Power System Protection and Control
ISSN:1674-3415

IMPLEMENTING DIGITAL INSPECTION PROTOCOLS FOR ENHANCED QUALITY CONTROL MANAGEMENT IN HIGH-RISE CONSTRUCTION

Parag Bharatkumar Parikh

14 Lincoln Place, Whitehall, Pennsylvania 18052
Paragparikh95@gmail.com

Received: 10/05/2026 **Revised**: 05/06/2026 **Accepted**: 01/07/2026

***ABSTRACT*:**

The rapid urbanization across developing economies has intensified the demand for high-rise construction, placing unprecedented pressure on quality control (QC) systems that remain largely paper-based and reactive. This study investigates the implementation of digital inspection protocols (DIPs) — encompassing mobile-based checklist platforms, Building Information Modelling (BIM) integration, drone-assisted visual inspection, and Internet of Things (IoT) sensor networks — as a systemic approach to enhancing QC management in high-rise residential and commercial buildings. Twelve high-rise construction projects in India (ranging from 18 to 54 floors) were monitored over 24 months, with six projects retaining conventional QC methods (control group) and six implementing DIPs (experimental group). Results demonstrate that DIP adoption reduced non-conformance incidents by 48.6%, cut inspection cycle time by 62%, and decreased rework costs as a proportion of total project cost from 4.7% to 1.9%. Defect detection rates improved from 71% (conventional) to 93.4% (digital), with mean defect-to-closure time reducing from 18.4 days to 6.1 days. BIM-integrated inspection workflows contributed to a 31% reduction in design-to-field information discrepancy. IoT-monitored concrete curing achieved 28-day compressive strength compliance rates of 97.2% versus 84.6% in control projects. These findings establish that digital inspection protocols are not merely a process improvement but a transformative quality management framework that substantially reduces project risk, enhances regulatory compliance, and supports sustainability certification requirements in high-rise construction.

***Keywords**: Digital inspection protocols; Quality control management; High-rise construction; BIM integration; IoT sensor networks; Drone inspection; Rework reduction; Non-conformance management; Construction technology*

INTRODUCTION

The high-rise construction sector represents one of the most complex and risk-laden segments of the built environment industry. Buildings exceeding fifteen floors involve intricate structural systems, multi-trade coordination across hundreds of concurrent activities, and regulatory compliance requirements spanning structural safety, fire protection, mechanical-electrical-plumbing (MEP) coordination, and environmental performance (UNEP, 2023). Quality control management in this environment has historically been executed through paper-based inspection checklists, periodic site visits by quality engineers, and retrospective audits — a model demonstrably inadequate for the pace, scale, and interdependence of modern high-rise projects.

Construction defects and non-conformances in high-rise projects carry compounded consequences. A structural defect in a transfer plate at podium level, for instance, may not manifest visually until several floors of additional loading have been applied, by which point the cost and programme implications of remediation are exponentially greater than early detection would have entailed. Studies consistently report that rework attributable to quality failures consumes 2–12% of total construction cost globally, with higher proportions in developing country markets where QC systems are less mature (Love & Li, 2000; Hwang et al., 2014). In India specifically, the Real Estate (Regulation and Development) Act 2016 (RERA) has introduced structural defect liability periods of five years post-handover, creating significant financial exposure for developers and contractors who cannot demonstrate robust QC documentation.

Digital technologies — encompassing mobile applications, Building Information Modelling (BIM), drone-based inspection, and Internet of Things (IoT) sensor systems — offer compelling theoretical advantages for quality

 DOI: 10.46121/pspc.54.3.12

management in construction. Mobile inspection platforms enable real-time capture of non-conformances with photographic evidence, GPS tagging, and immediate notification to responsible parties. BIM integration allows inspectors to link field observations directly to model elements, enabling three-dimensional traceability of defects and eliminating the ambiguity inherent in referencing two-dimensional drawings. Drones provide efficient visual inspection of facade elements, rooftop installations, and exterior structural elements that are hazardous or time-consuming to access via conventional scaffolding. IoT sensors embedded in concrete elements can monitor hydration temperature, relative humidity, and early-age strength development, enabling evidence-based decisions on formwork stripping, post-tensioning operations, and curing adequacy.

Despite the evident theoretical promise of these technologies, empirical evidence from structured field deployments — particularly in the context of high-rise construction in developing markets — remains limited. Most published research addresses individual technologies in isolation, in laboratory or controlled pilot settings, or in low-rise construction contexts. The interaction effects between multiple digital tools, the organizational change management requirements for successful adoption, and the quantified impact on measurable QC outcomes across a portfolio of comparable projects are not well established in peer-reviewed literature.

This study addresses the identified gap through a comparative field study across twelve high-rise construction projects in India, six implementing a comprehensive digital inspection protocol (DIP) framework and six maintaining conventional QC practices as a control group. The primary contribution is a quantified, multi-dimensional assessment of DIP effectiveness across process efficiency, defect detection, rework cost, and concrete quality outcomes, supported by a structured analysis of implementation barriers and enabling factors.

1.1 Research Objectives

This study has four primary objectives:

- To quantify the impact of digital inspection protocol implementation on non-conformance frequency, defect detection rate, and defect-to-closure time in high-rise construction projects.
- To evaluate the contribution of individual DIP components — mobile inspection platforms, BIM integration, drone-based inspection, and IoT sensor monitoring — to overall quality control performance.
- To assess the effect of digital concrete curing monitoring on 28-day compressive strength compliance rates relative to conventional curing supervision.
- To identify critical implementation barriers, organizational enablers, and cost-benefit characteristics of DIP adoption in Indian high-rise construction.

Literature Review

2.1 Quality Control Challenges in High-Rise Construction

High-rise construction quality failures are disproportionately costly relative to their incidence. Defects in structural elements — reinforcement placement errors, inadequate concrete cover, cold joints, and premature formwork stripping — may compromise structural integrity or durability performance over the design service life. MEP coordination errors frequently result in clashes that require expensive cutting of completed structural elements. Facade and finishing defects, while less structurally critical, generate the highest volume of snag items at project completion and carry significant reputational and contractual risk for contractors (Georgiou et al., 1999). Mohan et al. (2021) reported that in Indian high-rise residential projects, the top five defect categories — concrete surface defects, rebar cover violations, waterproofing failures, slab-level discrepancies, and tile alignment errors — collectively accounted for 73% of all QC non-conformances, suggesting that targeted digital monitoring of these categories would capture the majority of quality risk.

The root causes of quality failures in high-rise construction are well catalogued: inadequate design detailing and communication to field personnel; insufficient supervision staff relative to the volume of concurrent activities; lack of real-time visibility of inspection status to project management; poor traceability between defect identification and corrective action closure; and the physical inaccessibility of elements for inspection once subsequent construction has proceeded (Love et al., 2016). Conventional paper-based QC systems exacerbate these causes by introducing transcription delays, enabling selective or incomplete reporting, and producing documentation that is difficult to search, aggregate, or use for trend analysis.

 DOI: 10.46121/pspc.54.3.12

2.2 Mobile-Based Digital Inspection Platforms

The proliferation of smartphones and ruggedized tablets has enabled the development of purpose-built construction inspection applications that replace paper checklists with structured digital forms. Platforms such as PlanGrid, Procore, Autodesk Build, and Snag-R are widely deployed in international markets; Indian-developed alternatives including SpotScan, eSUB, and BuildSafe have gained traction in domestic projects. These platforms share common functional features: configurable inspection templates tied to project elements and locations; photographic capture with automatic metadata embedding (GPS coordinates, timestamp, weather conditions); assignment of non-conformance reports (NCRs) to responsible parties with deadline tracking; escalation workflows for unresolved items; and dashboard reporting of inspection completion rates and open NCR status (Bowden et al., 2006).

Research evaluating mobile inspection platforms in construction settings consistently reports improvements in documentation completeness, reporting speed, and audit traceability. Arslan et al. (2014) found that mobile inspection tools reduced inspection documentation time by 40% on a hospital construction project in Turkey. Costin et al. (2019) reported that photographic capture of defects via mobile platforms reduced disputed NCRs — where the responsible party contested the defect existence — by 68% compared with text-only paper records. In India, a study by Patil and Bhangale (2022) documented 55% reduction in NCR closure time in residential high-rise projects using Procore-based workflows.

2.3 BIM-Integrated Quality Inspection

Building Information Modelling integration elevates digital inspection from a documentation tool to a model-based quality intelligence system. When inspection checklists are linked to BIM model elements — identified by Global Unique Identifier (GUID) — each NCR carries spatial context that enables three-dimensional visualization of defect clusters, cross-discipline coordination verification, and automated conflict detection between as-built conditions (captured by laser scanning or photogrammetry) and design intent (represented in the BIM model). The BIM Execution Plan (BEP) Level of Development (LOD) framework provides a structured basis for linking inspection requirements to model element maturity (BIM Forum, 2022).

Quantitative studies of BIM-based inspection confirm significant process improvements. Kim et al. (2016) demonstrated that BIM-integrated punch list management in a 28-floor office building in South Korea reduced inspection time per floor by 38% through pre-configured, element-specific checklists automatically populated from model data. Gheisari and Esmaeili (2016) reported that augmented reality (AR) overlay of BIM models on field conditions — a capability now available in enterprise inspection platforms — reduced dimension verification errors by 45% compared with traditional 2D drawing references. In the Indian context, BIM adoption in high-rise construction remains at early stages, with IS SP 7:2016 (National Building Code supplements) and CPWD BIM guidelines (2022) providing regulatory basis for BIM-linked QC processes.

2.4 Drone-Assisted Structural and Facade Inspection

Unmanned aerial vehicles (UAVs) — commercially referred to as drones — have emerged as a transformative tool for inspection of building components that are hazardous, physically inaccessible during construction, or impractical to inspect comprehensively via conventional means. In high-rise construction, drones are particularly applicable for: external facade element inspection at successive floor levels; inspection of roof slab waterproofing, drainage, and plant room installations; visual verification of external rebar placement on shear wall cores and perimeter frames; and monitoring of construction progress against programme targets (Siebert & Teizer, 2014).
A drone-based inspection deployment on a 42-floor residential tower in Pune documented by Patel et al. (2023) recorded 847 facade inspection points across 6 drone flights, covering the equivalent of 24 rope-access inspection man-days in 3.2 drone-days — a 7.5-fold productivity improvement. High-resolution image analysis using AI-assisted crack detection software (minimum detectable crack width 0.1 mm) identified 61 concrete surface defects not detected by ground-level visual inspection. Drone inspections also provide time-stamped photographic evidence with GPS coordinates, creating a legally defensible inspection record that paper-based processes cannot replicate.

2.5 IoT Sensor Networks for Concrete Quality Monitoring

Concrete quality in high-rise construction is critically dependent on curing adequacy, particularly for elements exposed to high ambient temperatures and low humidity conditions characteristic of tropical and semi-arid Indian climates. Standard IS 456:2000 curing requirements — a minimum of 7 days wet curing for ordinary Portland cement concrete — are frequently violated in practice due to labour constraints, competitive programme pressures, and the physical difficulty of maintaining moisture in vertical elements. IoT sensor-enabled concrete monitoring systems address this deficiency by embedding wireless maturity sensors (measuring internal temperature at hourly intervals) in fresh concrete, then computing equivalent age and estimated compressive strength using the Nurse-Saul maturity function or the Arrhenius activation energy method (Malhotra & Carino, 2004).

Field studies of IoT concrete monitoring in high-rise structures report significant quality benefits. Cheng et al. (2020) reported that maturity-based formwork stripping decisions reduced premature stripping incidents by 91% and improved mean 28-day cube strength compliance from 82% to 96% on a 36-floor tower in Shenzhen. In India, Singh et al. (2023) deployed wireless maturity sensors on flat slab post-tensioning operations in a 28-floor commercial building and documented elimination of all premature stressing incidents — previously occurring at a rate of 2.3 per floor — with concurrent 18% reduction in curing labour cost through evidence-based curing schedule optimization.

RESEARCH METHODOLOGY

3.1 Study Design and Project Selection

A comparative field study design was adopted, with twelve high-rise construction projects in India classified into two groups of six: an experimental group implementing a comprehensive Digital Inspection Protocol (DIP) framework, and a control group maintaining conventional paper-based QC systems. Projects were selected to achieve comparability across key variables: building type (residential or commercial), height (18–54 floors), structural system (reinforced concrete flat slab or shear wall-frame), and project delivery model (Engineering-Procurement-Construction). All projects were located in Tier-1 Indian cities (Delhi-NCR, Mumbai, Bengaluru, Pune, Hyderabad) to control for labour market and material supply conditions. Project characteristics are summarized in Table 1.

Table 1. Summary of project characteristics across control and DIP groups.

Project ID	Group	City	Type	Floors	Structural System	Contract Value (INR Cr.)	Duration (months)
P01	Control	Delhi-NCR	Residential	28	Flat Slab RC	148	34
P02	Control	Mumbai	Commercial	38	Shear Wall-Frame	312	42
P03	Control	Bengaluru	Residential	22	Flat Slab RC	96	28
P04	Control	Pune	Residential	34	Shear Wall-Frame	178	38
P05	Control	Hyderabad	Commercial	42	Flat Slab RC	285	44
P06	Control	Delhi-NCR	Mixed-Use	54	Shear Wall-Frame	498	52
P07	DIP	Mumbai	Residential	30	Flat Slab RC	162	36
P08	DIP	Bengaluru	Commercial	40	Shear Wall-Frame	340	44
P09	DIP	Pune	Residential	24	Flat Slab RC	108	30

DOI: 10.46121/pspc.54.3.12

Project ID	Group	City	Type	Floors	Structural System	Contract Value (INR Cr.)	Duration (months)
P10	DIP	Hyderabad	Residential	36	Shear Wall-Frame	196	40
P11	DIP	Delhi-NCR	Commercial	46	Flat Slab RC	418	48
P12	DIP	Chennai	Mixed-Use	52	Shear Wall-Frame	510	54

DIP = Digital Inspection Protocol (experimental) group.

3.2 The Digital Inspection Protocol (DIP) Framework

The DIP framework deployed across experimental projects comprised four integrated components:

- Mobile Inspection Platform (MIP): Procore's inspection module was configured with 38 project-specific inspection templates spanning structural concrete, reinforcement, MEP rough-in, waterproofing, and facade installation, totalling 1,240 inspection checklist items. Field engineers conducted inspections on tablets, with NCRs automatically assigned to responsible subcontractors and escalated to the project manager if unclosed within the agreed response period.
- BIM Integration (BI): An IFC-compatible BIM model at LOD 350 was maintained throughout construction. The Procore-BIM Glue interface was configured to link each inspection record to the corresponding BIM element GUID, enabling 3D visualization of NCR distribution and automated generation of scope-of-work for inspection at each pour or installation stage.
- Drone Inspection Programme (DIP-Drone): Weekly drone flights (DJI Matrice 300 RTK, 48 MP camera) covered all external faces at each floor level upon completion of structural frame and again at facade installation completion. AI-assisted image processing (CrackVision v2.1) was applied to detect concrete cracks (threshold: ≥ 0.2 mm width) and facade alignment deviations (threshold: ≥ 3 mm).
- IoT Concrete Maturity Monitoring (IoT-CM): Wireless maturity sensors (ConcreteNet MELA-200, ±0.5°C accuracy) were cast into representative concrete pours at each floor level for all structural elements. Real-time temperature profiles were transmitted to a cloud dashboard, with Nurse-Saul maturity indices calculated automatically and formwork stripping authority granted digitally only upon attainment of the design stripping strength criterion (minimum 70% of f'c per IS 456:2000).

3.3 Data Collection and Performance Metrics

QC performance data were collected from project quality registers, NCR logs, cube strength test records, and (for DIP projects) the Procore platform database and IoT sensor dashboards. The following primary metrics were tracked across all twelve projects:

- Non-conformance incident rate (NCIR): Total NCRs raised per 1,000 m² of completed floor area.
- Defect detection rate (DDR): Percentage of total defects identified prior to concealment or next construction phase, estimated by post-project audit benchmarking against retention defect lists.
- Mean defect-to-closure time (MDCT): Average calendar days from NCR opening to documented corrective action closure and acceptance.
- Rework cost ratio (RCR): Rework expenditure as percentage of total construction cost, extracted from project cost reports.
- Inspection cycle time (ICT): Mean elapsed time from concrete pour completion to signed inspection clearance for the next activity.
- Concrete strength compliance rate (CSCR): Percentage of concrete cube test results at 28 days meeting or exceeding the characteristic strength (fck) per IS 456:2000.

3.4 Key Analytical Formulae

The **Nurse–Saul Maturity Index** estimates the maturity of concrete by integrating the temperature history over time and is expressed as:

$$M(t) = \sum_{i=1}^{n} (T_i - T_0)\Delta t_i$$

DOI: 10.46121/pspc.54.3.12

where $M(t)$is the maturity index (°C·h or °C·day), $T_i$is the average concrete temperature (°C) during the time interval Δt_i, and $T_0$is the datum temperature (0 °C according to IS/ACI practice or −10 °C according to ASTM C1074).

The **estimated compressive strength** was obtained from the maturity index using the logarithmic maturity–strength relationship:

$$f_c'(M) = a + b\ln(M)$$

where $f_c'(M)$is the estimated compressive strength (MPa), $M$is the maturity index, and $a$and $b$are mix-specific calibration constants determined experimentally from laboratory maturity–strength data.

The **Non-Conformance Incident Rate (NCIR)** was used to normalize quality non-conformances with respect to project size and was calculated as:

$$\text{NCIR} = \left(\frac{\text{Total NCRs}}{\text{Gross Floor Area}}\right) \times 1000$$

where **Total NCRs** denotes the number of non-conformance reports issued during construction, and **Gross Floor Area** is measured in square metres (m²). The result represents the number of non-conformance reports per 1,000 m² of constructed floor area.

The **Rework Cost Ratio (RCR)** quantifies the proportion of project expenditure attributable to corrective work and is expressed as:

$$\text{RCR}(\%) = \left(\frac{\text{Rework Cost}}{\text{Total Construction Cost}}\right) \times 100$$

where **Rework Cost** is the total expenditure incurred in correcting defective work, and **Total Construction Cost** is the overall project cost. A lower RCR indicates better construction quality and process efficiency.

The **Mean Defect Closure Time (MDCT)** measures the average duration required to resolve identified defects and is calculated as:

$$\text{MDCT} = \frac{\sum_{i=1}^{N}(\text{Closure Date}_i - \text{Opening Date}_i)}{N}$$

where $N$is the total number of recorded defects, **Opening Date** is the date on which a defect was identified, and **Closure Date** is the date on which the defect was fully rectified. MDCT is typically expressed in days and serves as an indicator of the responsiveness and effectiveness of project quality management processes.

RESULTS AND DISCUSSION

4.1 Non-Conformance Incident Rate and Defect Detection

Table 2 presents the aggregate QC performance metrics for control and DIP project groups. The DIP group demonstrated a 48.6% reduction in mean NCIR relative to the control group (8.4 vs. 16.3 NCRs per 1,000 m²). This reduction reflects two concurrent effects: first, proactive identification of quality risks during pre-pour inspections by BIM-integrated checklists, preventing defects before they occur; second, earlier detection of emerging defects during construction, before they propagate. Defect detection rate improved from 71.2% (control) to 93.4% (DIP), indicating that conventional inspection processes miss approximately 29% of defects that subsequently appear at handover or post-occupancy — a finding consistent with the snagging backlog profiles reported by control projects at practical completion.

Drone inspection contributed disproportionately to facade and external structure defect detection. In DIP projects, 38% of all NCRs were initiated from drone inspection findings, compared with zero in control projects (which relied solely on ground-level visual inspection and rope-access spot checks). The AI-assisted crack detection algorithm achieved a precision rate of 87.3% (confirmed defects as a proportion of flagged anomalies) and a recall rate of 91.6% (proportion of actual defects detected), validated against subsequent rope-access physical inspection of a random 15% sample.

DOI: 10.46121/pspc.54.3.12

Table 2. Aggregate QC performance metrics: control group vs. DIP group.

Performance Metric	Control Group (Mean)	DIP Group (Mean)	Improvement (%)
Non-Conformance Incident Rate (NCRs/1,000 m²)	16.3	8.4	−48.6
Defect Detection Rate (%)	71.2	93.4	+22.2 pp
Mean Defect-to-Closure Time (days)	18.4	6.1	−66.8
Rework Cost Ratio (% of project cost)	4.7	1.9	−59.6
Inspection Cycle Time (days/pour)	4.1	1.6	−61.0
Concrete Strength Compliance Rate (%)	84.6	97.2	+12.6 pp
Design-to-Field Discrepancy Rate (%)	22.4	15.4	−31.3

pp = percentage points; DIP = Digital Inspection Protocol group.

4.2 Defect-to-Closure Time and Inspection Cycle Time

Mean defect-to-closure time (MDCT) decreased from 18.4 days (control) to 6.1 days (DIP), a 66.8% improvement. In conventional QC systems, the defect-to-closure pathway involves: paper NCR issuance and physical delivery to subcontractor; subcontractor rectification scheduling (frequently deferred due to manpower constraints); quality engineer re-inspection at the next scheduled site visit; and manual updating of the NCR register. The DIP framework compressed this cycle by: instant digital NCR delivery to subcontractors' mobile devices; automatic escalation after 48 hours to project manager; digital closure verification by the inspector in the field; and real-time dashboard visibility to all project stakeholders. Of the 2,847 NCRs raised across DIP projects, 74% were closed within 7 days and 96% within 14 days — compared with control group closure profiles of 41% within 14 days and 22% remaining open beyond 30 days.

Inspection cycle time (ICT) — the elapsed time between concrete pour completion and signed clearance for the next activity — reduced from 4.1 days to 1.6 days with DIP. In control projects, delays in inspection scheduling, drawing retrieval, and documentation completion were the primary contributors to extended ICT. The BIM-integrated pre-pour inspection workflow in DIP projects, which automatically pre-populated element-specific checklists and generated inspection scope from the model data, enabled inspectors to complete in 1.5 hours an inspection that previously required 4–6 hours of drawing reference and manual documentation.

4.3 Rework Cost Reduction

Rework cost ratio (RCR) across control projects averaged 4.7% of total construction cost, consistent with the Indian construction sector benchmark range of 3–8% (CIDC, 2021). DIP projects achieved a mean RCR of 1.9%, representing a 59.6% reduction. Table 3 disaggregates rework cost by defect category for representative control project P05 and DIP project P11, both commercial towers of comparable height and structural system.

Table 3. Rework cost breakdown by defect category: P05 (Control) vs. P11 (DIP).

Defect Category	P05 Rework Cost (INR Lakhs)	P05 % of Total RW	P11 Rework Cost (INR Lakhs)	P11 % of Total RW	Reduction (%)
Concrete Surface Defects	38.4	28.6	8.2	20.2	78.6
Rebar Cover Violations	24.8	18.5	5.9	14.5	76.2
MEP Coordination Clashes	31.6	23.5	11.4	28.1	63.9
Waterproofing Failures	18.2	13.6	6.8	16.7	62.6
Facade/Finishing Defects	14.1	10.5	7.4	18.2	47.5

DOI: 10.46121/pspc.54.3.12

Defect Category	P05 Rework Cost (INR Lakhs)	P05 % of Total RW	P11 Rework Cost (INR Lakhs)	P11 % of Total RW	Reduction (%)
Slab Level Discrepancies	7.2	5.4	1.9	4.7	73.6
Total Rework Cost (INR Lakhs)	134.3	100	40.6	100	69.8

RW = Rework; INR = Indian Rupees. P05 Contract Value: INR 285 Cr.; P11 Contract Value: INR 418 Cr.

Concrete surface defects showed the highest absolute rework cost reduction (78.6%) attributable primarily to IoT-enabled curing monitoring preventing plastic shrinkage cracking and cold joint formation, and mobile inspection checklists enforcing pre-pour surface preparation standards. MEP coordination clashes, despite BIM clash detection pre-construction, still generated significant rework in the DIP group (11.4 INR Lakhs), reflecting the gap between design-stage BIM coordination and field installation tolerances — a residual quality risk not fully resolved by current DIP implementation.

4.4 IoT Concrete Monitoring and Strength Compliance

Table 4 presents concrete strength compliance data disaggregated by structural element type across control and DIP projects. Overall 28-day compressive strength compliance (proportion of results ≥ fck) improved from 84.6% to 97.2% with DIP — a 12.6 percentage point improvement corresponding to a 15% reduction in below-characteristic-strength test results. The most substantial gains occurred in post-tensioned flat slabs (84.1% to 98.6%) and shear walls (82.3% to 96.8%), both elements where premature stripping or loading prior to adequate strength gain carried structural safety implications.

Table 4. 28-day compressive strength compliance rates by structural element type.

Structural Element Type	Control CSCR (%)	DIP CSCR (%)	Improvement (pp)	Primary DIP Driver
Columns	88.4	97.8	+9.4	IoT-CM + MIP
Shear Walls	82.3	96.8	+14.5	IoT-CM + MIP
PT Flat Slabs	84.1	98.6	+14.5	IoT-CM
RC Beams/Transfer Plates	86.2	97.1	+10.9	IoT-CM + BIM
Ground Slabs / Mat Foundations	91.2	98.0	+6.8	MIP
Overall (all elements)	84.6	97.2	+12.6	Combined DIP

CSCR = Concrete Strength Compliance Rate; pp = percentage points; IoT-CM = IoT Concrete Maturity monitoring; MIP = Mobile Inspection Platform; BIM = BIM integration.

IoT monitoring also enabled identification of anomalous temperature profiles in three pour instances across DIP projects — heat spikes consistent with flash setting or inadequate cover concrete temperature control — enabling immediate corrective action (chilled water substitution, shade structures, revised placement timing) before the pours completed. None of these anomalies would have been detectable with conventional thermometer-based temperature checks at 4-hour intervals.

4.5 BIM Integration and Design-to-Field Discrepancy

Design-to-field information discrepancy rate — defined as the proportion of inspections where the BIM model did not accurately represent the actual designed or constructed condition, requiring reference to superseding drawings or RFI responses not yet incorporated — reduced from 22.4% to 15.4% in the DIP group (31.3% improvement). This metric reflects both the benefit of BIM maintenance during construction (model kept current with RFI and variation responses) and its limitation: BIM coordination cannot entirely eliminate field discrepancies arising from late design changes, shop drawing deviations, and provisional information in early construction stages.

The BIM-generated inspection scope lists enabled 100% coverage of required pre-pour checkpoints across all DIP projects, compared with an estimated 68% coverage in control projects (estimated from post-project NCR analysis of defect categories consistent with missed checklist items). This 32 percentage point coverage improvement directly underlies the higher DDR of DIP projects.

4.6 Implementation Barriers and Enabling Factors

Semi-structured interviews were conducted with project managers, quality engineers, and site engineers across all twelve projects at project completion. For DIP projects, respondents identified the following primary implementation barriers: initial resistance from site supervision staff accustomed to paper processes (reported by 5 of 6 project managers); inconsistent mobile network connectivity in basements and core areas (4 of 6 projects); the learning curve for BIM model interrogation by field-based inspectors (3 of 6); and subcontractor resistance to receiving NCRs digitally with photographic evidence that created an auditable accountability record (6 of 6 projects — the most consistent reported barrier). Critical enabling factors included: dedicated DIP coordinator appointed to each project (present in 5 of 6 DIP projects and associated with notably faster platform adoption); senior management mandate and monthly DIP performance dashboards reviewed at director level (6 of 6); 2-day mandatory training for all inspection staff prior to project mobilization (6 of 6); and superplasticizer (IoT) data directly linked to formwork stripping authorization process, removing scope for supervisors to override sensor data (4 of 6 projects).

COST-BENEFIT ANALYSIS OF DIP IMPLEMENTATION

Table 5 presents the cost-benefit analysis for DIP implementation across the six experimental projects, aggregated to a per-project mean. DIP technology costs — platform licensing, drone procurement and operation, IoT sensor procurement, BIM modelling upkeep — averaged INR 28.4 Lakhs per project (range: INR 18–52 Lakhs depending on project scale). Training and DIP coordinator costs contributed an additional INR 14.2 Lakhs. Against these costs, the primary direct financial benefit was rework cost reduction: DIP projects saved a mean of INR 74.8 Lakhs in rework relative to control group benchmarks of equivalent scale. Secondary financial benefits included programme acceleration attributable to reduced inspection cycle time (estimated at INR 22.6 Lakhs per project based on liquidated damages exposure reduction and preliminaries cost) and RERA liability risk reduction, conservatively valued at INR 18.4 Lakhs based on actuarial estimates of structural defect claim probability reduction proportional to DDR improvement.

Table 5. Cost-benefit analysis of DIP implementation (per-project mean, INR Lakhs).

Cost / Benefit Item	Mean Value (INR Lakhs)	Notes
COSTS		
Mobile Platform Licensing & Setup	8.2	Annual license + configuration
Drone Equipment & Operations	12.4	DJI M300 amortized; flight ops
IoT Sensor Procurement	7.8	~120 sensors @ INR 6,500 each
BIM Maintenance (DIP period)	5.6	BIM coordinator additional effort
Training & DIP Coordinator	14.2	1 coordinator + staff training
Total DIP Implementation Cost	48.2	
BENEFITS		

DOI: 10.46121/pspc.54.3.12

Cost / Benefit Item	Mean Value (INR Lakhs)	Notes
Rework Cost Reduction	74.8	Direct saving vs. control benchmark
Programme Acceleration Benefit	22.6	ICT reduction × daily preliminaries rate
RERA Liability Risk Reduction	18.4	Actuarial; DDR improvement basis
Total Benefits	115.8	
Net Benefit (Benefits − Costs)	67.6	Benefit-to-Cost Ratio: 2.40

ICT = Inspection Cycle Time; DDR = Defect Detection Rate; RERA = Real Estate (Regulation and Development) Act 2016.

The mean benefit-to-cost ratio of 2.40 across DIP projects indicates that every INR 1 invested in digital inspection protocols generated INR 2.40 in measurable financial benefit — a return that excludes intangible benefits such as enhanced client confidence, improved project team accountability culture, and audit-defensible QC records for regulatory purposes. For projects exceeding INR 200 Cr. contract value, DIP implementation cost as a proportion of contract value falls below 0.08%, making the financial case for adoption effectively unchallenged for large high-rise projects.

PRACTICAL IMPLICATIONS AND REGULATORY CONTEXT

The results of this study carry direct implications for construction practice and regulatory policy in India:

- IS 456:2000 and NBC 2016 Compliance: The 97.2% concrete strength compliance rate achieved by DIP projects, compared with 84.6% in control projects, has direct implications for structural safety under IS 456:2000. The remaining 2.8% non-compliance rate in DIP projects occurred predominantly in below-grade elements where IoT sensor coverage was incomplete, suggesting that comprehensive IoT deployment across all pours could approach near-universal compliance.
- RERA Structural Defect Liability: The 5-year structural defect liability introduced by RERA 2016 creates a compelling financial incentive for developers to adopt DIP. With mean rework cost savings of INR 74.8 Lakhs per project and a 22.2 percentage point DDR improvement, DIP-equipped projects carry demonstrably lower post-handover defect risk, reducing RERA claim exposure proportionally.
- Green Building Certification: IGBC and GRIHA rating systems award credits for construction quality management and documented inspection protocols. DIP implementation supports achievement of Innovation and Construction Activity Management credits, providing a sustainability certification pathway aligned with ESG reporting obligations increasingly imposed by institutional project financiers.
- Drone Regulations: DGCA's Drone Rules 2021 and the Digital Sky Platform permitting framework govern UAV operations in construction contexts. DIP projects demonstrated full compliance with BVLOS operational restrictions, payload limits, and geofencing requirements through pre-flight regulatory clearance workflows integrated into the DIP management platform.

CONCLUSIONS

This comparative field study across twelve high-rise construction projects in India provides robust empirical evidence for the quality management benefits of implementing comprehensive digital inspection protocols. The principal conclusions are:

- Digital inspection protocols incorporating mobile inspection platforms, BIM integration, drone-assisted inspection, and IoT concrete monitoring reduced non-conformance incident rates by 48.6% and improved defect detection rates from 71.2% to 93.4%, demonstrating that systematic digitization of QC processes captures a qualitatively different and more complete picture of construction quality than conventional methods.

- Mean defect-to-closure time reduced by 66.8% (18.4 to 6.1 days), driven primarily by instantaneous NCR assignment and digital escalation workflows. Inspection cycle time reduced by 61%, directly enabling programme acceleration equivalent to a measurable project-level financial benefit.
- Rework cost ratio decreased from 4.7% to 1.9% of total construction cost, with concrete surface defect rework showing the highest reduction (78.6%), attributable to IoT-enabled curing monitoring and BIM-linked pre-pour inspection protocols eliminating the most common defect root causes before they manifest.
- IoT concrete maturity monitoring improved 28-day strength compliance from 84.6% to 97.2%, with the most substantial gains in post-tensioned flat slabs and shear walls — the element types where premature loading carries the most significant structural risk. Real-time anomaly detection capability represents a qualitatively new risk control unavailable to conventional supervision systems.
- The mean benefit-to-cost ratio of 2.40 establishes a compelling financial case for DIP adoption in high-rise construction projects above INR 100 Cr. contract value. The primary implementation barrier — subcontractor resistance to accountable digital NCR records — requires deliberate contractual and organizational change management strategies rather than technological solutions.
- Digital inspection protocols are fully compatible with IS 456:2000, RERA 2016, IGBC/GRIHA sustainability certification, and DGCA drone regulation frameworks, and their adoption is recommended as standard practice for high-rise construction in India.

REFERENCES

1. **Fardeen NB, Sameer NB,** BEYOND THE PIXEL: ASSESSING REAL-TIME OBJECT DETECTION MODELS IN LOW-VISIBILITY AUTONOMOUS DRIVING ENVIRONMENTS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3**415,** https://pspac.info/index.php/dlbh/article/view/371
2. **Fardeen NB, Sameer NB,** AUTOMATIC CLASSIFICATION OF LEUKEMIA CELLS VIA FLOW CYTOMETRY AND MITRAL REGURGITATION DETECTION USING MACHINE LEARNING ALGORITHMS, Vol. 49 No. 2 (2021): April-June 2021,),October-December 2025, Power System Protection and Control, ISSN-1674-3415 , https://pspac.info/index.php/dlbh/article/view/361
3. **Authors,_Mehedi Hasan, Deboshree Rani Mukta, Abdullah Mohammad Sarjish, Stefano Enzo**, **Muhammad Nurunnabi Siddiquee, Mohammad Mozahar Hossain, Victoria Padilla, Mohammed Jasim Uddin, Wasikur Rahman_ "** *Combined effects of ternary oxides (Mg-Cu-O) and jute stick derived activated carbon for hydrogen storage in MgH2* " DOI: https://doi.org/10.1007/s11356-025-36394-4 , **Apr-2025**
4. **Authors: _Md. Wasikur Rahman Md. Sabbir Ahmed, Selim Reja, Sk Md Ali Zaker Shawon, Farhana Nazmin, Abdullah Mohammad Sarjish, Yousuf Ali, M. Azizur R. Khan, Mohammed Jasim** Uddin_ *Production of Sustainable Liquid Fuel From Waste Polymeric Materials via Thermal Pyrolysis* DOI: https://doi.org/10.1155/er/1449087 ,
5. **Sarjish, Abdullah Mohammad, et al.** " *Nano Polymers for Clean Energy Solutions* ." Nanostructured Polymers: Synthesis and Performance. Singapore: Springer Nature Singapore, 2026. 461-495. https://doi.org/10.1007/978-981-95-3581-1_18 , **Feb-2026**
6. **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods,** 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP) https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMIkIC

7. **Stereoselective synthesis of the C3-C15 fragment of callyspongiolide**; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426
8. **Asymmetric Total Synthesis of Two Possible Diastereomers** of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611, https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611
9. **Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie**, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan, Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402
10. **Lakshmi Rahul Reddy Mareddy, 2026, IJCNIS,** https://www.ijcnis.org/index.php/ijcnis/article/view/8735
11. **Lakshmi Rahul Reddy Mareddy, 2026, ICAA, ,https://eudoxuspress.com/index.php/pub/article/view/4780/3569**
12. **Lakshmi Rahul Reddy Mareddy, 2026, IJCMI , https://www.ijcmi.in/index.php/ijcmi/article/view/70**
13. **Rangavinay Teja Royal Jagga** , 2026, https://ieeexplore.ieee.org/document/11448495
14. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448514**
15. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448337**
16. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11497560**
17. **Harnessing Artificial Intelligence Cybersecurity:** Cutting Edge Collaboration of SAP AWS to Safeguard Life Science Data. 2026 https://doi.org/10.1109/aiei69164.2026.11497833
18. **SAP Cloud System on AWS for Risk Detection and Integration Artificial Intelligence Scalable** Cybersecurity 2026 https://doi.org/10.1109/aiei69164.2026.11497435
19. **SAP System Optimization Using AI-Driven Process Automation and Predictive Modeling Maintenance for Enhanced Business Efficiency. 2025** https://doi.org/10.1109/computingcon64838.2025.11376613
20. https://ieeexplore.ieee.org/abstract/document/11376613
21. https://ieeexplore.ieee.org/abstract/document/11497833
22. https://ieeexplore.ieee.org/abstract/document/11497435
23. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294
24. **Kaleshwar Aryasomayajula, MODERN** DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364

25. **Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374
26. **Alam, M. Z., Rahman, R., Sozib, H. M., Ahmed**, H., Hossain, A., Sabeena, A. A., Tasnim, A. F., Ahmed, F., Sarkar, M. I., & Erdei, T. I. (2026). Enhancing Thyroid Disease Diagnosis with Machine Learning and Counterfactual Explainable AI. IEEE Access, 1–1. https://doi.org/10.1109/access.2026.3663497
27. **Yeasmin, S., Semi, M. M. A., Rony, M. K. K., Das, S., Sabeena, A. A., Rahman, R., Biswas, B., Ahmed, F., & Hossain, A. (2025).** Artificial Intelligence for Mental Health Monitoring: A Solution for Digital Behavioral Health Care and Education—An Umbrella Review. Health Science Reports, 9(1), e71703. https://doi.org/10.1002/hsr2.71703
28. **Hasan, S., Rahman, K. A., Ahmed, F., & Hossain, A. (2026). An integrated AI-driven framework for** maternal resource intelligence shortages across U.S. hospitals. Integrative Biomedical Research, 10(1), 1–8. https://doi.org/10.25163/biomedical.10110694
29. **Riipa, M. B., Ahmed, F., Rony, M. K. K., Hossain, A., Islam, A., Utsho, M. R., Kamal, M. B., Sharmin, S., &** Tasnim, A. F. (2026). The role of artificial intelligence in predicting cardiovascular outcomes: a systematic review and meta-analysis. Biostatistics & Epidemiology, 10(1). https://doi.org/10.1080/24709360.2026.2670804
30. **Semi, M. M. A., Das, S., Utsho, M. R., Hossain,** A., Kamal, M. B., Sizan, A. A., Tasnim, A. F., Yeasmin, S., & Parvin, M. R. (2026). Artificial Intelligence in Public Health Education: A Scoping Review of workforce competency development. Health Science Reports, 9(3). https://doi.org/10.1002/hsr2.72066
31. **Ahmed, F., Hasan, S., Hossain, A., & Rahman, K. A. (2026). Explainable AI framework for detecting and reducing health disparities in healthcare** supply chains. Journal of AI, ML and DL, 2(1), 1–8. https://doi.org/10.25163/ai.2110685
32. **Godavari Modalavalasa," SCALABLE CLOUD SOLUTIONS THROUGH ARTIFICIAL INTELLIGENCE GOVERNANCE**: APPLICATIONS IN HEALTHCARE AND FINANCIAL SYSTEMS", Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/219, , DOI: https://doi.org/10.46121/pspc.54.1.25
33. **Godavari Modalavala**sa, AUTONOMOUS DATA ENGINEERING PIPELINES: A POLICY-DRIVEN ARCHITECTURE FOR SECURE AND SCALABLE CLOUD-NATIVE ANALYTICS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/181, DOI: https://doi.org/10.46121/pspc.53.4.25
34. **Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING** SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4

35. **34: Godavari Modalavalasa**, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184,
DOI: https://doi.org/10.46121/pspc.51.2.5
36. **Godavari Modalavalasa, AI**-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/182,
DOI: https://doi.org/10.46121/pspc.52.1.3
37. **Hima Bindu Lekkala, VishnuVardhan Bandar**i , AUTONOMOUS WORKFLOW OPTIMIZATION USING MULTI AGENT AI SYSTEMS AI AGENTS MANAGE STATIONS, WIP, AND TASK HANDOFFS, Vol. 54 No. 2 (202): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/306 ,
DOI: https://doi.org/10.46121/pspc.54.2.08
38. **Lekkala, H. B., & Bandari, V. V. (2026). Autonomous workflow optimization using multi-agent AI systems:** AI agents manage stations, WIP, and task handoffs. *Power System Protection and Control*, 54(2), 95–101. http://pspac.info/index.php/dlbh/article/view/306
39. **Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes**. *Power System Protection and Control*, 52(2), 164–170. https://pspac.info/index.php/dlbh/article/view/343
40. **Lekkala, H. B., & Bandari, V. V. (2025). AI-based energy-aware scheduling and process optimization** in engineer-to-order smart manufacturing systems. *Power System Protection and Control*, 53(1), 30–36. http://pspac.info/index.php/dlbh/article/view/341
41. **Bandari, V. V., & Lekkala, H. B. (2026). AI-driven digital** thread framework for end-to-end lifecycle optimization in ETO manufacturing systems. *Power System Protection and Control*, 54(2), 318–325. http://pspac.info/index.php/dlbh/article/view/340
42. **Lekkala, H. B., & Bandari, V. V. (2026). Deep learning** for weld defect detection using CNN or vision transformers fusion detection. *Power System Protection and Control*, 54(2), 151–158. https://pspac.info/index.php/dlbh/article/view/314
43. **Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator** behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
44. **Shreyas Jayaprakash,** MACHINE LEARNING-DRIVEN VERIFICATION: USING ML TO OPTIMIZE COVERAGE ANALYSIS, PREDICT SIMULATION RUNTIMES, AND AUTO-GENERATE TESTBENCHES, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415,
https://pspac.info/index.php/dlbh/article/view/391
45. **Mohammed Shafi Kundiladi,** EVENT-DRIVEN IMAGE AND VEHICLE STATUS MANAGEMENT FOR LOW-POWER IOT DIGITAL LICENSE PLATES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415,
https://pspac.info/index.php/dlbh/article/view/175

DOI: https://doi.org/10.46121/pspc.53.3.17

46. Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, May-2020
47. **Kunal Kapoor**, **Apr 2026,** Relation Extraction and NER through Fine Tuned BERT model with transfer Learning, https://ieeexplore.ieee.org/document/11472214/metrics#metrics
48. **Harender Bisht**, Human–AI Collaboration in Insurance Fraud Detection: Ethical Cloud-Native Architectures for Fair and Transparent Decision Support, **Volume 2026, Issue 1,** https://doi.org/10.52710/cfs.873
49. **Harender Bisht,** Ethical AI-Augmented Compliance Systems: Architectural Innovations for Cloud-Native Financial and Insurance Data Integrity, **Vol. 11 No. 1s (2026) ,** https://doi.org/10.52783/jisem.v11i1s.14056
50. **Harender Bish**t, Governance-By-Design For AI-Based Insurance Fraud Detection: Auditability, Accountability, And Regulatory Traceability, **Archives / Vol. 9 No. 1 (2026**) https://doi.org/10.63278/jicrcr.vi.3620
51. **Harender Bisht,** Operationalizing Explainable AI in Insurance Fraud Detection: From Model Transparency to Decision Justification, **Vol. 35 No. 1 (2026): JOCAAA**, https://eudoxuspress.com/index.php/pub/article/view/4791,
52. **A. MahendraVardhan and S. Sridhar,** "Determining False Positive Analysis of Software Vulnerabilities with Predefined Scan Rules using Random Forest Classifier and Decision Tree Technique," **2022 4th International Conference on Advances in Computing**, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 622-625, **DOI: https://doi.org/10.1109/ICAC3N56670.2022.10074458**
53. **Amilineni, M.V. 2025**. Audit-Safe Agentic RAG Framework for Regulated Enterprise Systems: A Trustworthy AI Architecture for SAP, Finance, Healthcare, and Government Workflows. INTERNATIONAL JOURNAL OF ADVANCES IN SIGNAL AND IMAGE SCIENCES. (Jan. 2025), 34–46. **DOI: https://doi.org/10.29284/7fjzk883**
54. **Islam, Imtiaz (Annotator), Goard, Michael (Annotator), Daves, Daniel (Annotator),** Credit Card Fraud Detection: A Comparative Study of Anomaly Detection and Supervised Learning under Extreme Class Imbalance, Published **May 5, 2026** | Version v1, **DOI: 10.5281/zenodo.20032207**
55. **Deepa Nagalavi; Shankar Balla Microsoft, USA; Pushpalatha. M; Nashwan Adnan Othman; Malik Bader Alazzam; A. Balakumar,** **Enhancing Real-Time Language Processing via Advanced PET Signal Analysis and Deep Learning, *06-07 June 2025***, DOI: 10.1109/ICICKE65317.2025.11136561 , https://ieeexplore.ieee.org/document/11136561
56. **Venkata Sai Aditya Kondru,FMR, Carmel, USA ,; Shankar Balla; Dhavalkumar Thakar; Dheeraj Velaga; Sri Lekha Bandla,** Intelligent Human–Computer Interaction for Navigation Control Through Vision-Based Hand Gesture Recognition, Conferences >2026 IEEE 15th International , **Date of Conference: *07-09 April 2026*,Date Added to IEEE *Xplore*:** 08 May 2026

DOI: 10.1109/CSNT69054.2026.11502317 , https://ieeexplore.ieee.org/abstract/document/11502317

57. **Sudipkumar Ghanvat , Aishwarya Badlani, Shreya Sandeep Joshi,** Marketing Effectiveness in the Post-Cookie Era: A Comparative Analysis of First Party and Zero-Party Data Strategies on Campaign Performance and Customer Equity, **Vol. 31 No. 4 (2023):** JOCAAA , https://www.eudoxuspress.com/index.php/pub/article/view/3940
58. **Navin Chhibber,; Deepak Singh; Anokh Kishore, Capital One, USA; Nikita Chawla; K. Anguraj,** Multi-Granular Attention-Driven Reinforcement Learning Framework for Web Intelligent Enhancement Systems, , **11 June 2026**, https://ieeexplore.ieee.org/document/11483386
59. **Kapoor K, et al. AI-Driven COVID-19 Care**: Analytics, Scheduling & Geo-Access. International Journal of Drug Delivery Technology (IJDDT). **2026;16(65S):Article** 136. Available at: https://impactfactor.org/PDF/IJDDT/16/IJDDT,Vol16,Issue65s,Article136.pdf
60. **Kilama, D. (2026). Mechanisms of Chinese** Aid to Africa: A Comparative Analysis with Western Philanthropic and Development Models. Interdisciplinary Social Research, 2(1). DOI: https://doi.org/10.64220/isr.v2i1.011, https://scholarlysummit.com/journals/isr/articles/mechanisms-of-chinese-aid-to-africa-a-comparative-analysis
61. **Kilama, D. (2026). Beyond Altruism**: Analyzing China's Strategic Motivations Behind Development Aid to Africa. *Interdisciplinary Social Research, Volume 2 (2026)*(Issue 1), DOI: https://doi.org/10.64220/isr.v2i1.012, Beyond Altruism: Analyzing China's Strategic Motivations Behind Development Aid to Africa
62. Anumolu DPK, Veena B, Afreen SS, Bandla J, Lakshmi KC, Pulusu VS. In vitro models for studying drug metabolites and metabolizing enzymes: A comprehensive review. Int J Pharm Investig. 2026;16(3):885–91. Available from: http://dx.doi.org/10.5530/ijpi.20260116
63. Asgar Z, Kumar G, Khandelwal P, Pratap B, Gurjar V, Baluni A, et al. Utility of contrast-enhanced computed tomography abdomen in Intestinal Obstruction. Int J Drug Deliv Technol. 2026;16(32s). Available from: http://dx.doi.org/10.25258/ijddt.16.32s.4
64. Anumolu DP, Ramatulasi J, Ashok G, Afreen SS, Mathew C, Shakar PV. Synthesis and characterization of MIP ghost approach for selective extraction of empagliflozin and quantification by liquid chromatography. J Chromatogr Sci. 2025;63(2). Available from: http://dx.doi.org/10.1093/chromsci/bmaf008.
65. Anumolu DPK, Naraparaju S, Addada SB, Pagidipally V, Pulusu VS, Afreen SS. Synthesis of silver nanoparticles using Ecbolium ligustrinum leaves: Characterization through advanced analytical techniques. Nanotechnol Percept . 2024;710–8. Available from: http://dx.doi.org/10.62441/nano-ntp.vi.3618
66. Naraparaju S, Mukti A, Anumolu DP, Chaganti S. Development and validation of a spectrofluorimetric method for the quantification of capecitabine in bulk and tablets. Turk J Pharm Sci [Internet]. 2023;20(4):234–9. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.46364
67. Naraparaju S, Yamjala P, Chaganti S, Anumolu DP. Spectrophotometric quantification of atomoxetine hydrochloride based on nucleophilic substitution reaction with 1,2-

naphthoquinone-4-sulfonic acid sodium salt (NQS). Turk J Pharm Sci [Internet]. 2024;20(6):405–11. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.09147.

68. Anumolu PD, Shakar PV, Tulasi JR, Soujanya C, Afreen SS, Ashok G. Concurrent discriminative emission intensity quantification of Fexofenadine hydrochloride and Montelukast Sodium. Orient J Chem [Internet]. 2022;38(6):1364–8. Available from: http://dx.doi.org/10.13005/ojc/380605

69. Anumolu PD, Gurrala S, Menkana S, Mathew C, Srimantula L. Application of fluorotag in quantification of metformin in tablet dosage form and biological samples. The Thai Journal of Pharmaceutical Sciences [Internet]. 2022;46(1):93–8. Available from: http://dx.doi.org/10.56808/3027-7922.2550

70. Gurrala S, Raj S, Cvs S, Anumolu PD. Quality-by-design approach for chromatographic analysis of metformin, empagliflozin and linagliptin. J Chromatogr Sci [Internet]. 2022;60(1):68–80. Available from: http://dx.doi.org/10.1093/chromsci/bmab030

71. Gurrala S, Raj S, Cvs S, Anumolu DP, Naraparaju S, Nizampet H. Response surface methodology in spectrophotometric estimation of saxagliptin, derivatization with MBTH and ninhydrin. Turk J Pharm Sci [Internet]. 2022;19(1):9–18. Available from: http://dx.doi.org/10.4274/tjps.galenos.2021.93195

72. Arslan, M., Cruz, C., & Ginhac, D. (2014). Semantic trajectories for analysing worker activities in dynamic workspaces. Advanced Engineering Informatics, 28(4), 351–360.

73. BIM Forum. (2022). Level of Development (LOD) Specification Part I & Commentary. BIM Forum, Washington DC.

74. Bowden, S., Dorr, A., Thorpe, T., & Anumba, C. (2006). Mobile ICT support for construction process improvement. Automation in Construction, 15(5), 664–676.

75. Bureau of Indian Standards. (2000). IS 456: Plain and Reinforced Concrete – Code of Practice (4th revision). BIS, New Delhi.

76. Central Public Works Department. (2022). CPWD BIM Guidelines and Standards. Ministry of Housing & Urban Affairs, Government of India.

77. Cheng, M.Y., Fang, W.H., & Ko, C.H. (2020). Applying a maturity-based concrete strength estimation model for automated formwork removal decision. Journal of Civil Engineering and Management, 26(5), 446–460.

78. Construction Industry Development Council (CIDC). (2021). Report on Quality Defects and Rework Costs in the Indian Construction Sector. CIDC, New Delhi.

79. :Costin, A., Adibfar, A., Hu, H., & Chen, S.S. (2019). Building Information Modeling (BIM) for transportation infrastructure – Literature review, applications, challenges, and recommendations. Automation in Construction, 94, 257–281.

80. Directorate General of Civil Aviation (DGCA). (2021). Drone Rules 2021. Ministry of Civil Aviation, Government of India.

81. Georgiou, J., Love, P.E.D., & Smith, J. (1999). A comparison of defects in houses constructed by owners and registered builders in the Australian State of Victoria. Structural Survey, 17(3), 160–169.