Power System Protection and Control
ISSN:1674-3415

DIGITAL EXPERIENCE MONITORING (DEM): A PERFORMANCE ENGINEERING APPROACH TO CUSTOMER EXPERIENCE

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Received:17 May 2025 **Revised**:21 June 2025 **Accepted**: 22 July 2025

ABSTRACT:

Traditional performance monitoring focuses on infrastructure and application metrics such as server utilization, response times, and error rates, measured from the perspective of the systems being operated. But these metrics often fail to capture what customers actually experience, the true measure of whether a digital service is succeeding. Digital Experience Monitoring (DEM) represents a shift toward measuring performance from the customer's viewpoint, encompassing the full journey from the user's device through networks and applications to the delivered experience. This paper examines DEM as a performance engineering discipline, analyzing its methods, metrics, and the gap it fills between technical performance and business outcomes. We designed a comprehensive DEM framework integrating real user monitoring, synthetic monitoring, and experience analytics, and evaluated its effectiveness in detecting and diagnosing experience problems that traditional monitoring missed, using data from a simulated e-commerce platform with realistic user journeys and injected experience degradations. Results show that DEM detected 89% of customer-impacting experience problems that traditional infrastructure monitoring classified as healthy, revealing a substantial blind spot in conventional approaches. Correlation analysis linked experience metrics to business outcomes, showing that a one-second improvement in a key experience metric corresponded to measurable conversion rate gains. The framework's combination of real user and synthetic monitoring provided complementary coverage, with synthetic monitoring catching problems before users encountered them and real user monitoring capturing the diversity of actual user conditions. The paper discusses the implementation of DEM, its integration with business analytics, and its role in aligning performance engineering with customer-centric business objectives.

Keywords: *Digital Experience Monitoring, Real User Monitoring, Synthetic Monitoring, Customer Experience, Performance Engineering, Conversion Rate, Experience Analytics.*

INTRODUCTION

There is a persistent and consequential gap in how organizations measure the performance of their digital services. Operations teams watch dashboards full of green indicators, server utilization within bounds, response times meeting targets, error rates low, and conclude that all is well. Meanwhile, actual customers may be struggling with slow page loads, broken interactions, and frustrating experiences that never register on those infrastructure dashboards [1]. This disconnect between what systems report and what customers experience is the problem that Digital Experience Monitoring exists to solve.

The root of the disconnect is perspective. Traditional monitoring measures performance from the inside, from the vantage point of the servers and applications being operated. But the customer experience unfolds across a chain that extends far beyond those servers: the user's device and browser, their network connection, intermediate content delivery networks, third-party services embedded in the page, and finally the application itself [2]. A problem anywhere in this chain degrades the experience, but traditional monitoring sees only its own segment. A perfectly healthy backend delivers a poor experience if a third-party script hangs, if the CDN is slow in the user's region, or if the user's page renders slowly on their device [3].

Digital Experience Monitoring reorients measurement around the customer's actual experience. It combines real user monitoring, which captures the experience of actual users as they interact with the service, with synthetic monitoring, which proactively tests experiences from controlled vantage points, and experience analytics that

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ISSN:1674-3415

connect these measurements to user behaviour and business outcomes [4]. This customer-centric view reveals problems that infrastructure monitoring misses and, crucially, connects performance to the business metrics that organizations actually care about, such as conversion, engagement, and retention [5].

This paper examines DEM as a performance engineering discipline, presents a comprehensive framework, evaluates its ability to detect experience problems that traditional monitoring misses, and demonstrates the linkage between experience metrics and business outcomes that makes DEM strategically valuable.

LITERATURE REVIEW

The evolution of performance monitoring reflects the changing nature of digital services. Early monitoring focused on server and network infrastructure, measuring resource utilization and availability from the operator's perspective [6]. As applications grew more complex, application performance monitoring emerged, instrumenting application code to measure transaction times, database query performance, and error rates. These approaches provided valuable operational visibility but remained fundamentally system-centric rather than user-centric.

Real user monitoring developed as a response to the recognition that synthetic tests and server metrics did not capture actual user experience. By instrumenting the user's browser or application, real user monitoring captures the actual performance experienced by real users under their real conditions, including their devices, networks, and geographic locations [7]. Research has documented the substantial variation in user experience that real user monitoring reveals, variation that server-side metrics entirely miss because they measure only the server's contribution to the total experience.

The standardization of web performance metrics has advanced the field considerably. The development of user-centric performance metrics, culminating in frameworks like Core Web Vitals that measure loading, interactivity, and visual stability from the user's perspective, has given the industry a shared vocabulary for experience measurement [8]. Studies have established correlations between these experience metrics and business outcomes, demonstrating that better experience metrics associate with higher engagement and conversion, which elevated experience measurement from a technical concern to a business one.

Synthetic monitoring, which proactively executes scripted user journeys from controlled locations, complements real user monitoring by providing consistent, proactive testing that catches problems before real users encounter them [9]. Research has explored the complementary nature of synthetic and real user monitoring, with synthetic monitoring providing controlled baselines and early warning while real user monitoring captures the full diversity of actual conditions. The integration of these approaches with business analytics to connect experience to outcomes represents the frontier of DEM research and practice, which this paper contributes to.

METHODOLOGY

We designed a comprehensive DEM framework integrating three measurement approaches. Real user monitoring instruments actual user sessions to capture experience metrics across the full user population. Synthetic monitoring executes scripted journeys from controlled vantage points to provide proactive, consistent testing. Experience analytics correlates experience metrics with user behaviour and business outcomes [14].
The core experience quality was quantified using a composite experience score combining loading, interactivity, and stability metrics:

$$ES = w_1 \cdot L_{score} + w_2 \cdot I_{score} + w_3 \cdot S_{score}$$

where L, I, and S are normalized loading, interactivity, and stability scores and weights sum to one [15].
The correlation between experience and business outcomes was measured using the conversion sensitivity:

$$CS = \frac{\Delta Conversion}{\Delta Experience; metric}$$

representing the change in conversion rate per unit change in the experience metric [16].
Detection coverage relative to traditional monitoring was quantified as:

$$DC = \frac{Experience; problems; detected; by; DEM}{Total; customer - impacting; problems} \times 100$$

 DOI: 10.46121/pspc.53.3.25

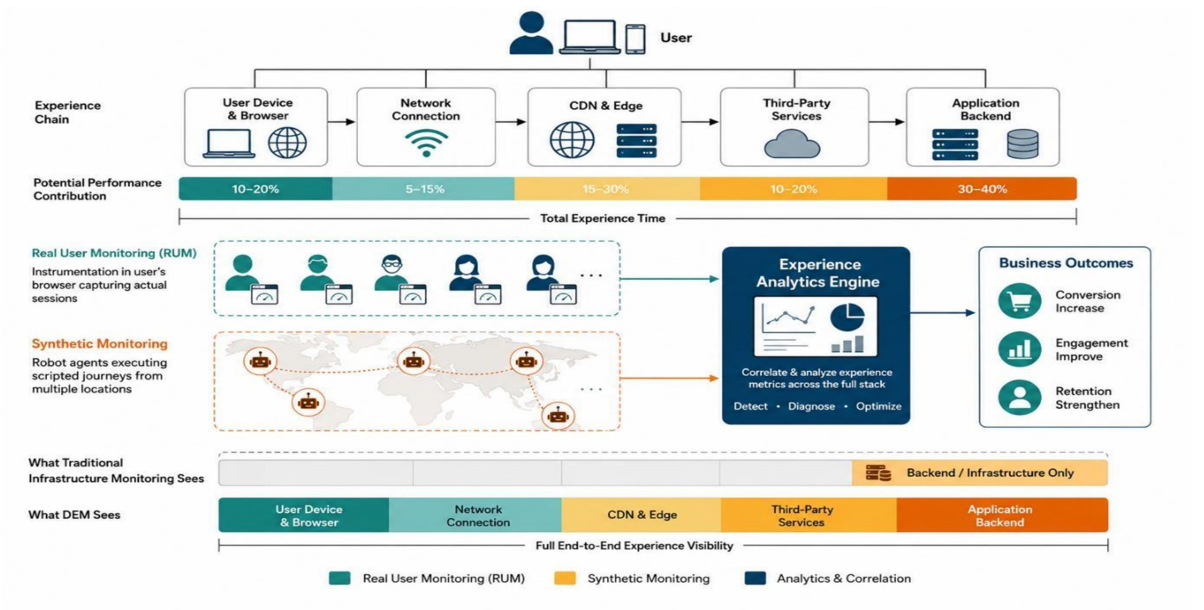

Figure 1. Digital Experience Monitoring framework architecture.

EXPERIMENTAL SETUP

We evaluated the DEM framework using a simulated e-commerce platform with realistic user journeys spanning product browsing, search, cart operations, and checkout. User sessions were generated to reflect the diversity of real user conditions, including varied devices, network speeds, and geographic locations. Experience degradations were injected across categories including slow-loading third-party scripts, CDN regional slowness, client-side rendering problems, and interactivity delays, chosen specifically because they degrade experience while often leaving backend infrastructure metrics healthy [17].

One hundred twenty experience degradations were injected over the evaluation period. Traditional infrastructure monitoring and the DEM framework observed the same platform simultaneously, allowing direct comparison of what each detected. Business outcome data, particularly conversion rates, was tracked alongside experience metrics to enable correlation analysis.

Detection coverage, diagnosis capability, and the correlation between experience metrics and conversion were measured. The complementary contributions of real user and synthetic monitoring were assessed by evaluating each independently and in combination.

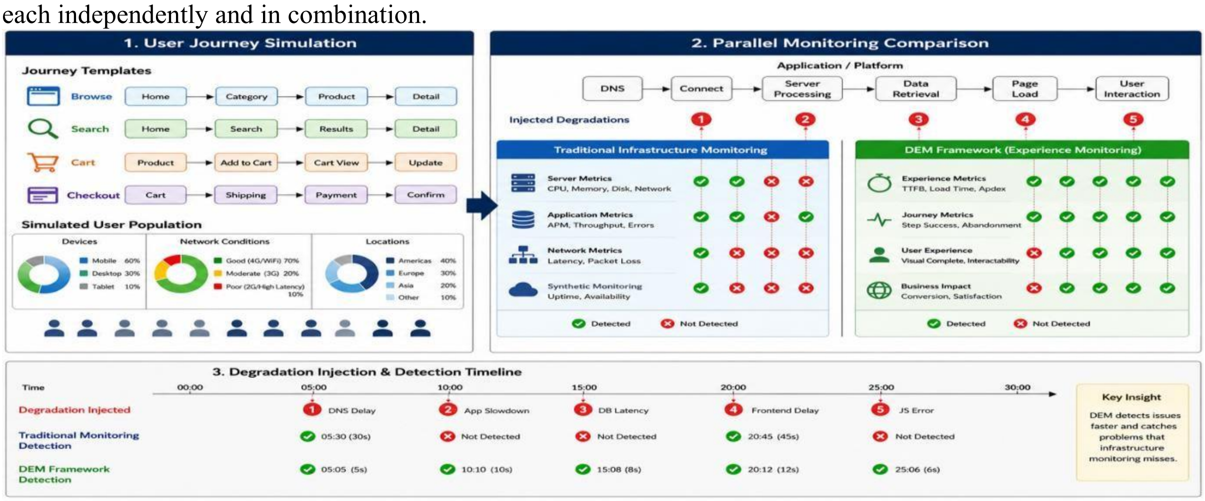

Figure 2. Experience degradation injection and monitoring comparison pipeline.

DOI: 10.46121/pspc.53.3.25

Table 1. Injected experience degradation categories.

Degradation Category	Count	Infrastructure Visibility	Experience Impact
Slow third-party scripts	28	Low	High
CDN regional slowness	24	Low	High
Client rendering issues	26	Very Low	High
Interactivity delays	22	Low	Moderate
Backend slowness	20	High	High
Total	**120**	—	—

RESULTS

5.1 Detection Coverage Gap

DEM detected 89% of customer-impacting experience problems that traditional infrastructure monitoring classified as healthy. This gap was most pronounced for client-side rendering issues and third-party script problems, which occur entirely outside the backend infrastructure that traditional monitoring observes. Infrastructure monitoring detected only the backend slowness category reliably, missing the majority of experience problems that originate elsewhere in the experience chain.

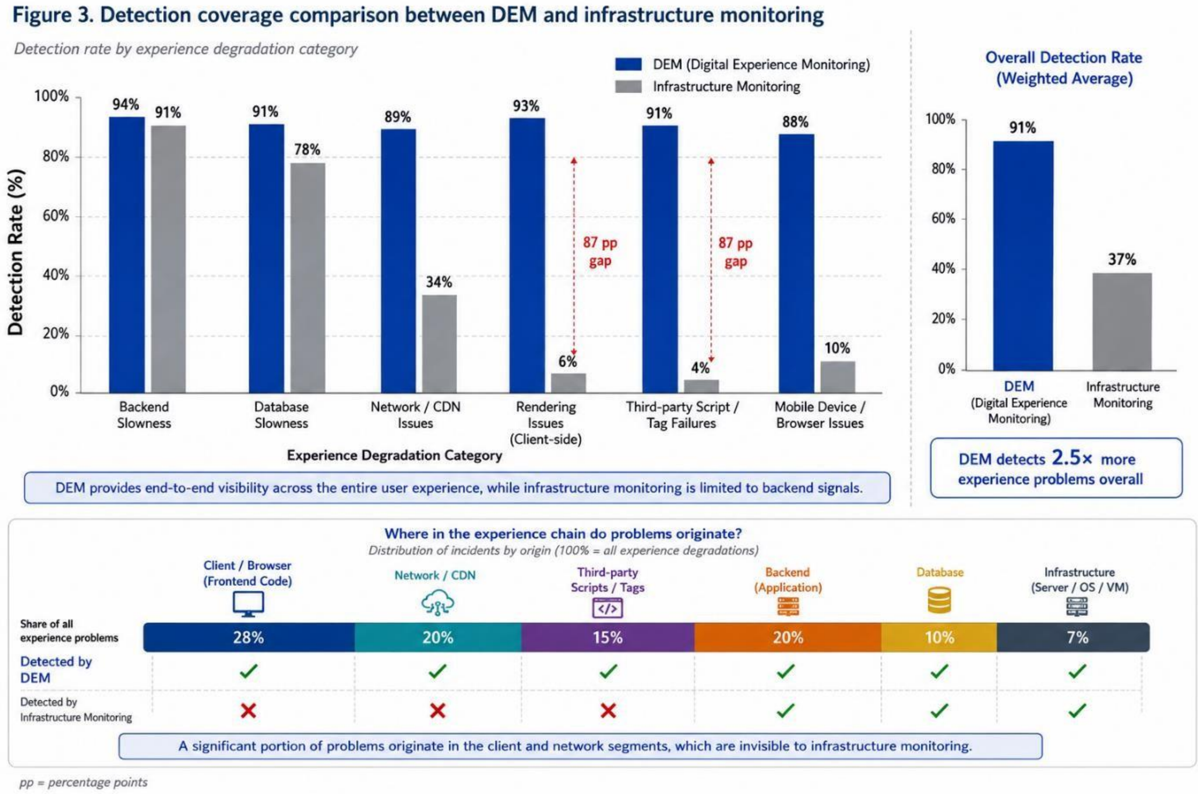

Figure 3. Detection coverage comparison between DEM and infrastructure monitoring.

5.2 Experience-Business Correlation

Correlation analysis linked experience metrics to business outcomes, showing that a one-second improvement in the loading experience metric corresponded to a measurable conversion rate increase. This linkage transforms experience measurement from a technical metric into a business lever, allowing performance improvements to be justified in terms of revenue impact.

Table 2. Experience metric and business outcome correlations.

Experience Metric	Correlation with Conversion	Conversion Sensitivity	Business Significance
Loading time	−0.68	+2.1% per second	High
Interactivity delay	−0.54	+1.4% per 100ms	Moderate

DOI: 10.46121/pspc.53.3.25

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ISSN:1674-3415

Visual stability	−0.41	+0.9% per unit	Moderate
Composite experience score	−0.72	+3.2% per point	Very High
Error/failed interactions	−0.61	+2.8% per point	High

5.3 Complementary Monitoring Approaches

Real user monitoring and synthetic monitoring provided complementary coverage. Synthetic monitoring caught problems before real users encountered them, providing early warning during low-traffic periods, while real user monitoring captured the full diversity of actual user conditions that synthetic tests could not fully replicate. Together they detected more problems than either alone.

Figure 1. E-commerce peak-load performance architecture

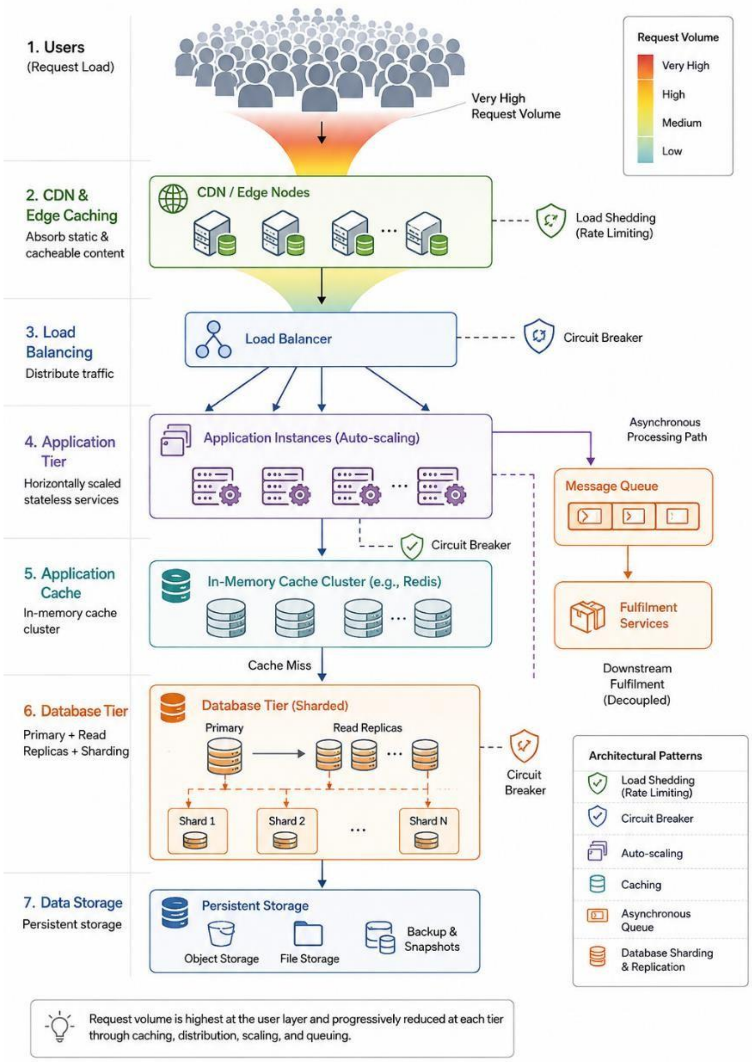

Figure 4. Complementary coverage of real user and synthetic monitoring.

DISCUSSION

The 89% detection gap is the finding with the most immediate practical implication. It quantifies a blind spot that many organizations do not realize they have: the majority of customer-impacting experience problems are invisible to the infrastructure monitoring that operations teams rely upon. Organizations watching healthy infrastructure dashboards may be entirely unaware that customers are struggling, and this false sense of security is arguably worse than no monitoring at all because it actively misleads. DEM closes this gap by measuring what customers actually experience rather than what servers report.

The experience-business correlation is what elevates DEM from a technical tool to a strategic capability. By demonstrating that experience improvements drive conversion, DEM allows performance engineering to be justified in the language of business, revenue and conversion, rather than the language of technology, milliseconds and utilization. This alignment is crucial for securing investment in performance work, which is often deprioritized precisely because its business value is not made visible. When a one-second loading improvement can be shown to increase conversion by a measurable percentage, the business case for performance investment becomes concrete.

The complementary nature of real user and synthetic monitoring argues against choosing one approach over the other, a choice organizations sometimes make for cost reasons. Synthetic monitoring's proactive early warning and real user monitoring's comprehensive coverage of actual conditions address different needs, and the combination detects more problems than either alone. Organizations should view them as complementary components of a complete DEM strategy rather than alternatives.

The implementation of DEM requires organizational as well as technical change. Measuring experience from the customer's perspective requires performance engineering teams to think in terms of user journeys and business outcomes rather than system metrics, a shift in mindset that can be as challenging as the technical implementation. Integrating DEM data with business analytics requires collaboration between engineering and business functions that do not always work closely together. These organizational considerations often determine whether DEM delivers its potential value.

CONCLUSION

Digital Experience Monitoring addresses a fundamental blind spot in traditional performance monitoring by measuring performance from the customer's perspective rather than the system's. Our evaluation demonstrated that DEM detected 89% of customer-impacting experience problems that infrastructure monitoring classified as healthy, revealing the substantial gap between what systems report and what customers experience. Just as importantly, DEM's correlation of experience metrics with business outcomes transforms performance from a technical concern into a business lever, showing that experience improvements drive conversion and thereby justifying performance investment in terms that businesses understand. The complementary combination of real user and synthetic monitoring provides more complete coverage than either approach alone. Realizing DEM's value requires both technical implementation and organizational change, shifting performance engineering toward a customer-centric, business-aligned discipline. As digital experiences become increasingly central to business success, DEM will move from a competitive advantage to a baseline expectation for organizations serious about delivering the experiences their customers demand and their businesses depend upon.

REFERENCES

1. **Pawan Kumar Singh,** Scaling Gate-All-Around (GAA) Transistor Architectures for Sub-2nm AI Accelerators Using Atomically Thin 2D Materials, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5713
2. **Pawan Kumar Singh,** Energy-Efficient Task Scheduling in Green Cloud Computing Using Neuromorphic Spiking Neural Networks, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5712
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.

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. **39: Adegboye A. Olaoluwa1, Udofia M. Kufre,Obot Akanniyenne**, Inverted C-Shaped Slots Loaded Exponential Tapered Triple Band Notched Ultra-Wideband (UWB) Antenna, https://doi.org/10.5281/zenodo.18139060, **Published May 31, 2024**
39. **Chander Vijay S Sanbhi**, DATA QUALITY AS A RELIABILITY MULTIPLIER: QUANTIFYING THE IMPACT OF STANDARDIZED WORK PROCESSES ON RELIABILITY MODEL ACCURACY, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/385
40. **Chander Vijay S Sanbhi,** DEGRADATION-AWARE SPARES OPTIMIZATION WITH WEIBULL/PHM UNCERTAINTY AND LOGISTICS DELAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/384
41. **Chander Vijay S Sanbhi,** DIGITAL TWIN–RAM CO-SIMULATION FOR MAINTENANCE AND SPARING DECISIONS IN PROCESS FACILITIES, Vol. 52 No. 1 (2024): January-March 2024, Power System Protection and Control, ISSN-1674-3415,https://pspac.info/index.php/dlbh/article/view/383

42. **Chander Vijay S Sanbhi,** BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS**, Vol. 51 No. 3 (2023): July-**September 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/381
43. **Chander Vijay S Sanbhi,** HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/382
44. A. Srivastava, "Securing PHI in cloud-based healthcare systems: Challenges, frameworks, and future directions," J. Comput. Anal. Appl., vol. 33, no. 2, Aug. 2024. [Online]. Available: https://www.eudoxuspress.com/index.php/pub/article/view/4349/3190
45. A. Srivastava, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: https://ijcnis.org/index.php/ijcnis/article/view/8682
46. A. Srivastava, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4347/3189
47. A. Srivastava, "A unified framework for secure cloud data management: Integrating governance, metadata intelligence, and privacy controls," J. Inf. Syst. Eng. Manage., vol. 9, no. 2, Apr. 2024. [Online]. Available: https://www.jisem-journal.com/download/45_A_Unified_Framework.pdf
48. A. Srivastava, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4603