2024), represent an emerging class of governance platforms that integrate multiple AI technologies to provide comprehensive governance capabilities. These systems combine machine learning for pattern detection and prediction, natural language processing for document analysis and policy interpretation, knowledge graphs for semantic integration and reasoning, and explainable AI for transparency and auditability.

Key capabilities of intelligent governance systems include automated data discovery that identifies and catalogs data sources across distributed construction systems, intelligent data lineage that traces data flows and transformations through complex pipelines, predictive data quality that forecasts quality degradation before it impacts operations, and adaptive policy enforcement that learns from governance decisions and improves over time (Kumari, 2024).

Emerging technologies that enhance intelligent governance include federated learning, which enables AI model training across distributed data sources without centralizing sensitive data, addressing data sovereignty and privacy concerns particularly relevant in Middle East contexts. Blockchain-based provenance tracking provides immutable audit trails for data transformations and governance decisions, enhancing accountability and trust. Edge computing enables real-time governance at construction sites where connectivity may be limited, processing sensor data locally and applying governance rules before data is transmitted to cloud platforms (Kumari, 2024).

The integration of these technologies creates governance systems that are more scalable, responsive, and effective than traditional manual governance approaches. However, intelligent governance systems also introduce new challenges including the complexity of integrating multiple AI technologies, the need for specialized expertise to develop and maintain AI-powered governance capabilities, the risk of over-reliance on automation that reduces human governance capacity, and the ethical implications of algorithmic governance decisions (Kumari, 2024).

Data Quality Challenges in Middle East Construction Projects

This section analyzes the specific data quality challenges that impede AI adoption and effectiveness in Middle East construction projects, drawing on empirical evidence from regional studies and case analyses. The challenges are organized into four categories: fragmentation and standardization issues, ownership and intellectual property ambiguities, data scarcity and labeling inconsistencies, and governance and control gaps.

Fragmentation and Standardization Issues

Data fragmentation across project phases, stakeholder organizations, and technology platforms represents a fundamental challenge to AI-enabled construction in the Middle East. Construction projects involve multiple phases (planning, design, procurement, construction, commissioning, operations) with different data requirements, formats, and systems at each phase. Data generated during design in BIM platforms often cannot be seamlessly transferred to construction management systems, and construction data is rarely integrated with operations and maintenance systems, creating discontinuities that impair lifecycle data analysis and digital twin development (Abdulqader et al., 2025).

The involvement of multiple organizations in construction projects—including owners, designers, contractors, subcontractors, suppliers, and regulators—each with their own data systems and practices, exacerbates fragmentation. Data exchange between organizations typically occurs through manual processes or custom integrations rather than standardized interfaces, resulting in data loss, transformation errors, and delays. The temporary nature of construction project organizations means that data integration solutions developed for one project often cannot be reused, requiring repeated investment in custom integration efforts (Alreshidi et al., 2018).

Lack of standardization in data formats, schemas, and metadata conventions across the Middle East construction industry prevents interoperability and data reuse. While international standards such as Industry Foundation Classes

(IFC) for BIM exist, their adoption in the region remains limited and inconsistent. Abdalla et al. (2023) found that UAE BIM adoption is fragmentary, with different organizations and projects using different BIM standards, software platforms, and data exchange protocols. This lack of standardization means that AI models trained on data from one project or organization cannot easily be applied to others, limiting the scalability and transferability of AI solutions (Abdalla et al., 2023).

The fragmentation and standardization challenges directly impact AI system performance in multiple ways. Training data for machine learning models must be manually collected and harmonized from multiple sources, increasing cost and time requirements. Predictive models developed for one project context may not generalize to others due to differences in data schemas and semantics. Digital twins require continuous data integration from heterogeneous sources, and fragmentation increases integration complexity and reduces data timeliness. Real-time AI applications such as safety monitoring depend on standardized sensor data formats, and lack of standardization impairs system reliability (Abdulqader et al., 2025).

Ownership and Intellectual Property Ambiguities

Unclear data ownership and intellectual property rights on collaborative BIM and cloud platforms create significant governance challenges in Middle East construction projects. When multiple organizations contribute data to shared platforms, questions arise regarding who owns the data, who has rights to use it for different purposes, who is responsible for data quality and security, and who retains data after project completion. These ambiguities create reluctance to share data, concerns about competitive information disclosure, disputes over data access and use, and archival challenges when projects conclude (Alreshidi et al., 2018).

Alreshidi et al. (2018) identified data ownership as a critical requirement for cloud-based BIM governance, noting that construction contracts typically do not address data ownership explicitly, leaving it to be negotiated or disputed during project execution. The study found that unclear ownership creates barriers to effective collaboration, as organizations are hesitant to contribute high-quality data to shared platforms when they lack confidence in their rights to the data and protection of their intellectual property (Alreshidi et al., 2018).

In AI contexts, ownership ambiguities are particularly problematic because AI systems require access to comprehensive datasets that span organizational boundaries. If organizations withhold data due to ownership concerns, AI models will be trained on incomplete data, reducing their accuracy and reliability. If ownership disputes arise during project execution, AI system development may be delayed or halted. If data cannot be retained after project completion due to ownership restrictions, opportunities for learning and improvement across projects are lost (Alreshidi et al., 2018).

The intellectual property dimensions of data ownership are complex in construction contexts. Design data may contain proprietary methods or innovations that designers wish to protect. Construction data may reveal operational efficiencies or cost structures that contractors consider competitive advantages. Sensor data from equipment may be claimed by equipment manufacturers as proprietary. These competing intellectual property interests must be balanced with the need for data sharing to enable AI-driven project optimization (Alreshidi et al., 2018).

Middle East construction projects involving international firms and local partners face additional ownership complexities related to cross-border data transfers, differing national data protection regimes, and cultural expectations regarding data sharing and privacy. Gorian et al. (2024) note that Islamic concepts of privacy and data protection, which emphasize dignity and trust, may differ from Western legal frameworks, requiring governance approaches that respect regional cultural and legal contexts (Gorian et al., 2024).

Data Scarcity and Labeling Inconsistencies

Data scarcity for supervised machine learning models represents a significant barrier to AI adoption in Middle East construction. Many AI applications, particularly in safety monitoring, quality inspection, and defect detection, require large labeled datasets for model training. However, construction projects generate limited quantities of labeled data for several reasons. Safety incidents and quality defects are relatively rare events, resulting in imbalanced datasets where negative examples vastly outnumber positive examples. Manual labeling of construction images, sensor data, and project documents is time-consuming and expensive, requiring domain expertise. Privacy and security concerns limit the sharing of labeled datasets across organizations and projects (Alnaser et al., 2025).

Alnaser et al. (2025) identified data scarcity as a critical challenge for AI-integrated digital twins in Saudi construction, noting that insufficient historical data limits the accuracy of predictive models for cost, schedule, and resource optimization. The study found that organizations often lack systematic data collection and archival practices, resulting in data loss when projects conclude and limiting the availability of training data for future AI initiatives (Alnaser et al., 2025).

Labeling inconsistencies compound the data scarcity problem. When labeled data is collected from multiple sources or projects, inconsistent labeling conventions reduce data usability. For example, safety hazard classifications may differ across projects, making it difficult to combine datasets for model training. Quality defect categories may be defined differently by different inspectors or organizations. Equipment and material classifications may use different taxonomies. These inconsistencies require data harmonization efforts that further reduce the effective quantity of usable training data (Alnaser et al., 2025).

The data scarcity challenge is particularly acute for AI applications targeting regional-specific conditions in Middle East construction. Climate conditions, building codes, construction methods, and material types in the GCC region may differ from other regions where AI models have been developed, requiring region-specific training data. However, the limited number of projects with comprehensive data collection in the region constrains the development of locally-adapted AI models (Alnaser et al., 2025).

Strategies to address data scarcity include synthetic data generation using simulation and generative models, transfer learning that adapts models trained on data from other regions or domains, active learning that prioritizes labeling of the most informative examples, and federated learning that enables model training across distributed datasets without centralizing data. However, these strategies require technical expertise and infrastructure that may not be readily available in regional construction organizations (Albaroudi et al., 2025).

Governance and Control Gaps

Insufficient lifecycle governance mechanisms represent a fundamental gap in Middle East construction data practices. Traditional construction project management focuses on deliverable-based milestones rather than continuous data governance, resulting in episodic attention to data quality rather than systematic monitoring and improvement. Data governance responsibilities are often unclear, with no designated roles for data stewardship, quality assurance, or metadata management. Governance policies and procedures, when they exist, are often generic IT policies not tailored to construction data types and AI requirements (Kayani, 2025).

Kayani (2025) emphasizes that lack of lifecycle governance means that data quality degradation, incidents affecting data integrity, and deviations from governance policies are not consistently detected or addressed. Without continuous monitoring, data quality issues accumulate over project lifecycles, ultimately compromising AI system performance and decision quality. The absence of traceability mechanisms means that when AI-driven decisions prove incorrect, it is difficult to diagnose whether the problem stems from data quality, model limitations, or inappropriate application (Kayani, 2025).

Insufficient adoption of data standards and protocols in regional BIM practice weakens metadata consistency required for AI model reuse and transfer. Alasmari et al. (2023) found that Saudi BIM adoption, while growing, lacks standardized protocols for metadata documentation, data exchange, and quality verification. This standards gap means that even when organizations implement BIM, the resulting data may not be suitable for AI applications without substantial additional processing and harmonization (Alasmari et al., 2023).

Governance gaps are particularly problematic for AI applications that require high data quality and reliability. Safety monitoring systems that fail to detect hazards due to poor data quality can result in injuries or fatalities. Predictive cost models that rely on inaccurate historical data can lead to substantial budget overruns. Digital twins that are not synchronized with physical assets due to data quality issues can support flawed decisions. These high-stakes applications require robust governance mechanisms that ensure data fitness for purpose (Alnaser et al., 2025).

The governance gaps in Middle East construction reflect broader organizational and industry maturity challenges. Many construction organizations lack data management capabilities and view data as a byproduct of operations rather than a strategic asset. Industry associations and professional bodies have not established comprehensive data governance standards for construction. Government regulations and procurement requirements rarely mandate specific data governance practices. Addressing these gaps requires coordinated action across organizations, industry associations, and regulatory authorities (Umar, 2021).

AI Applications in Middle East Construction

This section surveys the primary AI applications in Middle East construction projects, analyzing their data requirements, current adoption status, and the data quality factors that determine their effectiveness. The applications examined include predictive analytics and forecasting, safety monitoring and image recognition, design optimization and clash detection, digital twins and simulation, and project management information systems enhancement.

Predictive Analytics and Forecasting

Predictive analytics using machine learning models for cost estimation, schedule forecasting, and risk prediction represents one of the most widely adopted AI applications in construction. These applications leverage historical project data to identify patterns and relationships that inform predictions for new projects. Neural networks, random forests, support vector machines, and ensemble methods are commonly applied to predict final project costs based on early-stage design parameters, forecast activity durations based on resource availability and site conditions, and assess risk probabilities based on project characteristics and external factors (Savaş, 2025).

The effectiveness of predictive analytics depends critically on the availability of high-quality historical data. Models require comprehensive datasets spanning multiple projects with consistent data schemas, accurate cost and schedule actuals, detailed project characteristics and context variables, and documentation of risks and their impacts. In Middle East construction contexts, the availability of such historical data is often limited due to inconsistent data collection practices across projects, lack of standardized cost and schedule coding structures, reluctance to share data across organizations due to competitive concerns, and limited archival of project data after completion (Savaş, 2025).

Data quality dimensions particularly critical for predictive analytics include accuracy of historical cost and schedule data, completeness of project characteristic variables that influence outcomes, consistency of coding and classification schemes across projects, and representativeness of historical data relative to new project contexts. When historical data contains errors, omissions, or inconsistencies, predictive models learn incorrect patterns and produce unreliable forecasts. When historical data is not representative of new project conditions—for example, when models trained on conventional projects are applied to innovative megaprojects like NEOM—prediction accuracy degrades substantially (Allouzi et al., 2024).

Recent applications of predictive analytics in Middle East construction include cost forecasting for Saudi Vision 2030 infrastructure projects, schedule risk analysis for Dubai Expo 2020 developments, and resource optimization for Qatar World Cup facilities. These applications have demonstrated value in improving estimation accuracy and supporting proactive risk management, but their effectiveness has been constrained by data availability and quality challenges (Allouzi et al., 2024).

Safety Monitoring and Image Recognition

Computer vision and image recognition AI systems for construction safety monitoring represent high-impact applications that can reduce injuries and fatalities by detecting hazards and unsafe behaviors in real-time. These systems use convolutional neural networks trained on labeled images to identify personal protective equipment (PPE) compliance, detect unsafe worker positions or behaviors, recognize hazardous site conditions, and monitor equipment operation for safety violations. When integrated with IoT sensors and site cameras, these systems can provide continuous automated safety monitoring that supplements human inspection (Savaş, 2025).

The data requirements for safety monitoring AI include large labeled image datasets showing various safety conditions, hazards, and violations, diverse examples covering different lighting conditions, weather, and site configurations, high-resolution images that enable detection of small but critical safety features, and real-time data streams from site cameras and sensors. The development of accurate safety monitoring models requires thousands of labeled images for each hazard type, creating substantial data collection and labeling burdens (Savaş, 2025).

Data quality challenges for safety monitoring include the rarity of actual safety incidents in training data, creating imbalanced datasets where models may fail to detect infrequent but high-consequence hazards, variability in image quality due to camera positioning, lighting, and weather conditions, labeling inconsistencies when multiple annotators classify safety conditions differently, and privacy concerns regarding worker surveillance that may limit data collection. These challenges are particularly acute in Middle East contexts where extreme weather conditions (heat, dust storms) can degrade image quality and where cultural sensitivities regarding surveillance may affect worker acceptance (Shi et al., 2025).

Applications of safety monitoring AI in the Middle East include PPE detection systems deployed on Dubai construction sites, hazard recognition systems for Saudi megaprojects, and integrated safety management platforms combining computer vision with IoT sensors. Shi et al. (2025) documented an intelligent construction management system for utility works in a Dubai RTA project that integrated IoT sensors and AI for real-time monitoring, demonstrating improved data accuracy and automated resource allocation. The system's success depended on coordinated data governance that ensured sensor calibration, data quality verification, and integration with project management systems (Shi et al., 2025).

Design Optimization and Clash Detection

AI-enhanced design optimization and clash detection in BIM workflows represent applications that improve design quality and reduce rework during construction. Generative design algorithms use AI to explore large design spaces and identify optimal solutions based on specified objectives and constraints, such as minimizing material use while meeting structural requirements or optimizing building orientation for energy efficiency. Clash detection algorithms automatically identify geometric conflicts between building systems (structural, mechanical, electrical, plumbing) in BIM models, enabling resolution during design rather than costly rework during construction (Savaş, 2025).

The data requirements for design optimization include parametric BIM models that enable algorithmic manipulation, performance simulation data for evaluating design alternatives, constraint specifications defining feasible design spaces, and objective functions quantifying design quality. For clash detection, requirements include detailed 3D BIM models with accurate geometric representations, consistent modeling standards across disciplines, and up-to-date models reflecting design changes (Savaş, 2025).

Data quality challenges for design optimization and clash detection include incomplete or inaccurate BIM models that do not reflect actual design intent, inconsistent modeling standards across disciplines leading to false clash detections, lack of semantic information in BIM models limiting intelligent reasoning about design alternatives, and version control issues when multiple teams modify models concurrently. Abdalla et al. (2023) found that UAE BIM adoption is fragmentary across lifecycle stages, with design-phase BIM often not maintained or updated during construction, limiting the effectiveness of AI-enhanced design tools (Abdalla et al., 2023).

Regional applications of AI-enhanced design include generative design for Saudi NEOM developments exploring innovative architectural forms, clash detection for complex Dubai high-rise projects with dense building systems, and energy optimization for sustainable buildings aligned with regional green building standards. The effectiveness of these applications depends on BIM maturity and data quality, which vary substantially across GCC countries and project types (Abdalla et al., 2023).

Digital Twins and Simulation

Digital twins—dynamic virtual representations of physical construction assets that integrate real-time sensor data, BIM models, and simulation algorithms—represent one of the most data-intensive and potentially transformative AI applications in construction. Digital twins enable real-time monitoring of construction progress and asset performance, predictive maintenance based on sensor data and degradation models, scenario simulation for decision support, and optimization of resource allocation and logistics. The AI components of digital twins include machine learning models for prediction and anomaly detection, optimization algorithms for resource allocation, and simulation engines for scenario analysis (Alnaser et al., 2025).

Alnaser et al. (2025) conducted a comprehensive PLS-SEM study of 120 construction professionals in Saudi Arabia to identify critical success factors for AI-integrated digital twins and their impact on project deliverables. The study found that technology and infrastructure factors, which encompass data quality and scalable data infrastructure, had the strongest direct effects on digital twin success and project outcomes including time, cost, quality, resource utilization, and risk management. Governance factors and human factors also significantly influenced outcomes, with data quality and governance serving as critical mediators between AI capability and project performance (Alnaser et al., 2025).

The data requirements for digital twins are extensive and demanding. They require comprehensive BIM models with accurate geometric and semantic information, real-time sensor data from IoT devices monitoring construction activities and asset conditions, historical performance data for calibrating predictive models, integration of data from multiple sources including project management systems, supply chain systems, and external data sources such as weather, and continuous data synchronization to maintain alignment between physical and virtual representations (Alnaser et al., 2025).

Data quality challenges for digital twins include sensor calibration and reliability issues that introduce errors in real-time data, latency in data transmission and processing that reduces timeliness, data integration complexity when combining heterogeneous sources with different formats and update frequencies, and model calibration challenges when physical asset behavior deviates from simulation assumptions. Abdulqader et al. (2025) identified data integration and interoperability as major barriers to digital twin effectiveness in construction project management, noting that lack of standardized data exchange protocols impairs the development of comprehensive digital twins (Abdulqader et al., 2025).

Digital twin applications in Middle East construction include real-time progress monitoring for Saudi Vision 2030 megaprojects, predictive maintenance for Dubai smart city infrastructure, construction logistics optimization for complex urban projects, and integrated project delivery platforms combining digital twins with AI-driven decision support. The success of these applications depends critically on robust data governance frameworks that ensure data quality, integration, and lifecycle management (Alnaser et al., 2025).

Project Management Information Systems Enhancement

AI-augmented Project Management Information Systems (PMIS) represent applications that enhance traditional project management capabilities through intelligent automation, predictive analytics, and decision support. AI enhancements to PMIS include automated progress reporting using computer vision and sensor data, intelligent scheduling that adapts to real-time conditions and constraints, risk prediction and mitigation recommendation, resource optimization based on project dynamics, and natural language interfaces for querying project data and generating reports (Mahmood et al., 2023).

Mahmood et al. (2023) examined how AI can leverage PMIS and data-driven decision making in project management, identifying data quality as a critical mediating factor between AI capability and decision quality. The study emphasizes that AI algorithms cannot compensate for poor data quality in PMIS, and that investments in data governance and quality management are prerequisites for effective AI-driven decision support. The authors propose integrating data quality assessment mechanisms into PMIS architectures to provide real-time feedback on data fitness for AI applications (Mahmood et al., 2023).

The data requirements for AI-augmented PMIS include comprehensive project data covering schedule, cost, resources, risks, and quality, real-time updates reflecting current project status, integration with external systems including BIM, procurement, and financial systems, historical project data for training predictive models, and structured data formats that enable algorithmic processing. The effectiveness of AI enhancements depends on PMIS data quality, which is often compromised by delayed or incomplete data entry, inconsistent coding and classification, lack of integration with other project systems, and limited data validation (Mahmood et al., 2023).

Applications of AI-augmented PMIS in Middle East construction include intelligent project dashboards for Saudi megaprojects providing real-time insights and predictions, automated reporting systems for Dubai government projects reducing manual effort, risk management platforms for complex infrastructure projects, and integrated project delivery systems combining PMIS with BIM and digital twins. The success of these applications depends on data governance practices that ensure PMIS data quality, integration, and accessibility (Mahmood et al., 2023).

Case Studies and Regional Initiatives

This section presents detailed case studies and regional initiatives that illustrate the practical implementation of data governance and AI in Middle East construction. The cases examined include Dubai RTA intelligent construction management, client-driven Level 2 BIM in UAE, Saudi AI-integrated digital twins, NEOM applied AI initiatives, and national governance tools and frameworks.

Dubai RTA Intelligent Construction Management

Shi et al. (2025) documented an intelligent construction management system for utility works implemented in a Dubai Roads and Transport Authority (RTA) project, demonstrating how integrated IoT and AI systems can improve data accuracy and operational efficiency when supported by coordinated data governance. The system addressed challenges in utility works management including complex coordination among multiple utility providers, limited visibility into underground infrastructure, frequent conflicts between planned and actual utility locations, and inefficient resource allocation due to incomplete information (Shi et al., 2025).

The intelligent system integrated multiple data sources including IoT sensors monitoring excavation activities and equipment operation, GPS tracking of vehicles and equipment, BIM models of planned utility layouts, real-time project management data on activities and resources, and external data sources including traffic conditions and weather. AI algorithms processed these data streams to provide automated progress monitoring, conflict detection between planned and actual utility locations, optimized resource allocation based on real-time conditions, and predictive analytics for schedule and cost forecasting (Shi et al., 2025).

The success of the Dubai RTA system depended critically on data governance mechanisms that ensured data quality and integration. Key governance practices included standardized sensor calibration procedures to ensure measurement accuracy, real-time data validation rules that flagged anomalies and errors, clear data ownership and access control policies defining responsibilities for data quality, integration protocols that standardized data formats and update frequencies across systems, and continuous monitoring of data quality metrics with alerts when thresholds were breached (Shi et al., 2025).

The system delivered measurable improvements in project outcomes including 15% reduction in schedule delays through better coordination and conflict resolution, 12% reduction in costs through optimized resource allocation, improved data accuracy enabling more reliable decision-making, and enhanced stakeholder communication through real-time visibility into project status. These outcomes demonstrate that when AI systems are supported by robust data governance, they can deliver substantial value in complex construction environments (Shi et al., 2025).

The Dubai RTA case illustrates several important lessons for data governance in AI-driven construction. First, data governance must be designed into systems from the outset rather than added retrospectively, as the system's governance mechanisms were integral to its architecture.

Second, governance requires coordination across multiple organizations and systems, as the utility works involved multiple utility providers with different data systems. Third, real-time data quality monitoring is essential for AI applications that support operational decisions, as delays in detecting data quality issues can lead to incorrect decisions with immediate consequences. Fourth, governance investments yield returns through improved AI effectiveness and project outcomes rather than as standalone benefits (Shi et al., 2025).

Client-Driven Level 2 BIM in UAE

Shafiq (2021) presented a case study of client-driven Level 2 BIM implementation in a UAE construction project, examining how BIM adoption affects data governance and project outcomes. Level 2 BIM represents a maturity level where project participants use 3D BIM models with attached data, exchange models through common file formats, and maintain separate discipline models that are coordinated through model federation. The case study project involved a commercial building development where the client mandated BIM use to improve coordination, reduce clashes, and enhance facility management (Shafiq, 2021).

The BIM implementation established data governance mechanisms including BIM execution plan defining data requirements, responsibilities, and exchange protocols, common data environment (CDE) providing centralized platform for model sharing and version control, model coordination procedures specifying clash detection and resolution processes, data validation rules ensuring model quality and completeness, and handover requirements defining data deliverables for facility management. These governance mechanisms addressed data ownership, quality, and lifecycle management challenges inherent in collaborative BIM environments (Shafiq, 2021).

The case study revealed both benefits and limitations of the BIM implementation. Benefits included improved coordination among design disciplines reducing clashes, enhanced visualization supporting client decision-making, better quantity takeoff accuracy for cost estimation, and structured data for facility management. However, limitations included BIM use concentrated in design and construction phases with limited adoption in operations, lack of standardized data exchange protocols requiring custom integrations, insufficient training of project team members in BIM data management, and unclear contractual provisions for data ownership and intellectual property (Shafiq, 2021).

The data governance challenges identified in the case study reflect broader issues in UAE BIM adoption. Abdalla et al. (2023) found that UAE BIM implementation is fragmentary across lifecycle stages, with different organizations and projects using different BIM standards and protocols. This lack of standardization means that data governance practices developed for one project cannot easily be transferred to others, requiring repeated investment in project-specific governance solutions (Abdalla et al., 2023).

The UAE BIM case illustrates the importance of contractual and organizational governance mechanisms alongside technical data management capabilities. The case study emphasized that BIM execution plans and common data environments provide necessary but insufficient governance, and that clear contractual provisions for data ownership, quality responsibilities, and intellectual property rights are essential for effective collaborative data management. The case also demonstrates that governance mechanisms must span the full project lifecycle, as the concentration of BIM use in design and construction phases limits the value of BIM data for facility management and operations (Shafiq, 2021).

Saudi AI-Integrated Digital Twins

Alnaser et al. (2025) conducted a comprehensive empirical study of critical success factors for AI-integrated digital twins in Saudi construction, providing important insights into the role of data governance and quality in determining AI system effectiveness. The study surveyed 120 construction professionals including project managers, engineers, and technology specialists involved in projects implementing or planning to implement AI-enhanced digital twins. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examined relationships among technology and infrastructure factors, governance factors, human factors, and project deliverables including time, cost, quality, resource utilization, and risk management (Alnaser et al., 2025).

The study's key finding was that technology and infrastructure factors had the strongest direct effects on project deliverables, followed by governance factors and human factors. Technology and infrastructure factors encompassed data quality, scalable data infrastructure, AI algorithms and platforms, sensor networks and IoT devices, and cloud computing capabilities. The strong effect of these factors indicates that investments in data infrastructure and quality are critical enablers of AI-integrated digital twin success (Alnaser et al., 2025).

Governance factors, which included data governance policies and procedures, clear roles and responsibilities for data management, compliance with regulatory requirements, and alignment with organizational strategies, had significant effects on project deliverables both directly and through mediation of technology effectiveness. This finding indicates that governance serves dual roles: directly supporting project outcomes through better coordination and decision-making, and enabling technology effectiveness by ensuring data quality and appropriate use of AI capabilities (Alnaser et al., 2025).

Human factors, encompassing workforce skills in AI and data management, organizational culture supporting innovation and data sharing, change management practices, and stakeholder engagement, also significantly influenced outcomes. The study found that human factors interact with technology and governance factors, indicating that successful AI-integrated digital twin implementation requires simultaneous attention to technical capabilities, governance mechanisms, and human dimensions (Alnaser et al., 2025).

The study's recommendations for Saudi construction organizations include investing in data quality assessment and improvement mechanisms, establishing clear data governance frameworks with defined roles and responsibilities, developing workforce capabilities in AI, data management, and digital twin technologies, implementing scalable data infrastructure including cloud platforms and IoT networks, and aligning AI initiatives with organizational strategies and national Vision 2030 objectives. These recommendations emphasize that data governance is not a standalone activity but must be integrated with technology investments and human capability development (Alnaser et al., 2025).

The Saudi digital twin study provides empirical validation of the theoretical framework presented in Section 3, confirming that data governance and quality serve as critical mediators between AI capability and project outcomes. The study's findings have direct implications for policy and practice, suggesting that government mandates and incentives for AI adoption should be accompanied by support for data governance capability development and infrastructure investment (Alnaser et al., 2025).

NEOM and Applied AI in Megaprojects

NEOM, Saudi Arabia's flagship smart city megaproject, represents one of the most ambitious applications of AI in construction globally, with plans to integrate AI throughout design, construction, and operations. Allouzi et al. (2024) examined the potential impact of applied AI in NEOM construction projects, identifying opportunities and challenges for AI-driven project success. The study emphasizes that NEOM's AI ambitions require unprecedented levels of data integration, quality, and governance to realize the vision of a fully intelligent city (Allouzi et al., 2024).

NEOM's AI applications span multiple domains including generative design for innovative architectural forms optimized for sustainability and livability, construction robotics and automation for efficient and safe building processes, digital twins for real-time monitoring and optimization of construction and city operations, predictive analytics for resource optimization and risk management, and intelligent infrastructure systems for energy, water, transportation, and waste management. These applications generate and consume massive volumes of data, creating complex data governance challenges (Allouzi et al., 2024).

The data governance requirements for NEOM include unified data architecture spanning design, construction, and operations phases, standardized data schemas and metadata conventions enabling interoperability across systems and vendors, data sovereignty and security mechanisms ensuring compliance with Saudi regulations, quality assurance processes ensuring fitness of data for AI applications, and lifecycle data management ensuring data availability and usability throughout the city's operational life. Meeting these requirements necessitates governance frameworks that are more comprehensive and sophisticated than those typically employed in construction projects (Allouzi et al., 2024).

Challenges identified for NEOM's AI implementation include the scale and complexity of data integration across multiple megaprojects and systems, the need for real-time data processing and decision-making at unprecedented scales, coordination among numerous international vendors and contractors with different data practices, balancing innovation and experimentation with reliability and safety requirements, and developing workforce capabilities in AI and data management at the scale required. These challenges underscore that technological ambition must be matched by governance capability and organizational readiness (Allouzi et al., 2024).

NEOM's approach to addressing these challenges includes establishing centralized data governance authority with clear mandates and resources, mandating data standards and protocols in procurement contracts with vendors and contractors, investing in advanced data infrastructure including cloud platforms, IoT networks, and AI platforms, developing workforce capabilities through training programs and partnerships with universities, and implementing phased rollout of AI applications with learning and adaptation between phases. This comprehensive approach recognizes that data governance is a strategic enabler of NEOM's AI vision rather than a technical support function (Allouzi et al., 2024).

The NEOM case illustrates the importance of proactive, strategic data governance for ambitious AI-driven construction initiatives. Unlike traditional projects where data governance is often reactive and fragmented, NEOM's approach embeds governance into project planning and procurement from the outset. The case also demonstrates the need for governance frameworks that can accommodate innovation and experimentation while maintaining data quality and compliance, a balance that requires sophisticated governance capabilities (Allouzi et al., 2024).

National Governance Tools and Frameworks

Several national-level governance tools and frameworks have been developed in Middle East countries to support AI adoption and ensure alignment with national strategies and ethics principles. These tools provide important infrastructure for data governance in construction and other sectors.

Alboaneen et al. (2025) introduced Siyasat, an AI-powered governance tool developed to generate and improve AI policies according to Saudi AI ethics principles established by SDAIA. Siyasat uses GPT-4-turbo and a Retrieval-Augmented Generation (RAG) approach, drawing on a dataset of ten AI policies and SDAIA's official ethics document to generate contextually appropriate policies for organizations. The tool achieved strong performance metrics including BERTScore of 0.890 and Self-BLEU of 0.871 for policy generation, and 0.870 and 0.980 for policy improvement, indicating high-quality and consistent policy outputs (Alboaneen et al., 2025).

Siyasat addresses a critical challenge in AI governance: the difficulty organizations face in translating high-level ethics principles into specific operational policies. By automating policy generation while ensuring alignment with national principles, Siyasat reduces the time and expertise required for policy development and promotes consistency across organizations. For construction firms implementing AI systems, Siyasat can generate data governance policies that address data collection ethics, privacy protection, algorithmic transparency, and accountability while ensuring compliance with SDAIA principles (Alboaneen et al., 2025).

The tool's RAG approach, which retrieves relevant content from authoritative sources and uses it to ground policy generation, addresses concerns about AI-generated content lacking grounding in established principles. The high consistency metrics indicate that Siyasat generates policies that are coherent and aligned with SDAIA principles across multiple generation attempts, providing reliability for organizational use (Alboaneen et al., 2025).

Abudaqqa et al. (2025) examined opportunities for AI in IT governance in Saudi Arabia within COBIT 2019 and ISO/IEC 38500 frameworks, proposing adaptations of these established frameworks to incorporate AI-specific governance requirements. The study recommends developing national taxonomies for AI risks that provide consistent classification and assessment approaches across sectors, establishing incident reporting mechanisms for AI system failures or harms, creating regulatory sandboxes where organizations can test AI governance approaches before full implementation, and embedding governance requirements into public procurement to ensure vendors and contractors meet governance standards (Abudaqqa et al., 2025).

These national governance tools and frameworks provide important infrastructure for data governance in construction by establishing common principles and standards, providing tools that reduce the cost and complexity of governance implementation, creating mechanisms for learning and improvement across organizations, and ensuring alignment between organizational practices and national strategies. The development of such tools represents a proactive approach to AI governance that can accelerate responsible AI adoption in construction and other sectors (Abudaqqa et al., 2025).

Policy Recommendations and Regulatory Landscape

This section synthesizes policy recommendations for improving data governance and quality in AI-driven Middle East construction, grounded in the empirical evidence and case studies presented in previous sections. The section first analyzes the current regulatory environment, then presents targeted policy recommendations, and finally discusses implementation mechanisms.

Current Regulatory Environment

The regulatory landscape for AI governance in the Middle East is evolving rapidly but remains characterized by significant gaps and inconsistencies across countries and sectors. Trigui et al. (2024) conducted a comprehensive review of AI governance in the MENA region, identifying both progress and persistent challenges. Several GCC countries have articulated national AI strategies including Saudi Arabia's National Strategy for Data and AI, UAE's National Artificial Intelligence Strategy 2031, and Qatar's National AI Strategy. These strategies establish high-level objectives for AI adoption, innovation, and governance, but implementation mechanisms remain underdeveloped (Trigui et al., 2024).

Key regulatory gaps identified by Trigui et al. (2024) include insufficient monitoring frameworks for tracking AI system performance and impacts, lack of standardized incident reporting mechanisms for AI failures or harms, unclear enforcement mechanisms for AI ethics principles and guidelines, limited harmonization of AI governance approaches across GCC countries, and sector-specific guidance for AI governance in construction and other industries. These gaps create uncertainty for organizations implementing AI systems and limit the effectiveness of national AI strategies (Trigui et al., 2024).

In Saudi Arabia, SDAIA has established AI ethics principles covering transparency, fairness, accountability, privacy, security, safety, and reliability. These principles provide important guidance for AI development and deployment, but their translation into specific operational requirements and compliance mechanisms remains incomplete. Alboaneen et al. (2025) note that organizations struggle to translate high-level principles into specific policies and practices, creating demand for tools like Siyasat that automate policy generation aligned with SDAIA principles (Alboaneen et al., 2025).

The UAE has established multiple governance bodies including the UAE Artificial Intelligence Office, Dubai Government Accelerators, and sector-specific regulators, creating a complex governance landscape. Gorian et al. (2024) examined digital ethics of AI in Saudi Arabia and UAE, highlighting efforts to integrate Islamic ethics and privacy principles into AI governance frameworks. The study emphasizes that Middle East AI governance must balance technological advancement with cultural and religious values, requiring governance approaches that differ from Western models (Gorian et al., 2024).

Data sovereignty and localization requirements represent important regulatory considerations for AI in Middle East construction. Several GCC countries have established or are developing data protection laws that mandate local storage and processing of certain data types, restrict cross-border data transfers, and impose security and privacy requirements. Albaroudi et al. (2025) examined data sovereignty frameworks for AI in Saudi smart energy systems, proposing federated learning approaches that enable AI model training across distributed data sources without centralizing sensitive data. These approaches are equally applicable to construction contexts where data sovereignty requirements may constrain traditional centralized AI architectures (Albaroudi et al., 2025).

Targeted Policy Recommendations

Based on the evidence synthesized in this article, the following policy recommendations are proposed to improve data governance and quality in AI-driven Middle East construction:

Recommendation 1: Mandate Lifecycle Data-Quality Metrics in Public Procurement

Government agencies and public sector project owners should mandate the implementation of lifecycle data-quality metrics in construction project procurement, requiring contractors and vendors to measure and report data quality dimensions including completeness, accuracy, timeliness, consistency, and lineage throughout project execution. This recommendation is grounded in the CPMAI framework's emphasis on lifecycle-aligned governance and empirical evidence that data quality serves as a critical mediator of AI effectiveness (Kayani, 2025), (Alnaser et al., 2025).

Implementation should include development of standardized data quality metrics and measurement methods applicable across construction project types, incorporation of data quality requirements into project specifications and contracts, establishment of data quality reporting requirements at defined project milestones, and linking of payment or performance incentives to achievement of data quality targets. This approach creates accountability for data quality and ensures that governance is not treated as optional or secondary to other project objectives (Kayani, 2025).

Recommendation 2: Adopt Domain Data Contracts and Mesh Patterns

Industry associations and large project owners should promote adoption of data mesh principles and domain data contracts for construction projects, establishing decentralized data ownership with standardized interoperability mechanisms. This recommendation addresses scalability limitations of centralized data governance and aligns with the data mesh framework proposed by Mishra et al. (2024) for infrastructure construction (Mishra et al., 2024).

Implementation should include development of reference data contracts specifying schemas, quality requirements, and service levels for common construction data products (design data, procurement data, construction progress data, asset performance data), establishment of domain data ownership roles and responsibilities in project organizations, provision of self-serve data infrastructure platforms that enable domain teams to publish and maintain data products, and creation of federated governance mechanisms that establish cross-domain standards and resolve conflicts. This approach distributes governance responsibilities while maintaining interoperability and compliance (Mishra et al., 2024).

Recommendation 3: Promote Automated Governance Tooling

Government agencies and industry associations should incentivize adoption of AI-assisted governance tools that automate metadata discovery, data quality profiling, policy enforcement, and compliance monitoring. This recommendation is grounded in the intelligent data governance framework reviewed by Kumari (2024) and the Siyasat policy generation tool developed by Alboaneen et al. (2025) (Kumari, 2024), (Alboaneen et al., 2025).

Implementation should include development or procurement of AI-assisted governance platforms tailored to construction data types and requirements, provision of training and support for organizations adopting automated governance tools, establishment of standards for governance tool interoperability and data exchange, and creation of incentive programs (grants, tax benefits, procurement preferences) for organizations implementing automated governance. This approach reduces the cost and complexity of governance implementation while improving effectiveness (Kumari, 2024).

Recommendation 4: Strengthen Workforce Training in Data Governance and AI

Educational institutions, industry associations, and employers should collaborate to develop and deliver comprehensive training programs in data governance, data management, and AI for construction professionals. This recommendation addresses the skills gap identified as a major barrier to BIM and AI adoption in multiple regional studies (Umar, 2021), (Alasmari et al., 2023), (Alnaser et al., 2025).

Implementation should include integration of data governance and AI topics into construction management curricula at universities and technical colleges, development of professional certification programs in construction data management and AI, provision of continuing education and training programs for practicing professionals, and establishment of industry-academic partnerships to ensure training content reflects current practice and emerging technologies. This approach builds the human capabilities required for effective data governance and AI adoption (Alnaser et al., 2025).

Recommendation 5: Establish Clear Data Sovereignty and Residency Rules

Regulatory authorities should provide clear guidance on data sovereignty and residency requirements for construction projects, particularly those involving cross-border data transfers, international vendors, or sensitive infrastructure. This recommendation addresses regulatory uncertainty identified by Trigui et al. (2024) and data sovereignty challenges examined by Albaroudi et al. (2025) (Trigui et al., 2024), (Albaroudi et al., 2025).

Implementation should include development of sector-specific guidance on data classification and residency requirements for construction data, establishment of approved mechanisms for cross-border data transfers when necessary (e.g., federated learning, secure multi-party computation), provision of regulatory sandboxes where organizations can test sovereignty-compliant AI architectures, and harmonization of data sovereignty requirements across GCC countries to facilitate regional construction projects. This approach provides clarity while enabling innovation in sovereignty-compliant AI systems (Albaroudi et al., 2025).

Recommendation 6: Mandate BIM Standards and Data Protocols

Government agencies should mandate adoption of standardized BIM protocols and data exchange standards for public construction projects, addressing the fragmentation and lack of standardization identified as major barriers to data quality and AI effectiveness (Abdalla et al., 2023), (Umar, 2021).

Implementation should include adoption of international BIM standards (IFC, COBie) with regional adaptations as needed, development of national BIM execution plan templates and guidelines, establishment of BIM maturity requirements for contractors and consultants on public projects, and provision of training and support for BIM standard adoption. This approach creates consistency in data practices and enables data reuse and AI model transfer across projects (Abdalla et al., 2023).

Recommendation 7: Establish AI Governance Sandboxes for Construction

Regulatory authorities should establish regulatory sandboxes specifically for testing AI governance approaches in construction, enabling organizations to experiment with innovative governance mechanisms while maintaining oversight and learning. This recommendation is grounded in the sandbox approach proposed by Abudaqqa et al. (2025) for IT governance in Saudi Arabia (Abudaqqa et al., 2025).

Implementation should include definition of sandbox scope, eligibility criteria, and oversight mechanisms, provision of regulatory flexibility for sandbox participants to test novel governance approaches, establishment of learning and knowledge sharing mechanisms to disseminate insights from sandbox experiments, and pathways for successful sandbox approaches to be adopted more broadly. This approach enables innovation in governance while managing risks (Abudaqqa et al., 2025).

Implementation Mechanisms

Effective implementation of the policy recommendations requires coordinated action across multiple stakeholders and deployment of specific mechanisms:

Public Procurement Clauses: Government agencies should incorporate data governance requirements into standard procurement terms and conditions for construction projects, making governance compliance a contractual obligation. Procurement clauses should specify data quality metrics and targets, data ownership and intellectual property arrangements, metadata and documentation requirements, data security and privacy obligations, and audit and compliance verification procedures. This mechanism creates direct accountability for governance through contractual relationships (Kayani, 2025).

National Taxonomies and Incident Reporting: Regulatory authorities should develop national taxonomies for AI risks and establish incident reporting mechanisms that enable systematic tracking of AI system failures, data quality issues, and governance breakdowns. Taxonomies should classify risks by type, severity, and sector, enabling consistent risk assessment across organizations. Incident reporting should be mandatory for high-consequence failures and voluntary for lower-severity issues, with protections against punitive responses to encourage reporting. This mechanism enables learning and continuous improvement in governance practices (Abudaqqa et al., 2025).

Industry Standards and Certification: Industry associations should develop and promote data governance standards and certification programs for construction organizations, creating market incentives for governance capability development. Standards should specify governance structures, processes, and capabilities required for effective data management in AI-driven construction. Certification programs should assess organizational compliance with standards and provide recognition for high-performing organizations. This mechanism leverages market dynamics to promote governance adoption (Umar, 2021).

Research and Development Funding: Government agencies and industry associations should fund research and development of governance technologies, methods, and tools tailored to construction contexts. Funding priorities should include AI-assisted governance platforms, data quality assessment methods, federated learning and privacy-preserving AI techniques, and governance frameworks for emerging AI applications. This mechanism accelerates innovation in governance capabilities (Kumari, 2024).

Regional Harmonization Initiatives: GCC countries should collaborate to harmonize AI governance frameworks, data standards, and regulatory requirements, facilitating regional construction projects and enabling economies of scale in governance capability development. Harmonization efforts should focus on areas where consistency provides clear benefits (data standards, BIM protocols, AI ethics principles) while preserving national flexibility in areas where local context matters (data sovereignty rules, sector-specific regulations). This mechanism reduces complexity and cost for organizations operating across multiple GCC countries (Trigui et al., 2024).

Conclusion

This comprehensive review has examined the critical intersection of data governance, data quality, and artificial intelligence systems in Middle East construction, with specific focus on Gulf Cooperation Council countries including the United Arab Emirates, Saudi Arabia, Qatar, and Oman. Through systematic analysis of 91 scholarly sources, regional case studies including NEOM, Dubai RTA, and BIM adoption initiatives, and emerging governance frameworks including CPMAI, data mesh, DAMA-DMBOK, and intelligent governance systems, this article has established that data governance and quality serve as fundamental enablers of trustworthy and effective AI in construction contexts.

The key findings of this research can be synthesized across several dimensions. First, empirical evidence from Saudi construction projects demonstrates that technology and infrastructure factors, which encompass data quality and scalable data infrastructure, most strongly influence AI system success and project outcomes, with governance and human factors serving as critical mediating variables (Alnaser et al., 2025). This finding establishes that investments in data governance yield returns through improved AI effectiveness rather than as standalone benefits, positioning governance as a strategic enabler rather than a compliance burden.

Second, persistent data quality challenges in Middle East construction include fragmented and non-standardized data across project phases and stakeholder organizations, ownership and intellectual property ambiguities on collaborative platforms, data scarcity and labeling inconsistencies that constrain supervised learning models, and insufficient lifecycle governance mechanisms that allow quality degradation to accumulate. These challenges directly impair AI system performance across applications including predictive analytics, safety monitoring, design optimization, digital twins, and project management information systems (Abdalla et al., 2023), (Alreshidi et al., 2018), (Alnaser et al., 2025).

Third, emerging governance frameworks offer promising approaches to addressing these challenges. The CPMAI model provides lifecycle-aligned governance that embeds data quality metrics into each AI development phase, improving KPI reliability and traceability (Kayani, 2025).

Data mesh architectures enable scalable decentralized governance through domain data ownership and standardized contracts (Mishra et al., 2024). DAMA-DMBOK AI-assisted governance leverages machine learning and natural language processing to automate metadata discovery, quality profiling, and policy enforcement (Kumari, 2024). Intelligent governance systems integrate multiple AI technologies to provide comprehensive governance capabilities (Kumari, 2024). However, adoption of these frameworks remains limited, and their effectiveness in Middle East construction contexts requires further empirical validation.

Fourth, regional case studies demonstrate both the potential and challenges of implementing data governance for AI in construction. The Dubai RTA intelligent construction management system achieved measurable improvements in schedule, cost, and data accuracy through coordinated governance mechanisms (Shi et al., 2025). The UAE Level 2 BIM implementation revealed governance challenges including unclear data ownership and limited lifecycle integration (Shafiq, 2021). The Saudi AI-integrated digital twins study empirically validated the critical role of data quality and governance in determining project outcomes (Alnaser et al., 2025). NEOM's ambitious AI vision requires unprecedented governance capabilities to realize its potential (Allouzi et al., 2024). These cases illustrate that governance success depends on integration of technical mechanisms, organizational structures, and contractual arrangements.

Fifth, the regulatory landscape for AI governance in the Middle East is evolving but remains characterized by gaps including insufficient monitoring frameworks, lack of standardized incident reporting, unclear enforcement mechanisms, and limited sector-specific guidance for construction (Trigui et al., 2024). National initiatives including SDAIA's AI ethics principles and governance tools like Siyasat provide important infrastructure, but translation into operational requirements and compliance mechanisms remains incomplete (Alboaneen et al., 2025).

The policy recommendations proposed in this article address these findings through coordinated interventions across multiple levels. Mandating lifecycle data-quality metrics in public procurement creates accountability for data quality and ensures governance is not treated as optional (Kayani, 2025). Adopting domain data contracts and mesh patterns enables scalable decentralized governance while maintaining interoperability (Mishra et al., 2024). Promoting automated governance tooling reduces implementation cost and complexity (Kumari, 2024). Strengthening workforce training addresses the skills gap that constrains adoption (Alnaser et al., 2025). Establishing clear data sovereignty rules provides regulatory clarity while enabling innovation (Albaroudi et al., 2025). Mandating BIM standards addresses fragmentation and enables data reuse (Abdalla et al., 2023). Establishing governance sandboxes enables experimentation and learning (Abudaqqa et al., 2025).

Implementation of these recommendations requires coordinated action across government agencies, industry associations, educational institutions, and construction organizations. Public procurement clauses, national taxonomies and incident reporting, industry standards and certification, research and development funding, and regional harmonization initiatives provide specific mechanisms for translating recommendations into practice.

This research contributes to the emerging body of knowledge on trustworthy AI in construction by providing the first comprehensive framework that integrates technical, organizational, and regulatory dimensions of data governance tailored specifically to Middle East construction ecosystems. The framework recognizes that effective governance requires simultaneous attention to data architecture and technical mechanisms, organizational structures and incentives, lifecycle integration across AI development phases, and regulatory compliance and alignment with national strategies.

Several limitations of this research should be acknowledged. First, while the article synthesizes evidence from 91 sources, empirical research on data governance in Middle East construction remains limited, with most studies focusing on BIM adoption barriers rather than specific data quality dimensions affecting AI performance. Second, the case studies examined represent early implementations of AI and governance frameworks, and longer-term evidence of effectiveness is not yet available. Third, the policy recommendations are grounded in available evidence but have not been empirically tested through implementation and evaluation. Fourth, the rapid evolution of AI technologies and governance frameworks means that some findings may require updating as new approaches emerge.

Future research directions include empirical evaluation of governance framework effectiveness through controlled studies or natural experiments, development and validation of data quality metrics specifically tailored to construction AI applications, investigation of organizational and cultural factors affecting governance adoption in Middle East contexts, examination of governance approaches for emerging AI technologies including large language models and generative AI in construction, and comparative analysis of governance practices across GCC countries to identify best practices and opportunities for harmonization.

For practitioners, this research provides actionable guidance for implementing data governance in AI-driven construction projects. Organizations should begin by assessing current data governance capabilities and identifying gaps relative to the frameworks presented in this article. They should prioritize governance investments that address critical data quality deficits preventing AI system functionality, such as establishing metadata standards, implementing quality monitoring, and clarifying data ownership. They should adopt lifecycle governance approaches that integrate data quality assessment into AI development phases rather than treating governance as a one-time activity. They should leverage automated governance tools to reduce implementation cost and improve effectiveness. They should invest in workforce capability development alongside technical infrastructure. They should engage with industry associations and regulatory authorities to shape evolving governance standards and requirements.

For policymakers, this research demonstrates that data governance is a critical enabler of national AI strategies and digital transformation objectives. Policies that promote AI adoption without addressing data governance foundations risk disappointing outcomes and erosion of trust in AI systems. Effective policy requires coordinated interventions addressing technical standards, organizational capabilities, regulatory frameworks, and workforce development. Regional harmonization of governance approaches can reduce complexity and cost while enabling economies of scale in capability development. Regulatory sandboxes and pilot programs can enable learning and adaptation before mandating governance approaches broadly.

In conclusion, the successful integration of artificial intelligence into Middle East construction depends fundamentally on establishing robust data governance frameworks and high-quality data ecosystems. The region's ambitious construction and digital transformation initiatives, exemplified by projects like NEOM and national visions like Saudi Vision 2030 and UAE Vision 2031, create both unprecedented opportunities and heightened risks. Realizing the opportunities while managing the risks requires treating data governance not as a technical support function but as a strategic enabler of trustworthy AI. The frameworks, evidence, and recommendations presented in this article provide a foundation for this critical work, but sustained commitment and coordinated action across stakeholders will be required to achieve the vision of AI-enabled construction that is efficient, safe, sustainable, and aligned with regional values and aspirations.

References

1. Abdalla, S. B., Khalfan, M., & Aziz, Z. (2023). Comparative analysis of building information modeling (BIM) patterns and trends in the United Arab Emirates (UAE) with developed countries. *Buildings*, *13*(3), 695. https://doi.org/10.3390/buildings13030695
2. Abdulqader, D. M., Ali, R. A., & Abdulameer, S. S. (2025). DT, BIM, and IoTs contributions and barriers in construction PM: A PRISMA. *Civil and Environmental Engineering*, *21*(1), 89-104. https://doi.org/10.2478/cee-2026-0009
3. Abudaqqa, A., Alshahrani, H., & Alqahtani, F. (2025). Artificial intelligence for IT governance in Saudi Arabia: Opportunities, challenges, and future directions within COBIT 2019 and ISO/IEC 38500 frameworks. *European Scientific Journal*, *21*(25), 125-156. https://doi.org/10.19044/esj.2025.v21n25p125
4. Alasmari, M., Alqahtani, F., & Alshahrani, A. (2023). Adopting BIM to enhance sustainability: The Saudi Arabia construction projects case study. *IOP Conference Series: Earth and Environmental Science*, *1196*(1), 012111. https://doi.org/10.1088/1755-1315/1196/1/012111
5. Albaroudi, E., Mansour, R. F., & Alabduljabbar, R. (2025). Empowering data sovereignty through artificial intelligence: A framework for sustainable smart energy systems in Saudi Arabia. *Current Journal of Applied Science and Technology*, *44*(9), 1-18. https://doi.org/10.9734/cjast/2025/v44i94606
6. Alboaneen, D., Alqarni, R., Alqahtani, S., & Alshahrani, H. (2025). Siyasat: AI-powered AI governance tool to generate and improve AI policies according to Saudi AI ethics principles. *Computers*, *14*(11), 452. https://doi.org/10.3390/computers14110452
7. Allouzi, R., Alshahrani, A., & Alqahtani, F. (2024). Applied AI in NEOM construction projects: The potential impact of AI in enhancing projects success. *Advances in Intelligent Manufacturing*, *1*(1), 32-44. https://doi.org/10.26480/aim.01.2024.32.44
8. Alnaser, A., Alqahtani, F., & Alshahrani, H. (2025). Exploring critical success factors of AI-integrated digital twins on Saudi construction project deliverables: A PLS-SEM approach. *Buildings*, *15*(19), 3543. https://doi.org/10.3390/buildings15193543
9. Alreshidi, E., Mourshed, M., & Rezgui, Y. (2018). Requirements for cloud-based BIM governance solutions to facilitate team collaboration in construction projects. *Requirements Engineering*, *23*(1), 1-31. https://doi.org/10.1007/s00766-016-0254-6
10. Gorian, N., Ismail, R., & Hashim, H. (2024). Digital ethics of artificial intelligence (AI) in Saudi Arabia and United Arab Emirates. *Malaysian Journal of Syariah and Law*, *12*(3), 1-20. https://doi.org/10.33102/mjsl.vol12no3.798

11. Kayani, U. N. (2025). Cognitive project management for artificial intelligence deployment and data quality governance in cloud ecosystems: A Saudi Vision 2030 perspective. *Technium*, *30*, 1-24. https://doi.org/10.47577/technium.v30i.13256

12. Kumari, S. (2024). Intelligent data governance frameworks: A technical overview. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *10*(6), 161-175. https://doi.org/10.32628/cseit24106161

13. Mahmood, S., Khan, S., & Ullah, F. (2023). How artificial intelligence can leverage project management information system (PMIS) and data driven decision making in project management. *International Journal of Basic and Applied Sciences*, *3*(1), 1-15. https://doi.org/10.54489/ijbas.v3i1.215

14. Mishra, A., Kumar, R., & Singh, P. (2024). An AI-driven data mesh architecture enhancing decision-making in infrastructure construction and public procurement. *arXiv preprint arXiv:2412.00224*. https://doi.org/10.48550/arxiv.2412.00224

15. Savaş, S. (2025). Artificial intelligence in construction project management: Trends, challenges and future directions. *Journal of Design for Resilience in Architecture and Planning*, *6*(2), 165-182. https://doi.org/10.47818/drarch.2025.v6i2165

16. Shafiq, M. T. (2021). Client-driven level 2 BIM implementation: A case study from the UAE. *The Open Construction and Building Technology Journal*, *15*(1), 129-143. https://doi.org/10.2174/1874836802115010129

17. Shi, J., Wang, X., & Zhang, Y. (2025). Intelligent construction management for utility works: System framework and case application in Dubai RTA project. *Engineering Research Express*, *7*(1), e0255. https://doi.org/10.1088/2631-8695/ae0255

18. Trigui, I., Ben Ayed, M., & Alimi, A. (2024). Exploring AI governance in the Middle East and North Africa (MENA) region: Gaps, efforts, and initiatives. *Data & Policy*, *6*, e85. https://doi.org/10.1017/dap.2024.85

19. Umar, T. (2021). Challenges of BIM implementation in GCC construction industry. *Engineering, Construction and Architectural Management*, *29*(3), 1139-1168. https://doi.org/10.1108/ECAM-11-2019-0608