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AI-Enabled Non-Conformance Prediction and Corrective Action Management in Saudi Mega Infrastructure Projects

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Abstract-** Saudi Arabia's mega infrastructure pipeline under Vision 2030 requires quality systems that can prevent recurring defects rather than merely record them after inspection. Non-conformance reports (NCRs), corrective actions, preventive actions, audit findings, work inspection requests, laboratory test results and supplier quality records contain large volumes of information about recurring project risks. However, these records are often fragmented across packages, contractors, consultants and digital platforms, limiting their value for early warning, root-cause learning and management review. This review paper examines how artificial intelligence (AI) can enable predictive non-conformance management and closed-loop corrective action management in Saudi mega infrastructure projects. Drawing on recent literature on construction quality management, digital QA/QC, machine learning, natural language processing, explainable AI, digital twins, Quality 4.0 and ISO-based quality governance, the study develops a conceptual framework for converting historical NCR and CAPA records into actionable intelligence. The proposed framework integrates data governance, standardised NCR taxonomy, risk-feature engineering, AI-enabled severity and recurrence prediction, root-cause clustering, human validation, CAPA prioritisation, effectiveness verification and continuous learning. The paper argues that AI-enabled NCR prediction should not replace professional judgement; rather, it should support quality managers, client organisations and project management consultants by identifying high-risk patterns earlier and by strengthening accountability for preventive action. The contribution is a Saudi Vision 2030-aligned quality governance model that connects digital transformation with sustainable infrastructure delivery, reduced rework, improved traceability, faster NCR closure and better handover readiness.

***Keywords:** Artificial Intelligence, Non-Conformance Report, Corrective and Preventive Action, Construction Quality Management, Saudi Vision 2030, Mega Infrastructure, QA/QC, Predictive Analytics, ISO 9001, Quality 4.0.*

I. INTRODUCTION

Saudi Arabia is delivering one of the most ambitious infrastructure transformation programmes in the world. Vision 2030 places strategic importance on diversified economic growth, tourism, cultural assets, logistics, housing, mobility, urban development and quality of life. Mega infrastructure projects such as NEOM, Diriyah, airport expansion works, roads, bridges, tunnels, transport corridors and mixed-use developments are therefore not only construction programmes; they are national delivery platforms that must demonstrate reliability, safety, sustainability and long-term asset value. In this environment, quality assurance and quality control become strategic governance functions rather than routine inspection activities.

Non-conformance management is one of the most important control points in construction quality. A non-conformance report records a deviation from drawings, specifications, method statements, inspection and test plans, contractual requirements, approved materials, workmanship standards or regulatory obligations. Corrective action removes or resolves the detected problem, while preventive action addresses the underlying causes that may create recurrence. On complex projects, NCRs can reveal weak inspection planning, poor supplier quality, design coordination gaps, subcontractor capability issues, inadequate supervision, repeated material failures, incomplete documentation or interface problems between civil, structural, MEP and specialist packages.

Despite this value, NCR management in many infrastructure projects remains reactive. Records may be stored as PDF files, spreadsheets, e-mails or isolated platform entries. Root-cause categories may be inconsistent, severity may be assessed subjectively and lessons learned may not reach future work fronts. Corrective actions may close the visible defect while leaving the process cause unresolved. When projects contain thousands of inspections, multiple contractors and parallel packages, the manual review of NCR history becomes impractical. As a result, the same defects may reappear, hidden risks may escalate and management teams may see trends only after cost and schedule impact has already occurred.

Artificial intelligence offers a route to transform this situation. Machine learning can classify NCR severity, predict recurrence risk and highlight combinations of factors that increase defect probability. Natural language processing can extract root causes from unstructured NCR narratives, audit reports and inspection comments. Computer vision can detect visible defects, compare site conditions with drawings or BIM models and support objective evidence capture. Explainable AI can show why a case is considered high risk, allowing quality professionals to validate recommendations before action. Digital twins and common data environments can link non-conformances to assets, locations, work packages and handover records. Together these technologies can move quality management from after-the-fact defect control toward proactive quality intelligence.

The professional relevance of this topic is clear for a senior QA/QC and quality governance profile. The candidate's record includes more than thirteen years of experience in Saudi infrastructure and giga-project environments, including NEOM, Diriyah, roads, tunnels, bridges, airport runway works, ISO 9001:2015 quality management systems, project quality management systems, audits, NCR/CAPA management, supplier quality assurance, quality KPIs and executive reporting. This background creates a strong foundation for research on AI-enabled non-conformance prediction because the topic combines civil infrastructure delivery with practical quality governance, risk-based planning and continuous improvement.

II. AIM AND OBJECTIVES OF THE STUDY

The aim of this review paper is to develop a practical and research-oriented framework for AI-enabled non-conformance prediction and corrective action management in Saudi mega infrastructure projects. The study focuses on how construction quality records can be converted into predictive intelligence that supports earlier intervention, reduced recurrence and more reliable project delivery.

The objectives are fourfold. First, the paper reviews recent literature on digital construction quality management, defect prediction, NCR analysis, Quality 4.0 and AI adoption in construction. Second, it identifies the types of data and features required for predicting non-conformance risk in infrastructure projects. Third, it proposes a closed-loop model connecting NCR detection, severity classification, root-cause analysis, CAPA prioritisation, effectiveness verification and lessons learned. Fourth, it discusses governance, implementation and Saudi Vision 2030 alignment for client, PMC, consultant and contractor organisations working on roads, airports, bridges, tunnels and large-scale mixed-use assets.

III. RESEARCH METHODOLOGY

This paper adopts a structured review methodology supported by conceptual framework development. The review is not a statistical meta-analysis; rather, it synthesises peer-reviewed literature, international quality concepts and Saudi infrastructure priorities to produce a practical model for future empirical validation. The methodological logic is suitable because AI-enabled NCR prediction is an emerging interdisciplinary topic that sits across construction quality management, data science, project controls, digital delivery and organisational governance.

The literature selection was guided by a PRISMA-inspired logic. Search themes included construction quality management, digital QA/QC, non-conformance reports, defect prediction, machine learning, natural language processing, corrective and preventive action, root-cause analysis, digital twins, Quality 4.0, ISO-based quality systems and Saudi Vision 2030. Priority was given to sources published between 2020 and 2025, with emphasis on Scopus-indexed journals, Web of Science journals, recognised standards bodies, government sources and high-quality professional reports. Foundational quality standards were used where necessary to explain established concepts such as risk-based thinking, documented information and continual improvement. The review followed four analytical steps. The first step mapped the problem domain by defining NCRs, CAPA, recurrence, severity, defect impact and quality governance. The second step identified digital and AI techniques relevant to construction quality records, including supervised learning, anomaly detection, clustering, NLP, computer vision, explainable AI and dashboard analytics. The third step translated the evidence into an AI-enabled NCR prediction architecture suitable for Saudi mega infrastructure. The fourth step developed implementation considerations, performance indicators and future research directions.

IV. CONCEPTUAL BACKGROUND: NCR, CAPA AND QUALITY GOVERNANCE

A construction NCR is more than a defect note. It is a formal governance record that confirms a gap between required and observed performance. In a high-value infrastructure project, the NCR lifecycle normally includes initiation, description, reference to requirement, location, evidence, responsibility assignment, immediate correction, root-cause analysis, corrective action, preventive action, verification, closure and trend analysis. Strong NCR management ensures that a defect is not simply repaired but understood. The core question is not only what failed, but why it failed, how often it may happen again and what system control should be improved.

CAPA management provides the link between defect correction and organisational learning. Corrective action eliminates the detected non-conformity or its cause, while preventive action reduces the likelihood of similar non-conformities elsewhere. In practice, weak CAPA systems suffer from superficial causes, delayed closure, repeated extensions, unclear ownership and limited verification. In mega projects, these weaknesses are amplified because the same design detail, material, subcontractor or inspection gap can affect many assets. A defect in one package may indicate risk in another package even before a formal NCR is raised.

ISO-based quality management emphasises leadership, process approach, risk-based thinking, documented information, performance evaluation and continual improvement. These principles are directly compatible with AI-enabled NCR prediction. Risk-based thinking requires organisations to identify and control potential failure conditions; AI supports this by detecting patterns that are difficult to see manually. Documented information requires traceable evidence; digital QA/QC platforms improve the structure and retrieval of records. Continual improvement requires learning from performance; closed-loop analytics can convert NCR history into future controls.

Quality governance also depends on human accountability. AI models can identify likely risk, but they cannot replace engineering judgement, contractual interpretation or authority approval. For this reason, AI-enabled NCR prediction should be designed as decision support. Quality engineers, discipline leads, project quality managers and client representatives should retain responsibility for evaluating recommendations, selecting actions and confirming closure. The purpose of AI is to increase visibility, speed and consistency, not to remove professional responsibility.

V. DATA FOUNDATION FOR AI-ENABLED NCR PREDICTION

AI-enabled prediction requires a reliable data foundation. Construction quality records are often heterogeneous because different packages use different templates, descriptions, codes and naming conventions. An NCR may describe the same issue as a workmanship defect, specification deviation, inspection failure, missing approval, material non-compliance or method statement deviation. Without standard taxonomy, machine learning models may learn inconsistent labels and produce unreliable recommendations. Data governance is therefore a prerequisite, not an optional administrative step.

The most useful data sources for NCR prediction include inspection and test plan records, work inspection requests, material inspection reports, concrete and asphalt test results, supplier audit findings, method statement approvals, non-conformance histories, corrective action logs, punch lists, site walkdown observations, design revision records, request for information logs, handover checklists and authority approval records. For infrastructure projects, geographic and asset-level data are also important. A defect risk attached to a road chainage, tunnel section, bridge element, runway zone or building floor is more valuable than a generic risk entry because it allows targeted intervention.

Feature engineering converts raw records into predictive indicators. Useful features can include defect category, discipline, location, contractor, subcontractor, supplier, material type, inspection stage, weather condition, design revision frequency, number of previous NCRs in the same workfront, time between inspection request and approval, audit score, rejected material submittals, overdue corrective actions, supervisor experience, work package complexity and percentage of completed inspections. Text features can be extracted from NCR descriptions, audit observations and root-cause statements using NLP. Visual features can be extracted from images, drone records and laser scans where defects are observable.

Data quality must be controlled before model development. Missing fields, duplicate cases, inconsistent severity labels, vague root causes and incomplete closure evidence can bias predictions. For example, if some contractors underreport minor NCRs, a model may incorrectly infer that they have lower risk. If severity is entered differently by different engineers, model outputs may reflect personal judgement rather than true impact. A Saudi mega-project AI quality framework should therefore include data validation rules, minimum NCR field requirements, root-cause code libraries and periodic review of model-training datasets.

Table 1. Data features for AI-enabled NCR prediction in mega infrastructure projects

Data feature group	Examples of indicators	Prediction value for NCR/CAPA
Inspection and test records	ITP hold points, WIR rejection rate, inspection cycle time, missed inspections, test failures	Shows workfront quality maturity and areas where controls may fail before formal NCR creation.
Historical NCR profile	NCR type, severity, discipline, location, responsible party, recurrence, closure duration	Supports severity classification, recurrence prediction and contractor/package benchmarking.
Root-cause and narrative text	Cause statements, audit comments, corrective action text, lessons learned, photos captions	Allows NLP extraction of repeated process causes that may not be captured in dropdown fields.
Supplier and material data	Supplier audit score, rejected submittals, FAT findings, batch failures, delivery changes	Identifies supply-chain quality risks and supports targeted vendor surveillance.
Design and coordination signals	RFI frequency, drawing revisions, interface clashes, late approvals, BIM change history	Highlights packages where design instability may increase non-conformance probability.
Project context and location	Asset ID, chainage, floor, tunnel section, bridge element, weather, shift, supervision ratio	Links quality risk to actual infrastructure elements, enabling focused preventive action.

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VI. AI TECHNIQUES FOR NON-CONFORMANCE PREDICTION

Several AI techniques are relevant to NCR prediction. Supervised machine learning can classify whether a future NCR is likely to be low, medium or high severity based on historical labelled cases. Algorithms such as random forests, gradient boosting, support vector machines, neural networks and ensemble models can learn nonlinear relationships between package attributes, contractor performance, inspection history and defect outcomes. The advantage of these models is that they can process many variables simultaneously and identify interactions that are difficult to see through manual trend charts.

Unsupervised learning can support root-cause discovery when labels are weak or incomplete. Clustering algorithms can group NCRs with similar descriptions, locations, trades or process conditions. This can reveal hidden patterns such as repeated defects around the same supplier, design interface, work sequence or inspection hold point. Association rule mining can identify combinations of conditions that commonly appear before certain defect types. Anomaly detection can flag unusual inspection results, sudden increases in NCR frequency or outlier performance in a work package.

Natural language processing is particularly important because many NCRs contain valuable information in narrative form. NCR descriptions, corrective action statements, audit observations and lessons-learned notes may mention recurring causes that are not captured in dropdown fields. NLP can classify defect type, identify process causes, extract material names, detect weak root-cause statements and summarise recurring themes. Large language models may support drafting and knowledge retrieval, but they must be governed carefully because quality decisions require traceable evidence and professional validation.

Computer vision can complement NCR prediction in cases where defects are visible. It can support detection of cracks, surface defects, dimensional deviations, missing elements, poor workmanship and deviations between the physical site and the BIM model. In infrastructure assets such as pavements, bridges, tunnels, facades and concrete elements, visual AI can generate early warnings before defects are formally reported. However, computer vision models must be adapted to project-specific conditions because lighting, dust, access constraints, occlusion and variable workmanship can affect accuracy.

Explainable AI is essential for acceptance in quality governance. A quality manager is unlikely to act on a black-box score without understanding the drivers of risk. Techniques such as feature importance, SHAP values, decision rules and confidence levels can show whether a high-risk prediction is driven by previous NCR frequency, supplier performance, overdue inspections, design changes, poor test results or repeated audit findings. Explainability supports accountability and reduces the risk of blind automation.

VII. PROPOSED AI-ENABLED NCR AND CAPA FRAMEWORK

The proposed framework has five layers: data capture, data quality, AI prediction, CAPA decision support and governance feedback. The data capture layer connects inspection records, NCR histories, audit findings, material tests, supplier performance data, BIM locations, site images and project controls information. The data quality layer standardises taxonomy, validates required fields, resolves duplicates, links records to asset IDs and checks completeness. The AI prediction layer classifies severity, estimates recurrence probability, detects similar cases and highlights potential cost or schedule impact. The CAPA layer recommends priorities, owners, verification evidence and preventive controls. The governance layer monitors KPIs, updates the model and reports trends to management.

Figure 1 presents the conceptual architecture. The model does not treat AI as an isolated software tool. Instead, it positions AI inside the project quality management system. This is important because NCR decisions have contractual, technical and regulatory consequences. AI outputs should be reviewed by authorised quality personnel before action is assigned or closure is accepted. The framework also allows different maturity levels. A project may begin with analytics dashboards and automated classification,

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then progress to severity prediction, root-cause clustering and real-time risk alerts.

A practical example can illustrate the process. If a tunnel package shows repeated NCRs related to concrete surface defects, delayed inspections and similar supplier batches, the AI model can flag a recurrence hotspot. The dashboard can compare this pattern with previous bridge or runway packages and estimate the likelihood of further NCRs. The quality manager can then require additional hold points, supplier review, revised method statement controls, toolbox training and targeted inspection before further work proceeds. The final CAPA is verified by observing whether recurrence reduces in subsequent cycles.

The framework also supports portfolio-level learning. Lessons from one project package should not remain inside that package. Mega infrastructure programmes often include repeated design elements, similar materials and common contractor ecosystems. An AI-enabled quality knowledge base can transfer lessons from roads to bridges, from airports to tunnels or from early phases to later phases. This transforms NCR management from local correction to programme-wide prevention.

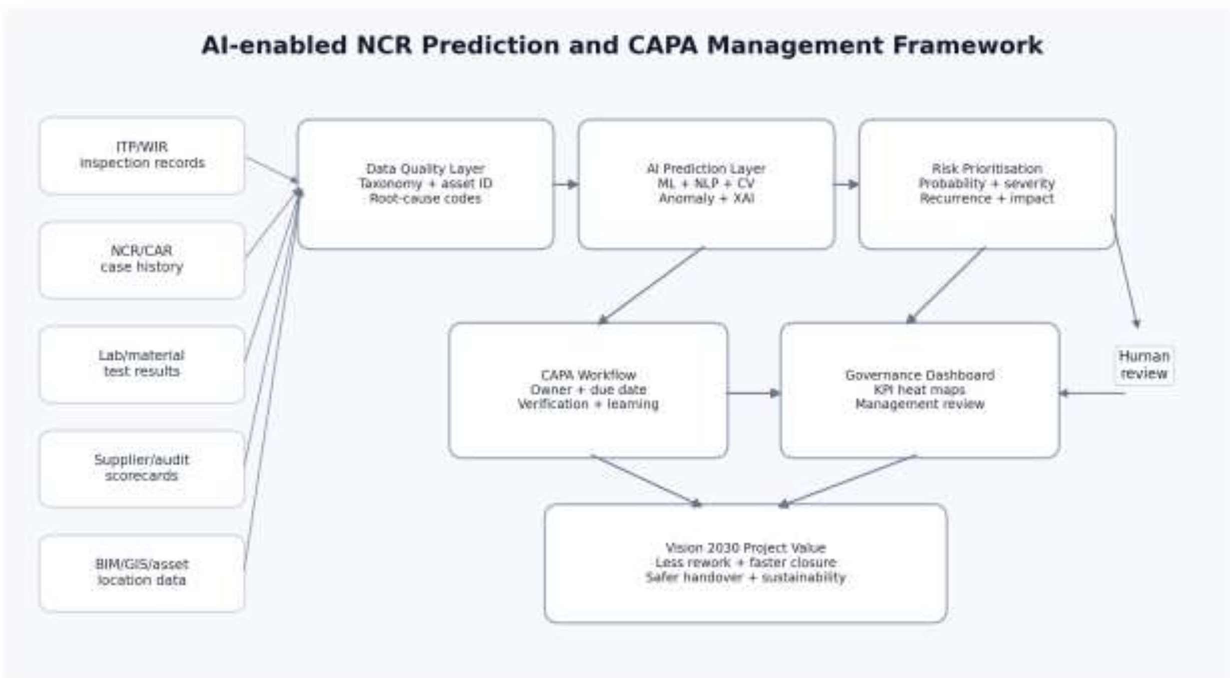

Figure 1. AI-enabled NCR prediction and CAPA management framework for Saudi mega infrastructure projects.

VIII. CORRECTIVE ACTION MANAGEMENT AND HUMAN OVERSIGHT

AI-enabled NCR prediction creates value only when it is connected to disciplined CAPA management. Predicting risk without acting on it may create dashboards but not improvement. A closed-loop CAPA system should begin with clear containment of the detected issue, followed by root-cause analysis, action planning, responsibility assignment, due-date control, evidence review and effectiveness verification. The AI system can support each stage by identifying similar cases, suggesting possible causes, prioritising actions and warning when closure is overdue.

Root-cause analysis should remain structured. Common tools such as the five whys, fishbone diagrams, Pareto analysis and failure mode thinking can be strengthened by AI-generated evidence. For example, the model may show that a defect type correlates with a specific subcontractor, material supplier, shift pattern or design revision. This helps the team avoid superficial causes such as 'worker error' when the deeper cause may be inadequate method statement control, missing training, unclear drawings or supplier process instability.

Human oversight must be designed into the workflow. AI recommendations should have approval gates, confidence levels and escalation rules. Low-risk suggestions may be used for dashboard trend monitoring, but high-impact actions such as stopping work, rejecting materials, changing inspection frequency or withholding handover should require formal human approval. The system should also preserve audit trails showing who reviewed the recommendation, what evidence was considered and why a decision was made. This is important for contractual defensibility and stakeholder trust.

Ethics and fairness also matter. AI models can unintentionally penalise contractors who report more transparently while favouring those who underreport issues. To reduce this risk, model governance should include reporting-normalisation checks, audit comparisons and periodic review of false positives and false negatives. The objective is not to use AI as a punitive surveillance tool, but to improve quality performance and protect project outcomes.

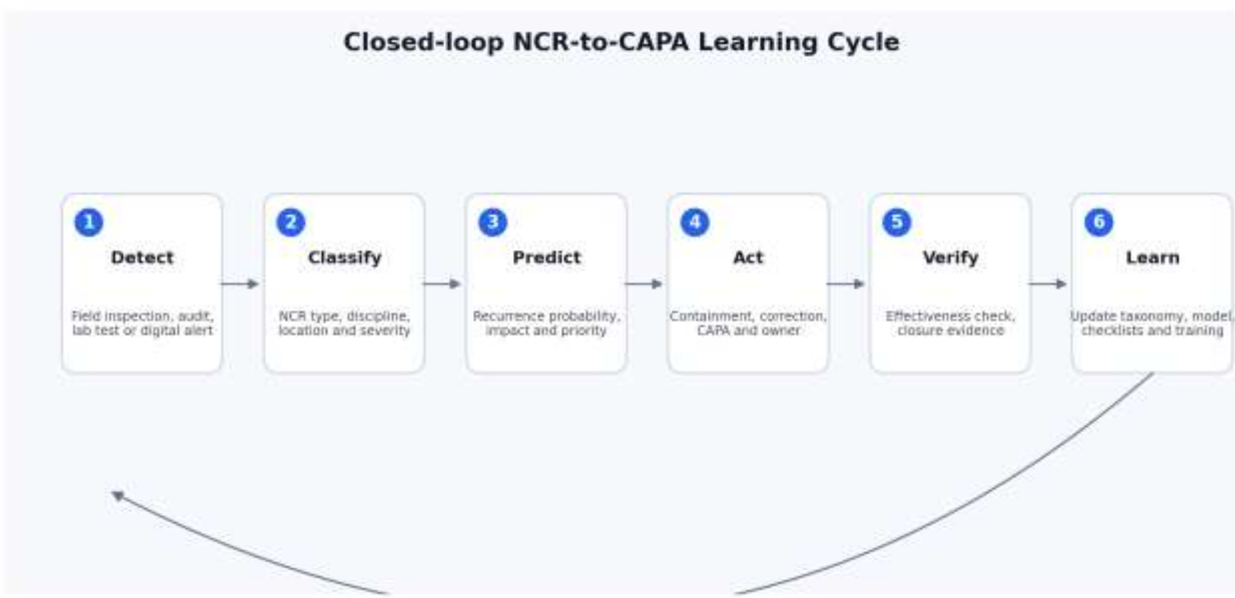

Figure 2. Closed-loop NCR-to-CAPA learning cycle that converts defect records into preventive controls.

IX. SAUDI MEGA INFRASTRUCTURE APPLICATION AREAS

Saudi mega infrastructure projects provide a strong use case because of their scale, complexity and multi-stakeholder delivery environments. Roads, bridges, airports, tunnels, utilities, luxury residences and mixed-use districts involve large numbers of inspection points, material tests, subcontractors and authority interfaces. Quality issues can affect not only current work but also handover, maintenance and future asset performance. Predictive NCR management can therefore support Vision 2030 outcomes by improving delivery reliability and reducing wasteful rework.

Airport and runway projects require strict control of pavement quality, material compliance, lighting systems, drainage, markings, navigational interfaces and regulatory standards. AI-enabled NCR prediction can help identify recurring material test failures, inspection delays, supplier risks or workfronts with high rework probability. Roads and bridges require similar predictive control for asphalt, concrete, reinforcement, bearings, expansion joints, drainage, slope protection and traffic safety elements. Tunnels require particular attention to excavation quality, lining defects, waterproofing, fire and life safety systems and MEP interfaces.

For urban and luxury mixed-use projects, predictive NCR management can support architectural, structural, MEP, facade, finishing and handover quality. These assets often include high expectations for user experience and stakeholder visibility, making defects costly even when they are not structurally critical. Quality analytics can help management teams monitor contractors, identify repeated workmanship defects, compare package performance and align closure status with handover milestones.

Supplier quality assurance is another major application. Saudi mega projects rely on complex supply chains for concrete, asphalt, steel, precast elements, MEP equipment, fire systems, finishes, airport systems and specialist materials. AI can combine supplier audit scores, material approval history, factory acceptance test findings, delivery delays and site NCRs to identify vendors that require closer monitoring. This allows quality managers to intervene earlier through audits, source inspection or revised acceptance controls.

X. EXPECTED BENEFITS AND PERFORMANCE INDICATORS

The expected benefits of AI-enabled NCR prediction can be grouped into compliance, traceability, productivity, cost, schedule and learning. Compliance improves because the system links NCRs to specifications, ITPs, approved drawings and regulatory requirements. Traceability improves because each case is connected to location, asset ID, evidence, root cause, action owner and verification. Productivity improves because quality teams can prioritise high-risk cases rather than reviewing all records manually. Cost and schedule performance improve when recurring defects are prevented before they require major rework.

Performance indicators should be selected carefully. Useful KPIs include NCR recurrence rate, average NCR closure time, percentage of overdue CAPAs, proportion of NCRs with verified root cause, defect density per work package, cost impact of NCRs, number of repeated supplier defects, inspection rejection rate, percentage of preventive actions completed before recurrence, handover punch-list reduction and model prediction accuracy. These indicators should be reviewed at project, package, contractor, discipline and asset levels.

A key indicator is CAPA effectiveness. Closure should not be measured only by signing off the correction. A corrective action is effective when the same non-conformance does not recur under similar conditions. AI can support this by monitoring recurrence after closure and by alerting managers when a supposedly resolved issue returns. This shifts quality culture from document closure toward performance improvement.

Another important benefit is knowledge retention. Mega projects often face staff turnover, contractor changes and package transitions. When lessons learned remain in individual experience or static reports, they may be lost. An AI-enabled NCR knowledge base can preserve patterns across projects and make them searchable for future teams. This is especially useful for national programmes where similar infrastructure works are repeated across regions.

Table 2. Implementation roadmap, outputs and performance indicators

Phase	Main activities	Key outputs	Suggested KPIs
1. Readiness assessment	Map NCR workflow, audit data quality, review platforms, define governance roles.	Data-readiness report; NCR taxonomy; integration plan.	Completeness of historical NCR fields; number of systems mapped; baseline closure time.
2. Digitisation and standardisation	Deploy structured forms, mobile evidence capture, asset coding and root-cause libraries.	Unified NCR/CAPA template; digital audit trail; dashboard baseline.	Required-field compliance; photo/evidence completeness; overdue CAPA percentage.
3. Predictive analytics	Clean historical data, train severity and recurrence models, validate outputs with quality experts.	Risk heat maps; severity model; recurrence alerts; explainability reports.	Prediction precision/recall; high-risk cases reviewed; false-positive rate.
4. Closed-loop optimisation	Connect AI outputs to CAPA, supplier quality, ITP revisions and lessons learned.	Preventive control updates; supplier action plans; lessons-learned knowledge base.	NCR recurrence reduction; CAPA effectiveness rate; rework cost reduction; handover punch-list reduction.

XI. IMPLEMENTATION ROADMAP

Implementation should be phased. The first phase is readiness assessment. Project teams should map current NCR and CAPA workflows, identify data sources, review platform integration, assess data quality and define the target taxonomy. The second phase is digitisation and standardisation. This includes unified NCR templates, mandatory root-cause fields, asset/location coding, mobile evidence capture, e-signatures and dashboard reporting. The third phase is analytics deployment, where historical data are cleaned and used for classification, trend analysis, recurrence heat maps and severity prediction. The fourth phase is optimisation, where AI insights are connected to preventive action, supplier quality management, ITP revisions and programme-wide lessons learned.

Leadership commitment is required throughout the roadmap. AI-enabled quality systems may fail if users see them as additional reporting burdens. Quality managers should demonstrate how the system reduces repeated work, improves management support and strengthens contractor accountability. Training is essential for engineers, inspectors, document controllers, project controls teams, suppliers and senior management. Users should understand not only how to enter data but also why structured data matters for prediction.

Contractual and data-governance arrangements should be established early. Project contracts may need to define platform use, digital signatures, record ownership, data retention, evidence standards, cybersecurity responsibilities and the role of AI recommendations. Where multiple organisations share a platform, access rights and confidentiality must be clear. Model governance should include validation, monitoring, change control and periodic review by a multidisciplinary quality and data committee.

The roadmap should be realistic. A project should not begin with fully automated AI decisions. The safer path is to start with structured data and dashboard analytics, then introduce predictive models after data quality is proven. Human-in-the-loop validation should remain part of the system until the organisation has strong confidence in model performance. Even then, high-impact quality decisions should remain under authorised professional control.

XII. CHALLENGES AND RISK CONTROLS

The first challenge is data fragmentation. Mega infrastructure projects often use different platforms for document control, inspections, submittals, BIM, ERP, procurement and project controls. If these systems are not integrated, AI models may receive an incomplete picture. A project may know that an NCR exists but not link it to the design revision, supplier batch or inspection delay that caused it. Integration through a common data environment, APIs and standard identifiers is therefore critical.

The second challenge is label quality. Predictive models depend on historical labels such as severity, root cause and status. If labels are inconsistent or inaccurate, the model may reproduce past errors. Periodic quality review of NCR coding is necessary. A practical approach is to create a controlled vocabulary for defect categories, root causes, disciplines, assets and severity levels while still allowing narrative details for context.

The third challenge is organisational adoption. Some contractors may fear that predictive analytics will be used to punish them. Some inspectors may see digital tools as reducing professional autonomy. To overcome this, the system should be positioned as a preventive quality improvement tool. Transparency is important: users should know what data are collected, how scores are calculated, how recommendations are reviewed and how performance is interpreted.

The fourth challenge is model drift. Construction processes, contractors, materials and project phases change over time. A model trained on early earthworks may not perform well during MEP installation or finishing. Models must be monitored and recalibrated. The governance process should track prediction accuracy, false alarms, missed high-risk cases and changes in data distribution. This is part of responsible AI management.

XIII. RESEARCH CONTRIBUTION AND FUTURE DIRECTIONS

This paper contributes to both research and practice by connecting AI-enabled prediction with construction NCR and CAPA governance in the Saudi mega infrastructure context. Existing studies often focus on defect detection, computer vision or general digital QA/QC, while practical NCR systems require integration with ISO-based quality management, project roles, contractual workflows, supplier quality and lessons learned. The proposed framework fills this gap by treating AI as part of a closed-loop quality governance system.

Future empirical research should test the framework using anonymised NCR datasets from Saudi infrastructure projects. Potential research questions include: Which features best predict NCR severity? Can NLP classify root causes more consistently than manual coding? Does AI-supported CAPA reduce recurrence rates? How do contractors and consultants perceive trust in AI recommendations? What contractual conditions are necessary for digital quality evidence to be accepted? These questions can be addressed through case studies, interviews, surveys and quantitative analysis.

Future work should also connect NCR prediction to sustainability. Rework consumes materials, labour, equipment time, energy and transport resources. Preventing defects can therefore support sustainable infrastructure delivery by reducing waste and improving lifecycle performance. This aligns quality management with broader Vision 2030 priorities related to efficient investment, sustainable assets and better quality of life.

XIV. CONCLUSION

Saudi mega infrastructure projects require quality systems that are proactive, traceable and intelligent. NCR and CAPA records contain valuable knowledge about recurring risks, but their value is often limited by fragmented documentation, inconsistent coding and reactive closure practices. AI-enabled non-conformance prediction can convert these records into early warning intelligence, helping quality teams identify recurrence risks before they become costly rework or handover obstacles.

The proposed framework integrates data capture, data quality, machine learning, natural language processing, explainable AI, CAPA decision support and governance feedback. It emphasises that AI should not replace professional quality judgement; it should support quality managers with evidence-based prioritisation, root-cause learning and preventive action. The closed-loop model connects detection, classification, prediction, action, verification and learning so that every NCR becomes a source of improvement rather than a repeated administrative event.

For Saudi Vision 2030, this approach supports more reliable infrastructure delivery, reduced rework, stronger supplier performance, improved compliance and sustainable asset handover. It also aligns closely with the expertise of senior QA/QC professionals who understand ISO 9001, PQMS, audits, NCR/CAPA, supplier quality and mega-project delivery. The future of construction quality in Saudi Arabia will depend not only on advanced technology, but on the ability to integrate digital intelligence with disciplined governance, professional accountability and continuous improvement.

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