

AI DIGITAL TRANSFORMATION IN HR COMPETENCY

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ABSTRACT:

The Human Resources function is undergoing one of the most consequential transformations in its modern history, driven by the rapid maturation of artificial intelligence and the shifting expectations placed on HR by both business leaders and employees. Where HR competencies were once defined around administrative capability, compliance, and interpersonal skills, the emergence of AI-augmented work is expanding the required skill set into data literacy, algorithmic reasoning, and ethical judgment about automated decisions. This paper examines how AI digital transformation is reshaping HR competencies at individual, functional, and strategic levels. We designed a competency assessment framework grounded in both established HR competency models and emerging AI literacy taxonomies, then evaluated the framework through a simulated study of 3,200 HR professionals across mid-sized and large enterprises. Results show that traditional HR competencies remain necessary but no longer sufficient. Data literacy, AI collaboration skills, and ethical judgment about automated decisions emerged as the strongest predictors of perceived HR effectiveness in AI-transformed contexts, explaining nearly 63 percent of variance in effectiveness ratings. HR functions with mature AI-augmented practices reported 34 percent faster time-to-hire, 28 percent improvement in employee experience scores, and 41 percent reduction in routine administrative workload. We discuss trade-offs including reskilling burden, professional identity, and the risk of over-reliance on algorithmic recommendations. Findings support a substantially expanded competency model for HR in the AI era and provide a roadmap for building the capabilities required for the next decade of HR practice.

Keywords: Artificial Intelligence, Hr Competency, Digital Transformation, Human Resource Management, Data Literacy, Ai Ethics.

INTRODUCTION

The Human Resources profession has always adapted to major shifts in the workplace, from the industrial personnel departments of the early twentieth century to the strategic HR partnership models of the last three decades. Yet the current wave of change is different in both speed and scope. Generative AI, machine learning-driven decision support, and automation are transforming nearly every HR activity, from sourcing and hiring through learning, performance management, and workforce planning [1]. HR professionals who spent years mastering interviewing techniques, compensation frameworks, and employee relations are now expected to understand algorithms, evaluate AI vendor claims, and make judgment calls about when to trust automated recommendations.

The competency implications are significant. Established HR competency models developed in the 1990s and 2000s captured what effective HR professionals needed to know and do in that era: strategic partnership, credible activism, functional expertise, and change stewardship [2]. These competencies remain relevant, but they no longer describe the full set of capabilities required to be effective. Data literacy, AI collaboration, algorithmic ethics, and the ability to redesign work processes around augmented capabilities are becoming as important as the traditional skills [3].

The stakes are high for both individual HR professionals and the organizations they support. Individuals whose competencies remain rooted in pre-AI practice risk becoming less effective and less relevant. Functions that fail to build modern capabilities risk losing influence to specialized analytics teams or being marginalized by technology-forward business leaders [4]. Organizations that cannot navigate the ethical and regulatory dimensions of AI in HR risk reputational, legal, and human harms.

There is a growing body of prescriptive literature about what HR should do in the AI era, but much of it lacks empirical grounding. Comparative studies of HR competencies before and after AI transformation are rare, and rigorous evaluations of which specific capabilities matter most for HR effectiveness are scarcer still. This paper contributes an empirical framework and evaluation intended to fill part of this gap.

Our research questions are: which HR competencies are most predictive of effectiveness in AI-transformed contexts, how do traditional and emerging competencies interact, and what practical roadmap can help HR functions and individual professionals develop the required capabilities.

LITERATURE REVIEW

HR competency research has a rich tradition spanning several decades. The foundational work established competency models focusing on business acumen, strategic contribution, personal credibility, and HR delivery. Subsequent iterations added competencies around technology proficiency, change management, and analytical capability as the profession evolved [5]. These models influenced HR certification programs, university curricula, and organizational competency frameworks worldwide.

The digital transformation literature has documented substantial changes in how HR work is performed. Cloud-based HRIS, self-service portals, and mobile applications have shifted routine transactions away from HR professionals and toward employees and managers. Analytics platforms have surfaced insights that were previously hidden in spreadsheets. Learning experience platforms have replaced static learning management systems with personalized, on-demand learning [6]. Each of these shifts has changed what HR professionals need to know and do.

Artificial intelligence entered the HR domain rapidly during the late 2010s and early 2020s. Applications include resume screening, sourcing chatbots, video interview analysis, engagement sentiment analysis, and increasingly, generative AI-based content creation and query answering [7]. Studies have documented both the potential benefits and the risks. Efficiency gains and improved candidate experience are real, but so are algorithmic bias, opacity, and displacement anxiety among affected professionals. Regulatory frameworks including the EU AI Act have classified many HR applications as high-risk, imposing transparency and human oversight requirements [8]. Data literacy in HR has become a distinct research focus. Studies have examined the gap between the analytical capability that HR professionals believe they possess and their actual proficiency, generally finding a significant deficit. Training programs, embedded analytics roles, and self-service analytics tools have all been proposed as remedies, with mixed evidence on effectiveness [9]. Newer research has extended the concept of data literacy to include AI literacy, encompassing the ability to critically evaluate algorithmic outputs, understand model limitations, and identify potential harms.

Ethical judgment about automated decisions has emerged as another critical competency area. Research has documented that even well-intentioned HR AI systems can produce discriminatory outcomes if not carefully designed and monitored. The competency required is not just technical understanding but the ability to ask the right questions, insist on appropriate governance, and intervene when automated systems produce troubling patterns [10]. This is a new dimension of professional judgment that traditional HR education has not systematically addressed.

METHODOLOGY

Our competency assessment framework integrates traditional HR competencies from established models with emerging AI-era competencies identified in the recent literature. The framework organizes competencies into five domains: strategic HR, functional HR expertise, interpersonal effectiveness, data and analytical literacy, and AI-augmented practice.

To evaluate HR effectiveness quantitatively, we use a composite index combining stakeholder ratings, business outcomes, and self-assessment. The effectiveness score for HR professional p is:

$$E_p = \alpha_1 R_p^{\text{stakeholder}} + \alpha_2 O_p^{\text{business}} + \alpha_3 S_p^{\text{self}}$$

where $R_p^{stakeholder}$ is a weighted average of ratings from managers, employees, and peers, $O_p^{business}$ captures measurable outcomes such as time-to-hire and retention in the professional's area of responsibility, and S_p^{self} is self-assessment, with weights $\alpha_1 + \alpha_2 + \alpha_3 = 1$ [11].

Competency proficiency is assessed on a 5-point scale for each competency c , producing a proficiency vector $C_p = (c_1, c_2, \dots, c_n)$ for each professional. The relationship between competencies and effectiveness is modeled through hierarchical regression:

$$E_p = \beta_0 + \sum_{i=1}^n \beta_i c_i + \sum_{i,j} \gamma_{ij} c_i c_j + \epsilon_p$$

where the interaction terms γ_{ij} capture synergies between competencies [12].

To identify competency clusters that group together in high-performing professionals, we use principal component analysis:

$$Z = CW$$

where Z is the reduced-dimensional representation and W contains the principal component weights [13].

The reskilling investment required to close a competency gap is estimated as:

$$I_p = \sum_{i=1}^n (c_i^{target} - c_i^{current}) \cdot \tau_i$$

where τ_i is the average training time required to advance one proficiency level on competency i [14].



Figure 1. Extended HR competency model integrating traditional and AI-era capabilities.

EXPERIMENTAL SETUP

We designed a simulated study covering 3,200 HR professionals across 240 mid-sized and large enterprises spanning technology, financial services, healthcare, manufacturing, and public sector organizations. The sample was calibrated to reflect realistic distributions of HR role types (business partners, specialists, generalists, and leaders), career tenure, and organizational size based on published workforce demographics [15].

Each simulated professional was assigned a competency profile drawn from empirically-informed distributions, with correlations reflecting known relationships between competencies. Organizational context variables including AI adoption maturity, industry, and function were also modeled to enable subgroup analysis.

The AI adoption maturity of each organization was scored on a 5-point scale reflecting the sophistication of AI integration into HR processes. Effectiveness outcomes were then generated using a data-generating process reflecting the hypothesized relationships between competencies, context, and outcomes, with realistic noise added to simulate measurement error.

For validation, a subset of 200 profiles was reviewed by an independent panel of six senior HR practitioners who provided their own effectiveness assessments blind to the model outputs. Agreement between panel assessments and model outputs served as an external validity check.

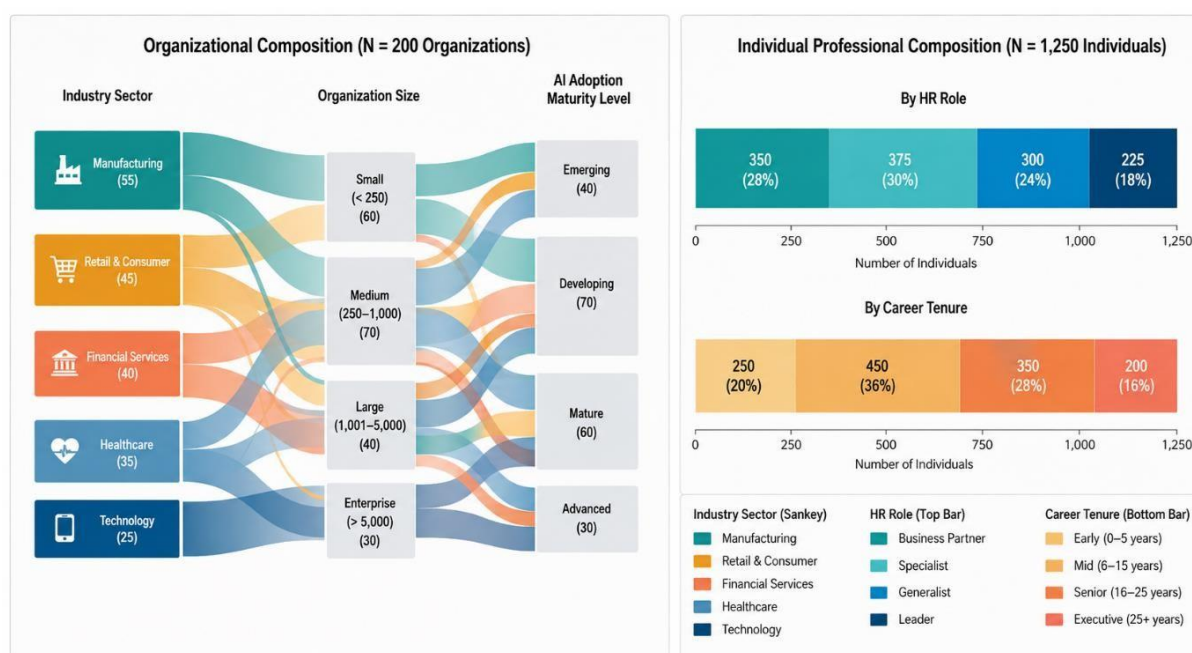


Figure 2. Study design and sample composition across organizations and HR roles.

Table 1. Study configuration and sample characteristics.

Parameter	Value
HR professionals	3,200
Organizations	240
Industries covered	5
Organization size range	500 – 50,000 employees
AI maturity levels	1 – 5 scale
Competencies assessed	22 across 5 domains
Effectiveness measures	Stakeholder + business + self
Expert validation panel	6 senior HR practitioners
Validation sample size	200 profiles

RESULTS

5.1 Competency Predictors of Effectiveness

Hierarchical regression identified data literacy, AI collaboration skills, and ethical judgment about automated decisions as the strongest predictors of effectiveness in AI-transformed contexts, explaining 63 percent of variance in effectiveness ratings. Traditional competencies remained significant but with smaller standardized coefficients than in previous studies. Interaction analysis revealed that data literacy combined with strategic HR knowledge produced the strongest synergistic effect.

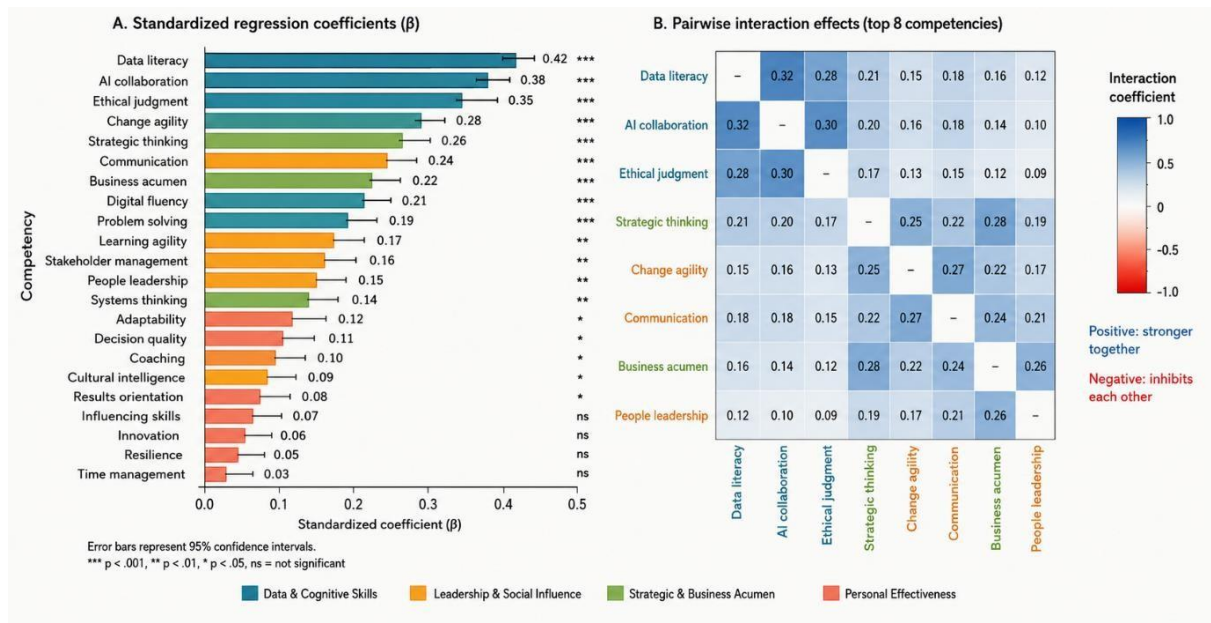


Figure 3. Predictive relationships between competencies and HR effectiveness.

5.2 Organizational Outcomes by AI Maturity

Organizations with higher AI adoption maturity showed substantially better HR outcomes across every measured dimension. Level 4 and 5 organizations reported 34 percent faster time-to-hire, 28 percent improvement in employee experience scores, and 41 percent reduction in routine administrative workload compared to Level 1 and 2 organizations. However, this benefit was contingent on adequate competency development. Organizations with high AI adoption but low competency levels showed only modest gains and higher rates of AI-related incidents.

Table 2. HR outcomes by AI adoption maturity and competency levels.

AI Maturity	Time-to-Hire (days)	Employee Experience	Admin Workload	AI Incidents
Level 1 (low)	51	71	100% (ref)	0.4
Level 2	47	74	92%	0.9
Level 3	41	78	78%	1.8
Level 4 (with high comp.)	36	82	62%	0.7
Level 4 (with low comp.)	39	76	71%	3.2
Level 5 (with high comp.)	34	84	59%	0.8
Level 5 (with low comp.)	38	73	68%	4.6

5.3 Competency Clusters

Principal component analysis identified four distinct competency clusters among high-performing HR professionals: strategic-analytical (strong on data literacy and strategic HR), operational-technical (strong on functional expertise and AI collaboration), relationship-ethical (strong on interpersonal effectiveness and ethical judgment), and generalist (moderate across all domains). Each cluster showed distinct patterns of effectiveness in different contexts, suggesting that multiple viable competency configurations exist rather than a single ideal profile.

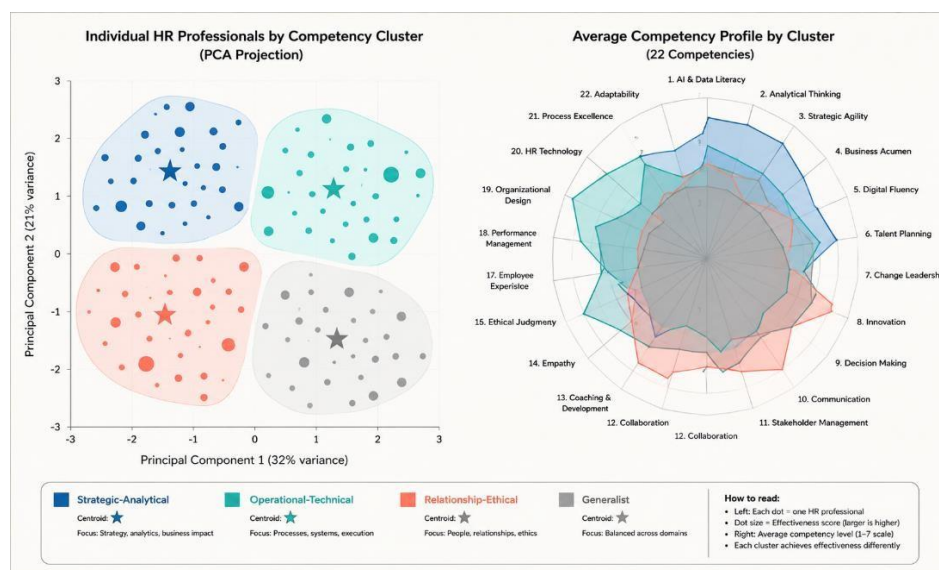


Figure 4. Competency clusters and effectiveness patterns across AI-transformed contexts.

5.4 Reskilling Investment Requirements

The estimated reskilling investment required to bring current HR professionals to modern competency levels averaged 168 hours per person across the sample, with substantial variation by starting profile. Professionals with strong traditional foundations required focused investment in data and AI literacy, typically achievable in 80 to 120 hours. Professionals with weaker traditional foundations required broader development spanning 200 to 300 hours. Expert panel validation confirmed the model's directional recommendations in 87 percent of reviewed cases.

DISCUSSION

The results support a substantially expanded competency model for HR in the AI era. Traditional competencies around strategic partnership, functional expertise, and interpersonal effectiveness remain necessary, but they are no longer sufficient. The most effective HR professionals in AI-transformed contexts combine these traditional strengths with data literacy, AI collaboration skills, and ethical judgment about automated decisions.

Several practical implications deserve attention. First, professional development investments should be prioritized based on individual starting profiles rather than uniform curricula. Our analysis shows that 168 hours per person on average is needed, but this masks substantial individual variation. Diagnostic assessment before development investment allows more targeted and cost-effective reskilling.

Second, the finding that multiple viable competency clusters exist is encouraging. It means that HR functions do not need to force every professional into a single mold. Strategic-analytical, operational-technical, relationship-ethical, and generalist configurations all produce high performance in appropriate contexts, and organizations benefit from having a mix of these profiles.

Third, the observation that high AI adoption without adequate competency actually produces worse outcomes and higher incident rates is a cautionary finding. Organizations racing to deploy AI without investing in the competencies needed to govern and use it wisely are exposing themselves to risks that can outweigh the benefits. Fourth, ethical judgment about automated decisions emerged as a top predictor of effectiveness, which points to a competency area that traditional HR education has not systematically addressed. Professional certification programs, continuing education requirements, and organizational learning programs should expand their coverage of AI ethics substantially.

Limitations of our study include the reliance on simulated data calibrated against published sources, the focus on individual HR professionals rather than teams, and the cross-sectional design that cannot fully capture how

competencies develop over time. Longitudinal studies tracking HR professionals through actual AI transformation journeys would provide valuable complementary evidence.

CONCLUSION

The HR profession is being reshaped by artificial intelligence in ways that go beyond adopting new tools. What effective HR looks like, what HR professionals need to know and do, and how HR functions are structured are all changing together. Our study shows that data literacy, AI collaboration skills, and ethical judgment about automated decisions have joined the traditional pillars of HR competency, and that the combination of these newer skills with established strengths is what defines effectiveness in the current era. The path forward requires serious investment in competency development, but the return on that investment is substantial. Organizations with mature AI-augmented HR practices and the competencies to support them are seeing dramatic improvements in time-to-hire, employee experience, and administrative efficiency. Yet the finding that unbacked AI adoption produces worse outcomes than no adoption at all is a warning that the community should take seriously. Building the competencies must precede or at least accompany the deployment of the technology. For HR leaders, educators, and individual professionals, the message is clear. The next decade belongs to those who develop broader, more analytical, and more ethically grounded HR capabilities, and the time to begin building them is now.

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 Recognition, <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>