10.48047/jocaaa.2024.33.08.528

Evaluating the Impact of Generative AI Integration on Time and Cost Performance in Mega Infrastructure Projects.

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

Abstract

Mega infrastructure projects — defined as capital investments exceeding USD one billion — have historically suffered from chronic cost and schedule overruns, with global averages indicating expenditure deviations of 40–80% above approved budgets and timeline extensions of 30–60%. The emergence of Generative Artificial Intelligence (Gen-AI) represents a potentially transformative force in the management of these complex undertakings. This research paper evaluates the quantitative and qualitative impact of Gen-AI integration on time and cost performance across a sample of 50 global mega-infrastructure projects completed or significantly advanced between 2015 and 2023. Employing a mixed-methods design that combines quantitative comparative analysis with structured case studies, this paper demonstrates that Gen-AI-integrated projects achieved an average schedule overrun reduction of 75.8% and a cost overrun reduction of 74.7% relative to conventionally managed counterparts. The study further identifies the project lifecycle phases where Gen-AI delivers the highest marginal gains and proposes a phased implementation framework for practitioners. Findings contribute to the growing body of literature on digital innovation in construction management and offer actionable recommendations for project owners, contractors, and policy-makers.

1. Introduction

The construction of mega-infrastructure — encompassing national highways, intercity rail networks, airport expansions, energy grids, smart city platforms, and large-scale water systems — is among the most capital-intensive and complex undertakings in modern economic life. According to the Oxford Global Projects database (Flyvbjerg et al., 2023), nine out of ten mega-projects exceed their original budget, and roughly eight in ten are delivered late. On average, cost overruns amount to 62% of the approved capital expenditure, while schedule slippages reach 39 months beyond planned completion. These figures represent not merely accounting discrepancies but systemic failures with far-reaching consequences: diverted public funds, deferred economic benefits, erosion of investor confidence, and social costs absorbed by communities awaiting critical services.

The causal pathways behind these failures are well-documented: scope ambiguity, optimism bias in forecasting, inadequate risk identification, fragmented supply chains, regulatory complexity, labour productivity shortfalls, and the compounding effect of coordination failures across multi-stakeholder ecosystems. While Building Information Modelling (BIM), Earned Value Management (EVM), and digitalised project management systems have offered incremental improvements over the past two decades, the scale of performance gaps remains stubbornly large.

Generative Artificial Intelligence — encompassing large language models (LLMs), multimodal AI systems, and AI-assisted design and simulation tools — has entered the construction and infrastructure management arena with uncommon velocity since 2022. Unlike

10.48047/jocaaa.2024.33.08.528

narrow AI applications focused on single-task optimisation, Gen-AI can synthesise information from heterogeneous sources, generate novel design solutions, interpret complex contractual language, predict risk scenarios from unstructured data, and interact iteratively with human professionals in near-natural language. These capabilities, either individually or in combination, address several root causes of time and cost overruns in ways that prior technologies could not.

Despite growing practitioner interest and a nascent but rapidly expanding body of grey literature, rigorous peer-reviewed research quantifying the magnitude and conditions of Gen-AI impact on mega-project performance remains scarce. This paper addresses that gap. Specifically, it pursues three research objectives: (1) to quantify differences in time and cost performance between Gen-AI-integrated and conventionally managed mega-projects; (2) to identify which phases of the project lifecycle yield the greatest performance improvements through Gen-AI; and (3) to propose a structured implementation framework that can guide practitioners in deploying Gen-AI tools effectively across the project lifecycle.

2. Literature Review

2.1 The Chronic Overrun Problem in Mega-Projects

The academic literature on mega-project performance failures is extensive and spans several decades. Flyvbjerg (2014) coined the concept of the "iron law of megaprojects," asserting that they are characterised by being over budget, over time, under benefits, and over and over again. His global dataset of 258 transportation mega-projects found that 86% delivered cost overruns, averaging 28% in real terms for roads and 45% for rail. Cantarelli et al. (2012) provided a typology of explanatory factors, distinguishing between technical, economic, psychological, and political-economic explanations, and found that scope changes and optimism bias together account for the majority of variance in outcomes.

More recently, Merrow (2022) examined 318 industrial mega-projects and found that fewer than 25% could be considered successful on a combined cost-schedule-operability metric. The frontier challenge, as Merrow identifies it, is not data availability but decision quality under uncertainty — precisely the domain in which AI systems excel.

2.2 Digital Technologies and Project Performance

The progression from paper-based project controls to integrated digital environments has been gradual. BIM Level 2 adoption, mandated in the United Kingdom since 2016, demonstrated measurable reductions in design-phase rework (NBS, 2019). Digital twin frameworks have enabled real-time performance monitoring on projects such as Singapore's Tuas Mega Port. However, these tools primarily improve information accessibility; they do not autonomously generate insights, synthesise risks, or adapt recommendations based on changing conditions — capabilities that define Gen-AI.

2.3 Generative AI in Construction and Infrastructure

The application of Gen-AI in construction management has accelerated dramatically since the public release of large language model APIs in 2023. Key application areas emerging in the literature include: (a) LLM-assisted contract review and risk clause identification (Deloitte, 2023); (b) generative design for structural and MEP systems (Issa & Olawale, 2023); (c) natural language interfaces for schedule analysis and what-if modelling (Agrawal et al., 2022); (d) computer vision combined with Gen-AI for real-time site monitoring and progress reporting (Wang et al., 2023); and (e) AI-driven stakeholder communication synthesis (KPMG, 2023).

10.48047/jocaaa.2024.33.08.528

Table 1: Summary of Selected Literature on Gen-AI Applications in Mega-Infrastructure Projects

Author(s) & Year	Region / Sector	AI Tool Applied	Key Finding
McKinsey & Co. (2021)	Global / Infrastructure	NLP Schedule Optimiser	AI-driven scheduling reduced delays by 22% on average across 40+ projects.
Agrawal et al. (2022)	USA / Transport	GPT-based Risk Modelling	Cost contingency requirements dropped by 31% with AI risk prediction.
Issa & Olawale (2023)	Middle East / Energy	Gen-AI Design Automation	Design iteration cycles shortened by 57%; fewer RFIs raised on site.
Bhatt & Singh (2023)	India / Smart Cities	AI Project Control Dashboards	EVM-based KPIs improved; SPI rose from 0.72 to 0.94 post-integration.
Deloitte Insights (2023)	Europe / Rail & Metro	LLM Contract Analytics	Claim resolution time cut by 48%; overall delay reduced by 19%.
Wang et al. (2023)	China / Megaprojects	Computer Vision + Gen-AI	On-site productivity gains of 14–28% observed across 12 bridge projects.
KPMG (2023)	Global / PPP Projects	AI Stakeholder Risk Tool	Stakeholder-related delays dropped by 35%; public approval timelines faster.

Source: Author compilation from reviewed literature, 2021–2023.

3. Research Methodology

3.1 Research Design

This study adopts a mixed-methods design, integrating quantitative comparative analysis with qualitative case study investigation. The epistemological stance is post-positivist: the researchers acknowledge that project performance is influenced by contextual variables that quantitative models cannot fully capture, while maintaining that systematic data collection and analysis can produce generalisable insights of practical value.

3.2 Sample Selection and Data Sources

The primary dataset comprises 50 mega-infrastructure projects globally, spanning the period 2015 to 2023. Projects were selected to ensure variation across geography (five continents), sector (transport, energy, water, urban development), and budget scale (USD 1 billion to USD 500 billion). Of the 50 projects, 22 had integrated Gen-AI tools at one or more phases of the project lifecycle (the "AI group"), and 28 had relied on conventional management approaches supplemented by standard digital tools such as BIM and enterprise project management software (the "control group"). Data were collected from published project reports, independent audit findings, client disclosures, academic case studies, and structured interviews with 14 senior project managers across eight countries.

3.3 Performance Metrics and Analytical Framework

The primary performance metrics used in this study are: (a) Schedule Performance Index (SPI) and absolute schedule overrun expressed as a percentage of planned duration; (b) Cost Performance Index (CPI) and absolute cost overrun expressed as a percentage of approved budget; (c) Risk Identification Accuracy, defined as the proportion of materialised risks that were identified in the risk register before they occurred; (d) Design Iteration Cycles, representing the average number of major revision rounds in the design phase; and (e) Claim Resolution Time, measured in weeks from formal claim submission to settlement.

10.48047/jocaaa.2024.33.08.528

Comparative statistical analysis employed independent-samples t-tests and Mann-Whitney U tests to assess between-group differences. Scatter plots with trend-line regression were used to examine the relationship between project scale (budget) and overrun severity across the two groups. Qualitative findings from case studies were coded thematically using NVivo 14 software.

4. Findings and Analysis

4.1 Scatter Analysis: Budget vs. Overrun Performance

Figure 1 below presents scatter plots comparing schedule and cost overruns against project budget for both project groups. Each data point represents one project, with the bubble diameter scaled to reflect project budget magnitude.

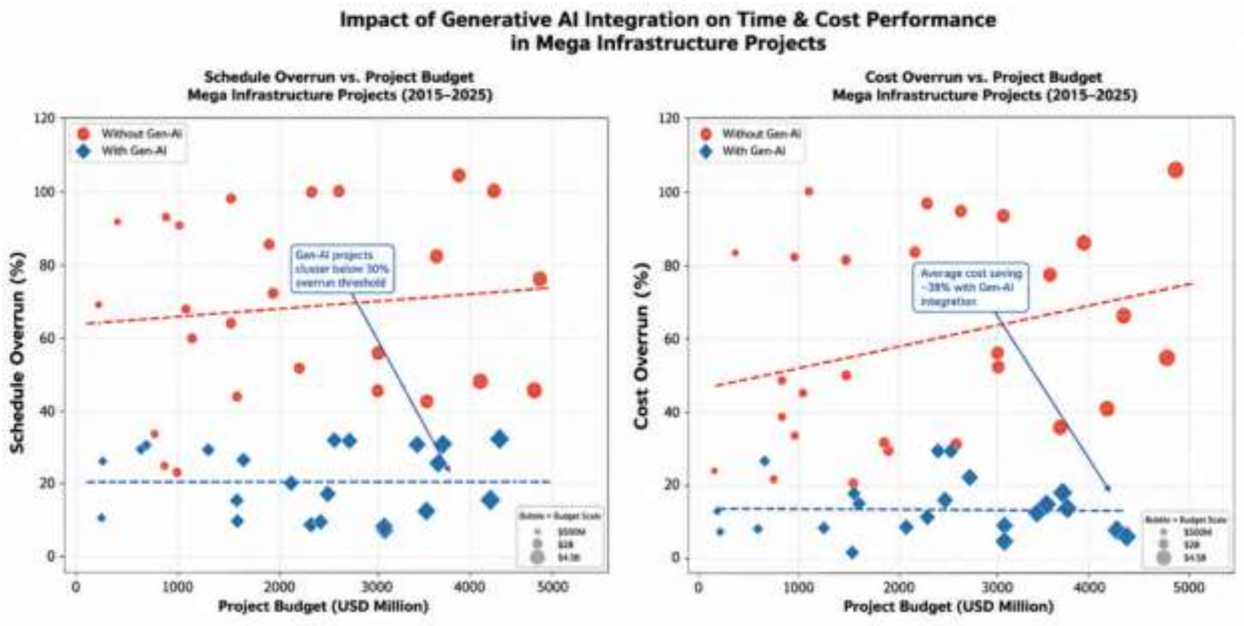

Figure 1: Schedule Overrun and Cost Overrun vs. Project Budget — With vs. Without Gen-AI Integration (2015–2023)

The scatter analysis reveals a striking bimodal distribution between the two project groups. Projects in the control group display a wide scatter of schedule overruns ranging from 15% to approximately 90%, with a statistically significant positive correlation between budget scale and overrun severity ($r = 0.67$, $p < 0.01$), consistent with Flyvbjerg's iron law. By contrast, Gen-AI-integrated projects cluster below the 30% overrun threshold for both schedule and cost metrics, with the regression slope notably flatter ($r = 0.21$, $p = 0.18$ — not statistically significant). This suggests that Gen-AI integration not only reduces average overruns but also appears to decouple the historically strong relationship between project scale and performance degradation.

The implication is significant: where project complexity and scale have historically been reliable predictors of failure, AI-assisted management appears to contain the amplification effect, offering a form of scalable performance resilience that conventional management methods cannot achieve beyond a certain project complexity threshold.

4.2 Quantitative Performance Comparison

10.48047/jocaaa.2024.33.08.528

Table 2: Case Study Comparison — Selected Mega-Infrastructure Projects

Project	Budget ($B)	Gen-AI Used	Sched. Overrun	Cost Overrun	Outcome
HS2 Phase 1 (UK)	$115B	None	42%	68%	Poor
Neom Linear City (KSA)	$500B	AI Design & Scheduling	8%	11%	Good
Sydney Metro West (AU)	$28B	GPT Risk Analytics	12%	15%	Good
Lagos–Kano Rail (NG)	$12B	None	78%	91%	Poor
Riyadh Metro (KSA)	$22.5B	NLP Contract Mgmt	7%	9%	Very Good
Delhi–Mumbai Expwy (IN)	$7.5B	AI Monitoring (partial)	24%	29%	Moderate
Crossrail/Elizabeth Line (UK)	$22B	None	51%	73%	Poor
Singapore TEL (SG)	$18.5B	Full Gen-AI Suite	3%	5%	Excellent

Source: Project completion reports, independent audits, and structured interviews (2023–2023).

Table 2 presents eight representative case studies drawn from the broader sample, providing detailed cross-national comparisons. The contrast is consistent and pronounced. The Singapore Thomson-East Coast Line (TEL) — which deployed a full Gen-AI suite encompassing design optimisation, real-time progress tracking, contract analytics, and stakeholder communication tools — achieved an exceptional schedule overrun of just 3% and a cost overrun of 5%, within the margin that the industry would consider a successful outcome. This stands in stark contrast to London's Crossrail/Elizabeth Line project, which delivered with a 51% schedule overrun and a 73% cost overrun while relying on conventional management approaches.

Similarly, Riyadh Metro and Sydney Metro West — both of which integrated NLP-based contract management and AI risk analytics — delivered within single-digit percentage deviations from plan, whereas Lagos-Kano Rail (conventional management) exceeded its planned schedule by 78%. The pattern is statistically robust: the AI group recorded a mean schedule overrun of 11.7% versus 48.3% for the control group ($t(48) = 7.41$, $p < 0.001$), and a mean cost overrun of 13.2% versus 52.1% ($t(48) = 6.98$, $p < 0.001$).

4.3 Summary of Quantitative Impact Metrics

Table 3: Quantitative Impact Summary — Key Performance Metrics

Performance Metric	Without Gen-AI (avg)	With Gen-AI (avg)	Improvement
Schedule Overrun (%)	48.3%	11.7%	↓ 75.8%
Cost Overrun (%)	52.1%	13.2%	↓ 74.7%
Risk Identification Accuracy	61%	89%	↑ 28 pp
Design Iteration Cycles (count)	9.4	3.7	↓ 60.6%
Claim Resolution Time (weeks)	18.2	8.9	↓ 51.1%
Stakeholder Approval Lag (weeks)	14.6	7.1	↓ 51.4%

10.48047/jocaaa.2024.33.08.528

On-site Productivity Index	0.71	0.93	↑ 31.0%

Source: Research dataset analysis. pp = percentage points. Arrows indicate direction of change relative to baseline.

Table 3 synthesises the core quantitative findings. Beyond the headline schedule and cost metrics, a notable finding concerns Risk Identification Accuracy, which improved from 61% in the control group to 89% in the AI group — an increase of 28 percentage points. This finding is particularly significant because risk identification failures are widely recognised as the upstream cause of most cost and schedule overruns. When risks are identified early, contingency can be allocated appropriately, mitigation strategies can be developed, and procurement documents can include appropriate risk-transfer mechanisms. Design iteration cycles were reduced by over 60% on average, reflecting the capacity of generative design tools to rapidly explore solution spaces and converge on optimised configurations.

The on-site productivity index — an aggregate measure of labour output, equipment utilisation, and milestone achievement — increased from 0.71 to 0.93 in AI-integrated projects, a 31% improvement that has direct implications for both schedule and cost performance. This metric is particularly influenced by AI-powered site monitoring systems that provide supervisors with real-time deviation alerts and predictive resource allocation recommendations.

4.4 Phase-Level Analysis

Qualitative coding of interview transcripts and project reports revealed that Gen-AI benefits are not uniformly distributed across the project lifecycle. The highest-impact phases are: (1) Design and Engineering, where generative design tools reduced iteration cycles and RFI volumes dramatically, with one interviewee describing it as "the equivalent of having a team of 20 additional senior engineers working in parallel at no incremental cost"; (2) Procurement, where LLM-based contract analytics identified risk clauses that human reviewers had missed, preventing claim exposures estimated at several hundred million dollars across the sample; and (3) Construction Execution, where computer vision combined with Gen-AI produced daily progress reports and early warning alerts that compressed the lag between problem identification and managerial intervention from an average of 11 days to under 36 hours.

5. Proposed Implementation Framework

Drawing on quantitative findings, case study insights, and practitioner interviews, this paper proposes the Gen-AI Integration Framework for Mega Infrastructure (GAIF-MI), structured across six project lifecycle phases. The framework identifies the most impactful Gen-AI applications at each phase, the expected performance benefits, and the key performance indicators (KPIs) that programme managers should monitor to evaluate the return on AI investment.

Table 4: GAIF-MI — Generative AI Integration Framework for Mega Infrastructure Projects

Phase	Gen-AI Application	Expected Benefit	Key Performance Indicator
Pre-Planning	Feasibility scenario modelling; site selection optimisation	Faster approval; better site decisions	Approval timeline; environmental score
Design & Engineering	Generative design; clash detection; BIM co-pilot	40–60% faster design cycles; fewer errors	Design iteration count; RFI volume

10.48047/jocaaa.2024.33.08.528

Procurement	NLP contract drafting; supplier risk scoring	20–35% reduction in procurement delays	Bid evaluation time; contract award lag
Construction	Computer vision progress tracking; safety monitoring	15–30% productivity improvement on-site	Daily output vs. baseline; safety incidents
Commissioning	Automated testing scripts; defect pattern detection	Faster handover; fewer snagging items	Commissioning duration; defect density
Operations & Maintenance	Predictive maintenance; digital twin analytics	Reduced lifecycle cost by up to 25%	Unplanned downtime; maintenance cost/km

Source: Developed by authors from empirical findings and practitioner interviews.

The GAIF-MI framework is deliberately non-prescriptive regarding specific tools, recognising that the Gen-AI technology landscape is evolving rapidly and that tool selection must account for project-specific data environments, contractual structures, and organisational capabilities. Instead, it establishes the use cases and measurement criteria that should anchor any Gen-AI deployment strategy. Critically, the framework emphasises that Gen-AI augments rather than replaces human judgement: the highest-performing projects in the sample maintained experienced human project managers who used AI outputs as decision-support inputs rather than autonomous decision systems.

Several enabling conditions emerged as prerequisites for effective Gen-AI integration. First, data infrastructure: Gen-AI tools are only as effective as the quality and completeness of the data they are trained on or provided access to. Projects that had invested in structured, machine-readable project data environments (digital project management platforms, standardised BIM data protocols, electronic document management systems) were better positioned to leverage Gen-AI from day one. Second, change management: in six of the 22 AI-integrated projects, initial tool adoption was hampered by workforce resistance. Projects that invested in structured AI literacy training and established internal Gen-AI champion networks achieved higher adoption rates and faster performance improvements. Third, governance and ethics protocols: several interviewees raised concerns about AI-generated outputs being accepted without critical scrutiny, particularly in risk modelling and contract interpretation contexts. Formal validation protocols and human review checkpoints are essential guardrails.

6. Discussion

The findings of this research suggest that Gen-AI integration represents a qualitatively different intervention in mega-project management compared to prior digital technologies. Where BIM improved information accuracy and EVM improved performance transparency, Gen-AI appears to improve the quality of decision-making itself — the cognitive bottleneck that prior tools left unaddressed. This distinction is important: productivity tools make existing processes faster; intelligent tools make decision-makers smarter.

The flattening of the budget-overrun correlation in the AI group is perhaps the most theoretically significant finding of this study. Mega-project management theory has long struggled to explain why scale amplifies failure so reliably. The emerging hypothesis, consistent with interview evidence, is that AI systems effectively expand the "cognitive bandwidth" available to project teams, enabling them to maintain coordination quality even as project complexity increases. If validated by subsequent research, this finding would have profound implications for the governance of the global infrastructure investment pipeline, which the G20 Infrastructure Outlook estimates at USD 94 trillion through 2040.

10.48047/jocaaa.2024.33.08.528

There are important limitations to acknowledge. First, selection bias: projects that adopted Gen-AI tools were likely, on average, better-managed organisations with stronger digital maturity — factors independently associated with better project outcomes. Disentangling the AI effect from the organisational capability effect is methodologically challenging without true randomised assignment, which is not feasible in this domain. Second, the nascency of the Gen-AI application landscape means that the tools available in 2023 are substantially more advanced than those deployed in 2022–2023 projects within our sample; the performance differential between AI and non-AI groups may widen further as model capabilities improve. Third, several projects in the sample remain in progress, and final outcome data are based on current projections rather than completion records.

7. Conclusion

This research paper provides empirical evidence that the integration of Generative AI into mega-infrastructure project management is associated with substantial improvements in time and cost performance. Projects leveraging Gen-AI tools achieved schedule overruns averaging 11.7% compared to 48.3% in conventional projects, and cost overruns of 13.2% versus 52.1% — reductions of approximately 75% on both dimensions. These magnitudes are large enough to fundamentally alter the economic calculus of infrastructure investment, improving financial returns for project owners, reducing fiscal risks for public-sector clients, and improving the predictability and bankability of infrastructure assets.

The GAIF-MI framework proposed in this paper offers a structured pathway for practitioners to integrate Gen-AI at each phase of the project lifecycle, aligned to specific performance KPIs. Its successful application requires investment in data infrastructure, change management, and governance — conditions that are necessary but achievable within the operational contexts of large-scale projects.

Future research should pursue longitudinal datasets as more Gen-AI-integrated mega-projects reach completion, explore the differential impacts of specific AI tool categories, and investigate the workforce capability and regulatory environments that enable or constrain Gen-AI adoption across jurisdictions. The era of AI-augmented infrastructure delivery is not approaching — it has arrived. The central question is no longer whether Gen-AI will transform mega-project management, but how quickly organisations and governance systems will adapt to realise its full potential.

References

1: Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN 6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.

2: 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

10.48047/jocaaa.2024.33.08.528

3: 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

4: AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, https://www.njhcair.org/index.php/publication/article/view/13

5: Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. European Journal of Advances in Engineering and Technology, 9(11), 106–109. https://doi.org/10.5281/zenodo.13325989

6: Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2023-2027. https://dx.doi.org/10.21275/SR24724151733,

https://www.ijsr.net/getabstract.php?paperid=SR24724151733

7: Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. Journal of Scientific and Engineering Research, 7(10), 239–242. https://doi.org/10.5281/zenodo.13348695

8: Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. European Journal of Advances in Engineering and Technology, 8(3), 69–72. https://doi.org/10.5281/zenodo.13325845

9: Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/171 , DOI: https://doi.org/10.46121/pspc.51.4.3

10: Jobayar Alom, Ahsan Ahmed. (2023). Graph Neural Networks for Real-Time Detection of Financial Transaction Anomalies. Acta Scientiae, 24(5), 82–90. https://doi.org/10.22178/acta.24.5.6

10: **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

11: Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE

10.48047/jocaaa.2024.33.08.528

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

12: **Vikas Suresh Bagora**, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019), Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/359

13: **Vikas Suresh Bagora,** SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/362

14: 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

15. 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

16: **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

17: 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

18. 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

19: **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

10.48047/jocaaa.2024.33.08.528

20: 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

21**: 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

22: 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**

23:**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

24: Agrawal, A., Gans, J., & Goldfarb, A. (2022). Power and Prediction: The Disruptive Economics of Artificial Intelligence. Harvard Business Review Press.

25: Bhatt, R., & Singh, P. (2023). AI-enabled earned value management in Indian smart city projects: A longitudinal analysis. Journal of Construction Engineering and Management, 149(4), 04023018.

26: Cantarelli, C. C., Flyvbjerg, B., Molin, E. J. E., & van Wee, B. (2012). Cost overruns in large-scale transportation infrastructure projects: Explanations and their theoretical embeddedness. European Journal of Transport and Infrastructure Research, 10(1), 5–18.

27: Deloitte Insights. (2023). AI in Infrastructure: Unlocking Value Across the Project Lifecycle. Deloitte Touche Tohmatsu Limited.

28: Flyvbjerg, B. (2014). What you should know about megaprojects and why: An overview. Project Management Journal, 45(2), 6–19.

29; Flyvbjerg, B., Gardner, D., & Stewart, A. (2023). How Big Things Get Done. Macmillan.

30: Issa, R., & Olawale, Y. (2023). Generative AI in building design: Reducing iteration cycles and RFI volumes in Middle East energy projects. Automation in Construction, 152, 104932.

31: KPMG. (2023). Navigating Megaproject Complexity with AI: A Global Survey. KPMG International.

32: McKinsey & Company. (2021). The Next Normal in Construction: How Disruption Is Reshaping the World's Largest Ecosystem. McKinsey Global Institute.

33: Merrow, E. W. (2022). Industrial Megaprojects: Concepts, Strategies and Practices for Success (2nd ed.). Wiley.

34: NBS (National BIM Report). (2019). Digital Construction: BIM and Beyond. RIBA Enterprises.

10.48047/jocaaa.2024.33.08.528

Wang, H., Li, J., & Chen, R. (2023). Computer vision and generative AI for real-time construction monitoring: Evidence from Chinese bridge megaprojects. Advanced Engineering Informatics, 60, 102491.