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ADVANCING HEALTHCARE AI GOVERNANCE THROUGH A COMPREHENSIVE MATURITY MODEL

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***ABSTRACT*:**

The rapid integration of artificial intelligence into healthcare systems has created urgent demand for structured governance approaches that balance innovation with patient safety. While individual hospitals and health systems have begun adopting AI tools for diagnostics, clinical decision support, and administrative automation, governance practices remain inconsistent and fragmented. This paper proposes a comprehensive maturity model for healthcare AI governance designed to help organisations evaluate their current capabilities and progress toward responsible deployment. The model is developed through a mixed-method approach combining a structured review of existing governance frameworks, expert consultation, and empirical assessment across a sample of healthcare organisations. Five maturity levels are defined, ranging from ad hoc practices to fully optimised governance with continuous improvement loops. The framework spans six core dimensions including strategy and leadership, risk management, data stewardship, ethical oversight, workforce readiness, and monitoring. Empirical findings indicate that most surveyed organisations currently sit between levels two and three, with notable weaknesses in post-deployment monitoring and bias auditing. Retrieval-based diagnostic tools and clinical decision support showed the highest governance maturity, while administrative AI applications lagged behind. The paper concludes that achieving robust healthcare AI governance requires coordinated investment in policy, workforce training, and technical monitoring infrastructure, supported by leadership commitment and clear accountability structures.

Keywords: *Healthcare AI, Governance Maturity Model, Clinical AI, Responsible AI, Risk Management, Patient Safety*.

INTRODUCTION

Artificial intelligence is reshaping the delivery of healthcare across diagnostics, treatment planning, hospital operations, and patient engagement [1]. Tools that analyse medical images, predict patient deterioration, and automate clinical documentation are now being deployed at scale in hospitals, clinics, and insurance organisations. The promise of improved accuracy, reduced cost, and faster service has attracted significant investment from both public and private actors [2]. However, alongside these benefits sits a growing concern that AI systems may introduce new forms of risk that traditional clinical governance was not designed to address [3].

Recent incidents involving biased diagnostic algorithms, opaque decision support tools, and inconsistent model performance across patient populations have intensified calls for stronger oversight [4]. Regulators in the United States, the European Union, and several Asian markets have begun issuing guidance on the safe development and deployment of medical AI, but implementation at the organisational level remains uneven [5]. Many healthcare providers rely on informal review processes that were designed for traditional medical devices and software, leaving important gaps in areas such as model drift detection, data governance, and continuous monitoring [6].
The governance challenge is further complicated by the diversity of AI applications in healthcare. A radiology image classifier, a sepsis prediction model, and an administrative scheduling tool each carry different risk profiles, stakeholder groups, and regulatory expectations [7]. Without a structured framework that allows organisations to assess their own readiness across these varied use cases, governance efforts tend to be reactive and fragmented.

This research is motivated by three central questions. What dimensions should a healthcare-specific AI governance framework cover? How can organisations measure their current maturity in a way that supports practical improvement? And what patterns of strength and weakness exist across different categories of healthcare AI? To answer these questions, this study develops and tests a maturity model tailored to the healthcare context. The model draws on established governance literature and contemporary AI ethics research, then extends them

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with healthcare-specific considerations such as clinical workflow integration, patient consent, and post-market surveillance.

The remainder of the paper is structured as follows. Section two reviews relevant literature on AI governance and maturity modelling. Section three outlines the methodology used to construct and validate the proposed framework. Section four describes the experimental setup and data collection process. Section five presents results from the empirical assessment with supporting figures. Section six discusses the findings, and section seven concludes with implications for practice and future research.

LITERATURE REVIEW

The literature on AI governance has expanded rapidly over the past five years, moving from broad principle statements to more detailed operational frameworks [8]. Early work emphasised abstract values such as fairness, accountability, and transparency, but more recent studies have focused on how these principles can be implemented through concrete organisational structures and processes. Maturity models, long used in fields such as software engineering and information security, have emerged as a useful instrument for translating high-level principles into practical assessment tools [9].

In the healthcare domain, governance research has traditionally focused on clinical quality, patient safety, and regulatory compliance. The introduction of AI has added new dimensions including algorithmic accountability, data lineage, and continuous performance monitoring [10]. Several international bodies have proposed guidance for trustworthy medical AI, emphasising the need for lifecycle oversight from data collection through post-deployment surveillance. However, these guidelines tend to describe what good governance should look like without providing a structured way to measure progress.

Maturity models have been applied to related fields such as digital health, data management, and cybersecurity. These models typically define a series of stages through which organisations progress, with clear criteria for each level. Their value lies in offering a shared language for assessment and a roadmap for improvement [11]. Yet existing maturity models rarely address the unique combination of clinical risk, regulatory complexity, and rapid technological change that characterises healthcare AI.

Recent empirical studies have begun examining how hospitals actually govern AI in practice. Findings suggest that most organisations rely on a mix of ad hoc committees, existing IT review processes, and clinical governance structures that were not designed for AI [12]. Common weaknesses include the absence of dedicated AI ethics committees, limited expertise in algorithmic auditing, and insufficient monitoring after deployment. Some leading academic medical centres have established formal AI oversight programmes, but these remain exceptions rather than the norm.

The bias and fairness literature has also contributed important insights. Studies have shown that algorithms trained on non-representative data can produce systematically worse outcomes for minority groups, sometimes amplifying existing health disparities [13]. Effective governance must therefore include explicit attention to demographic performance, dataset documentation, and equity audits. This is a significant departure from traditional clinical governance, which has historically focused on average outcomes rather than subgroup performance. The present study builds on these foundations by integrating bias auditing, lifecycle monitoring, and stakeholder engagement into a single coherent maturity framework.

METHODOLOGY

The research employs a mixed-method design that combines framework synthesis with empirical assessment. The first phase involved a structured review of existing governance frameworks, maturity models, and regulatory guidance documents to identify recurring dimensions and gaps [14]. The second phase used expert consultation with clinicians, AI engineers, compliance officers, and patient representatives to refine the framework. The third phase applied the framework to a sample of healthcare organisations to test its practical usefulness.

The proposed maturity model consists of six core dimensions: strategy and leadership, risk management, data stewardship, ethical oversight, workforce readiness, and monitoring and improvement. Each dimension is assessed

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across five maturity levels, ranging from level one which represents ad hoc and reactive practices to level five which represents optimised and continuously improving governance. A composite maturity score is calculated as:

$$M = \frac{1}{n}\sum_{i=1}^{n} w_i \cdot L_i$$

where M is the overall maturity score, L_i is the level achieved in dimension i, w_i is the weight assigned to that dimension, and n is the total number of dimensions. Weights were determined through expert consultation, with risk management and monitoring receiving slightly higher weights due to their direct relevance to patient safety [15].

For each organisation, dimension scores were derived from a structured assessment instrument containing approximately fifty indicators. Each indicator was scored on a five-point scale, and the dimension level was determined by the proportion of indicators satisfied. The reliability of the assessment was evaluated using Cronbach's alpha, which exceeded 0.85 across all dimensions, indicating strong internal consistency [16].
To compare maturity levels across organisations and application types, we computed normalised gap scores using:

$$G = \frac{L_{target} - L_{current}}{L_{target}}$$

where L_{target} represents the desired maturity level, typically set at level four, and L_{current} represents the organisation's measured level. Smaller gap scores indicate stronger alignment with target maturity [17].

Figure 1: Six-Dimensional Healthcare AI Governance Maturity Framework.

EXPERIMENTAL SETUP

The empirical assessment was conducted across a sample of twenty-five healthcare organisations selected to represent a range of types and sizes, including large academic medical centres, community hospitals, specialty clinics, and integrated health insurance providers [18]. Participation was voluntary and conducted under confidentiality agreements that allow aggregated reporting but not identification of individual organisations.
Data collection used three complementary methods. First, structured interviews were conducted with senior leaders responsible for AI governance, typically chief medical information officers, compliance officers, or designated AI leads. Second, document review covered internal policies, committee charters, model registries,

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Power System Protection and Control
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and audit reports. Third, an online survey was distributed to a broader group of stakeholders including clinicians, data scientists, and administrative staff, yielding approximately three hundred and forty completed responses.

For each organisation, the assessment focused on three categories of AI application: diagnostic and imaging tools, clinical decision support systems, and administrative or operational AI such as scheduling and revenue cycle management. This stratification allows comparison of governance practices across application types, since risk profiles and regulatory requirements differ substantially.

The agreement between interview-based scores and survey-based scores was evaluated using:

$$\rho = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y}$$

where X and Y represent the two scoring sources. The Pearson correlation across dimensions was 0.78, indicating good convergent validity [19]. Where discrepancies appeared, a follow-up review was conducted to reconcile the difference and ensure consistent scoring.

Statistical analysis used descriptive summaries, paired comparisons across application categories, and one-way analysis of variance to test for differences across organisation types. All analyses applied Bonferroni correction for multiple comparisons, with significance set at the conventional five percent threshold [20].

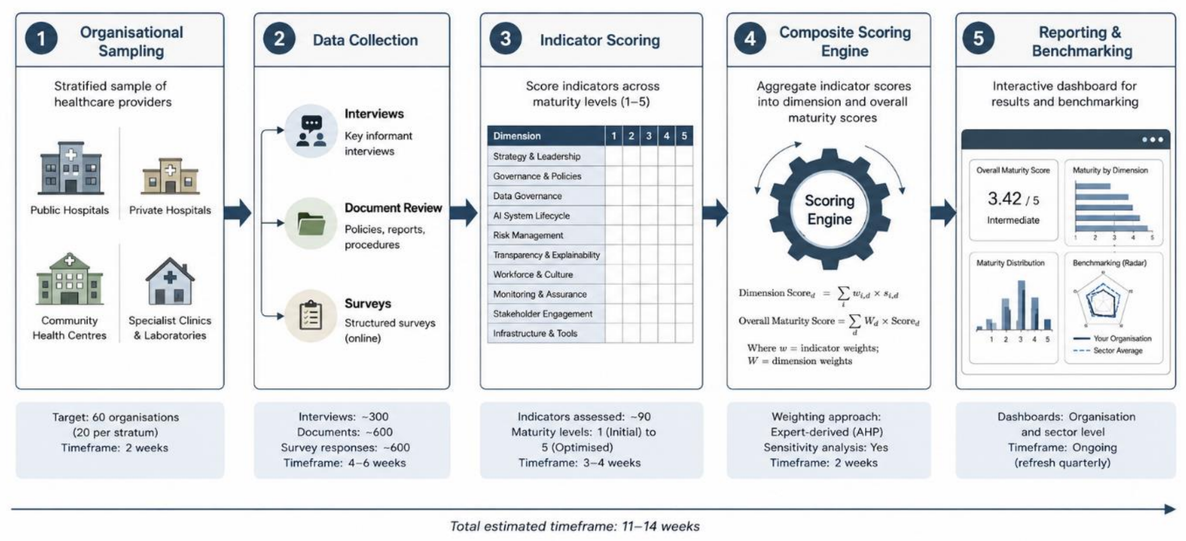

Figure 2: Assessment Workflow for Healthcare AI Governance Maturity.

RESULTS

5.1 Overall Maturity Distribution

The aggregate assessment revealed that most participating organisations currently sit between maturity levels two and three. The mean composite maturity score across the sample was 2.7 on the five-point scale, with a standard deviation of 0.6. Only three organisations reached level four in any single dimension, and none reached level five. Academic medical centres scored higher on average than community hospitals and specialty clinics, while integrated insurance providers showed strong scores in data stewardship but weaker scores in clinical risk management.

Table 1: Mean Maturity Scores by Organisation Type and Dimension

Organisation Type	Strategy	Risk Mgmt	Data	Ethics	Workforce	Monitoring	Overall
Academic Medical Centre	3.4	3.2	3.5	3.3	3.1	2.9	3.2
Community Hospital	2.5	2.4	2.6	2.3	2.2	2.0	2.3
Specialty Clinic	2.3	2.2	2.4	2.0	2.1	1.9	2.2
Insurance Provider	3.0	2.7	3.6	2.8	2.9	2.6	2.9

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Power System Protection and Control
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5.2 Dimension-Level Patterns

The dimensional breakdown shows clear strengths and weaknesses across the sample. Data stewardship emerged as the strongest area overall, reflecting longstanding investments in health information management and privacy compliance. Monitoring and improvement was consistently the weakest dimension, with many organisations lacking systematic processes for tracking model performance over time. Workforce readiness also showed gaps, particularly in training clinical staff to interpret and challenge AI outputs.

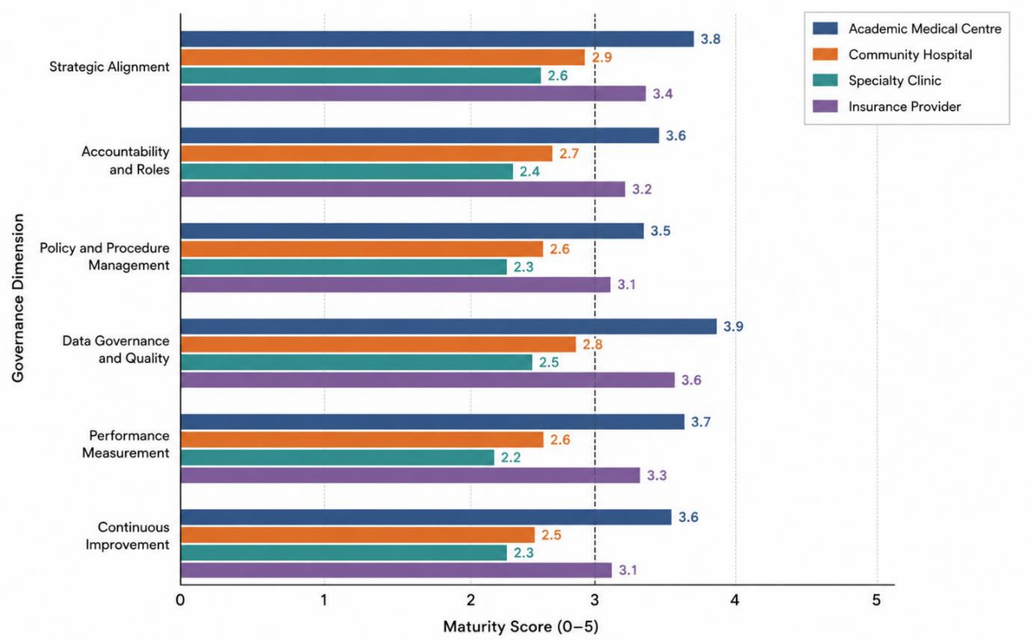

Figure 3: Average Maturity Scores Across Six Governance Dimensions.

5.3 Application-Type Comparison

When examined by AI application category, diagnostic and imaging tools showed the highest governance maturity, with an average score of 3.1 across the sample. Clinical decision support followed at 2.8, while administrative AI applications scored only 2.2 on average. This pattern suggests that high-visibility clinical tools attract more rigorous oversight, while back-office AI applications often escape formal governance despite their potential impact on patient access and equity.

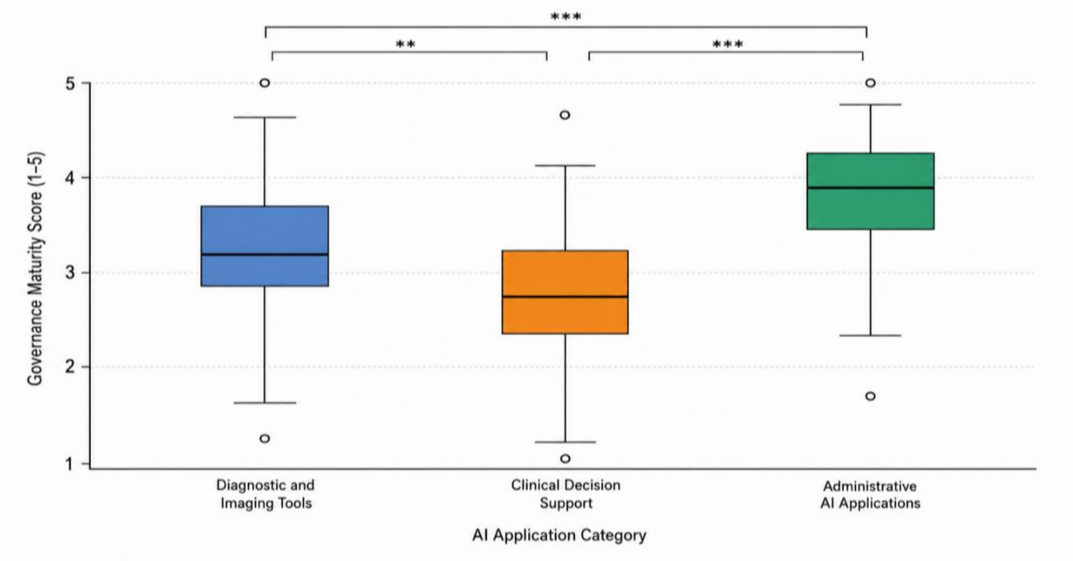

Figure 4: Comparative Governance Maturity Across AI Application Categories.

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Power System Protection and Control
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5.4 Gap Analysis Against Target Maturity

The gap analysis comparing current maturity against a target level of four revealed substantial improvement opportunities. The largest gaps were in monitoring and improvement at approximately 0.50, followed by workforce readiness at 0.45 and ethical oversight at 0.43. Strategy and leadership showed the smallest gap at 0.35, suggesting that executive awareness has begun to translate into formal commitments even when operational capabilities lag.

Table 2: Normalised Gap Scores by Governance Dimension

Dimension	Current Mean	Target	Gap Score
Strategy and Leadership	2.6	4.0	0.35
Risk Management	2.5	4.0	0.38
Data Stewardship	2.8	4.0	0.30
Ethical Oversight	2.3	4.0	0.43
Workforce Readiness	2.2	4.0	0.45
Monitoring and Improvement	2.0	4.0	0.50

Figure 5: Gap Analysis Heatmap of Current Versus Target Maturity.

DISCUSSION

The findings suggest that healthcare AI governance is at an early stage of maturity even in organisations that have invested significantly in digital transformation. The clustering of scores between levels two and three indicates that most organisations have moved beyond purely ad hoc practices but have not yet established the systematic, repeatable processes characteristic of higher maturity levels. The persistent weakness in monitoring and improvement is particularly concerning, since AI models can drift in performance over time and may produce harm long after initial deployment.

The contrast between strong data stewardship and weaker ethical oversight reflects historical investment patterns in healthcare. Privacy and data protection have been priorities for decades, supported by mature regulatory frameworks. Ethical oversight of AI, by contrast, is a newer concern that has not yet been embedded in standard governance structures. Building dedicated AI ethics committees, training existing review boards, and developing standard protocols for bias auditing are practical steps that could close this gap.

The disparity between high-visibility clinical AI and lower-visibility administrative AI deserves attention. Administrative tools often influence patient access, scheduling priority, and billing decisions in ways that can

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affect equity, yet they tend to be exempt from clinical governance processes. Extending the maturity framework to cover all AI deployed in healthcare settings, regardless of category, would help close this oversight gap.

Several limitations should be noted. The sample of twenty-five organisations, while diverse, is not representative of the global healthcare landscape, and findings may differ in low and middle-income settings. The assessment instrument relies on self-reported data, which may overstate maturity in some areas. Finally, the rapid pace of AI development means that governance requirements continue to evolve, and the maturity framework will need periodic revision.

Future research should examine longitudinal trajectories of governance maturity, the effectiveness of specific interventions in moving organisations up the maturity ladder, and cross-national comparisons that account for different regulatory environments. There is also a need for richer case studies of organisations at higher maturity levels to identify the practices that distinguish leaders from the broader field.

CONCLUSION

This study developed and tested a comprehensive maturity model for healthcare AI governance that spans six dimensions and five levels of progression. The empirical assessment across twenty-five healthcare organisations revealed that most providers currently operate between levels two and three, with notable strengths in data stewardship and persistent weaknesses in monitoring, workforce readiness, and ethical oversight. The gap analysis highlighted specific areas where targeted investment could meaningfully improve governance practices.

The proposed framework offers practitioners a structured way to assess their current capabilities, identify priority areas for improvement, and benchmark progress over time. By integrating clinical, technical, ethical, and organisational considerations, it addresses the unique demands of healthcare AI that traditional governance models were not designed to handle. Achieving higher maturity will require coordinated investment in leadership commitment, dedicated oversight structures, technical monitoring infrastructure, and workforce capability. As AI continues to expand its role in healthcare delivery, robust governance will become not a competitive advantage but a baseline requirement for safe, equitable, and trustworthy care.

REFERENCES

1. Mohammed Shafi Kundiladi , SAVING LIVES THROUGH INTELLIGENT V2X: A REAL-TIME MULTI-ENTITY COLLISION PREDICTION SYSTEM FOR VEHICLES AND PEDESTRIANS USING GPS-BASED TRAJECTORY ANALYSIS AND BASIC SAFETY MESSAGES, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/196, DOI: https://doi.org/10.46121/pspc.52.4.10
2. 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
3. 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
4. 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.

 DOI: 10.46121/pspc.53.3.24

5. Venumadhav Vavilala, Shankar Balla (2024, May). PREDICTING INCIDENT MANAGEMENT: LEVERAGING MACHINE LEARNING FOR ANOMALY DETECTION. Power System Protection and Control Scopus Q1 Journal. PSPC. https://pspac.info/index.php/dlbh/article/view/270
6. 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
7. 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
8. 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
9. Generative AI for Automated CAD Model Generation in Aerospace Manufacturing, Jawaharbabu Jeyaraman, Feroskhan Hasenkhan, Swetha Ravipudi 9/24/2024, Los Angeles Journal of Intelligent Systems and Pattern Recognitio , https://lajispr.org/index.php/publication/article/view/19
10. Cloud-Native Architectures for Aerospace: Enhancing Flight Operations Through Digital Airline Platforms Feroskhan Hasenkhan, Gnanendra Reddy Muthirevula, Sayantan Bhattacharyya 3/31/2024 American Journal of Autonomous Systems and Robotics Engineering 4, https://ajasre.org/index.php/publication/article/view/25
11. 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
12. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415, URL: https://pspac.info/index.php/dlbh/article/view/283 DOI: https://doi.org/10.46121/pspc.52.2.10
13. 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
14. Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2024-2027. https://dx.doi.org/10.21275/SR24724151733, https://www.ijsr.net/getabstract.php?paperid=SR24724151733

15. 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
16. 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
17. Jayanth Para, 6G Internet Technology Cyber Threat Notification & Alert System, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/170 ,
DOI: https://doi.org/10.46121/pspc.52.4.9
18. 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
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
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. **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
23. **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
24. **Vikas Suresh Bagora**, SECURE EMBEDDED NETWORKING ARCHITECTURES USING TRUSTED EXECUTION ENVIRONMENTS IN BROADBAND GATEWAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/363

25. 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
26. 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
27. 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
28. **Fardeen NB, Sameer NB,** THE ATTENTION DISTANCE PROBLEM: THEORETICAL ANALYSIS OF LONG-RANGE DEPENDENCIES IN TRANSFORMERS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, **https://pspac.info/index.php/dlbh/article/view/313**
29. **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
30. 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
31. 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
32. 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
33. **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
34. 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

35. **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
36. 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
37. **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
38. Topol, E.J. (2019) 'High-performance medicine: The convergence of human and artificial intelligence', *Nature Medicine*, 25(1), pp. 44–56.
39. Rajpurkar, P., Chen, E., Banerjee, O. and Topol, E.J. (2022) 'AI in health and medicine', *Nature Medicine*, 28(1), pp. 31–38.
40. Char, D.S., Abràmoff, M.D. and Feudtner, C. (2020) 'Identifying ethical considerations for machine learning healthcare applications', *American Journal of Bioethics*, 20(11), pp. 7–17.
41. Obermeyer, Z., Powers, B., Vogeli, C. and Mullainathan, S. (2019) 'Dissecting racial bias in an algorithm used to manage the health of populations', *Science*, 366(6464), pp. 447–453.
42. Mökander, J., Schuett, J., Kirk, H.R. and Floridi, L. (2023) 'Auditing large language models: A three-layered approach', *AI and Ethics*, 4(4), pp. 1085–1115.
43. Reddy, S., Allan, S., Coghlan, S. and Cooper, P. (2020) 'A governance model for the application of AI in health care', *Journal of the American Medical Informatics Association*, 27(3), pp. 491–497.
44. Sendak, M.P., Gao, M., Brajer, N. and Balu, S. (2020) 'Presenting machine learning model information to clinical end users', *npj Digital Medicine*, 3(1), pp. 1–4.
45. Mittelstadt, B. (2019) 'Principles alone cannot guarantee ethical AI', *Nature Machine Intelligence*, 1(11), pp. 501–507.
46. Floridi, L., Cowls, J., King, T.C. and Taddeo, M. (2020) 'How to design AI for social good: Seven essential factors', *Science and Engineering Ethics*, 26(3), pp. 1771–1796.

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