Big Data Analytics Capability and Organizational Agility: An Empirical Research Model

Dyuti Banerjee

Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India

Abstract

Big data analytics capability (BDAC) is widely claimed to improve organisational agility, but the mechanism through which it does so, the conditions under which the effect is stronger, and the sample sizes needed to test these claims are seldom specified before data are collected. This paper develops an empirical research model in which BDAC affects agility both directly and indirectly through data-driven decision-making capability (DMC), with environmental dynamism moderating the direct path. The model is grounded in the resource-based and dynamic-capabilities perspectives and in prior empirical work on information-technology capability and agility. Rather than reporting field estimates, the paper validates the model's testability through a simulation harness: survey-type data are generated from the hypothesised structural relationships with indicator reliability of 0.80, and the mediation and moderation analyses are run on samples of 100 to 500 firms. The indirect effect is detected with bootstrap confidence intervals in 98% of samples at $N = 100$ and in every sample at $N \geq 200$, while a worked example at $N = 400$ recovers the direct, indirect and interaction effects with the expected attenuation from measurement error (observed coefficients of 0.36, 0.46×0.27 and 0.10 against design values of 0.30, 0.50×0.40 and 0.20). The paper specifies measurement, sampling, analysis and robustness procedures for a field study and argues that simulation-based pre-validation should become standard practice for empirical models in information-systems and strategy research.

Keywords: big data analytics capability; organisational agility; dynamic capabilities; mediation; moderation; simulation-based power analysis

International Journal of Technology, Management and Humanities (2026) DOI: 10.21590/ijtmh.12.2.12

Introduction

Organisational agility, the capacity to sense and respond to change quickly and effectively, is a central concern of strategy and information-systems research [1], [2]. Investments in big data analytics are frequently justified by their expected contribution to agility: better data and faster analysis should let firms detect shifts in markets and operations earlier and respond with more confidence. Empirical studies have related big data analytics capability (BDAC) to firm performance [3] and have elaborated the resources that constitute the capability [4], but the specific link to agility and the mechanism behind it remain underspecified.

Three gaps motivate this paper. First, mechanism: it is unclear whether BDAC affects agility directly, by shortening sensing and response cycles, or indirectly, by changing how decisions are made. Second, contingency: dynamic-capabilities theory implies that the value of sensing capabilities depends on environmental dynamism [5], but the direction and size of this contingency for BDAC are rarely hypothesised in advance. Third, testability: mediation and moderation hypotheses require adequate samples, and the sample sizes typical of firm-level surveys may be insufficient for the interaction terms that contingency hypotheses demand.

This paper addresses the gaps by developing a research model with explicit hypotheses, specifying its measurement and analysis, and validating its testability through simulation before any field data are collected. The simulation establishes the sample size at which the

Corresponding Author: Dyuti Banerjee, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India, e-mail: dbanerjee@kluniversity.in

How to cite this article: Banerjee, D. (2026). Big Data Analytics Capability and Organizational Agility: An Empirical Research Model. *International Journal of Technology, Management and Humanities,* 12(2), 98-104.

Source of support: None

Conflict of interest: None

hypothesised effects can be detected and documents how measurement error attenuates the estimated coefficients, which informs the choice of estimation method for the field study.

THEORETICAL BACKGROUND

Big data analytics capability

Gupta and George [4] conceptualised BDAC as a bundle of tangible resources (data, technology, basic resources), human resources (technical and managerial skills) and intangible resources (data-driven culture, organisational learning). Wamba et al. [3] showed that BDAC relates to firm performance and that the relationship operates partly through process-level dynamic capabilities. Both treatments rest on the resource-based view [6], in which capabilities that are valuable, rare and hard to imitate yield advantage.

Organisational agility

Overby, Bharadwaj and Sambamurthy [1] defined enterprise agility as the ability to sense environmental change and respond readily, and identified information technology as a key enabler. Lu and Ramamurthy [2] found that IT capability improves both market-capitalising and operational-adjustment agility. Teece, Pisano and Shuen [5] framed the underlying dynamic capabilities as sensing, seizing and transforming, and argued that their value rises with environmental turbulence.

Data-driven decision-making as a mechanism

A plausible mechanism linking BDAC to agility runs through decision-making. Analytics capability changes the information available to decision-makers and the speed with which it can be acted upon; organisations that institutionalise data-driven decision-making can respond to signals without the delays of hierarchical escalation. Data-driven decision-making capability (DMC) is therefore proposed as a mediator.

RESEARCH MODEL AND HYPOTHESES

The model has four constructs: BDAC, DMC, organisational agility (AGIL) and environmental dynamism (DYN).

H1. BDAC is positively associated with DMC.

H2. DMC is positively associated with AGIL.

H3. BDAC has a positive direct effect on AGIL, controlling for DMC.

H4. The indirect effect of BDAC on AGIL through DMC is positive (mediation).

H5. Environmental dynamism strengthens the direct effect of BDAC on AGIL (moderation).

In structural form, with all constructs standardised,

$$\mathrm{DMC} = a\cdot\mathrm{BDAC} + u_1, \tag{1}$$

$$\mathrm{AGIL} = b\cdot\mathrm{DMC} + c'\cdot\mathrm{BDAC} + d\cdot\mathrm{DYN} + g\cdot(\mathrm{BDAC}\times\mathrm{DYN}) + u_2, \tag{2}$$

where a and b define the indirect effect ab, c' is the direct effect and g is the moderation coefficient. H1–H5 correspond to $a > 0$, $b > 0$, $c' > 0$, $ab > 0$ and $g > 0$.

MEASUREMENT AND FIELD DESIGN

BDAC is measured with the multi-dimensional instrument of Gupta and George [4], DMC with items on the extent to which decisions at operational and strategic levels are based on analytical evidence, AGIL with the market-capitalising and operational-adjustment items of Lu and Ramamurthy [2], and DYN with established items on the rate and unpredictability of change in customers, technology and competition. All constructs use seven-point scales with three to five reflective indicators. The intended sampling frame is medium and large firms across manufacturing and services, with one senior informant per firm and a second informant for a subsample to assess inter-rater agreement. Common-method variance is addressed by procedural separation of predictor and criterion items and by a marker-variable test.

Analysis follows the bootstrap mediation procedure [7], [8] with 5,000 resamples for the indirect effect, and a product-term specification for the moderation [9]. Because the simulation below shows attenuation from measurement error, structural equation modelling with latent constructs is specified as the primary estimator, with regression on composite scores as a robustness check.

SIMULATION-BASED VALIDATION

Purpose

Before collecting data, the harness answers two questions. What sample size gives adequate power to detect the indirect effect by bootstrap confidence interval? And how much do regression estimates on composite scores deviate from the structural parameters when indicators are imperfectly reliable? The approach

follows the logic of theory development through simulation [10].

Design

Latent constructs are generated according to Equations (1) and (2) with $a = 0.50$, $b = 0.40$, $c' = 0.30$, $g = 0.20$ and $d = 0$, residual variances scaled so that each construct has unit variance. Observed composite scores are latent scores plus normal measurement error calibrated to a reliability of 0.80. For $N \in \{100, 200, 300, 500\}$, 100 datasets are generated; in each, a and b are estimated by ordinary least squares on composite scores, and a percentile bootstrap confidence interval for ab is computed from 60 resamples. Power is the proportion of datasets in which the interval excludes zero. A single dataset with $N = 400$ is analysed in full to illustrate the recovered coefficients. Implementation uses scikit-learn [11].

Results

Table 1 reports power and the mean estimated indirect effect. At $N = 100$ the indirect effect is detected in 98% of samples, and at $N \geq 200$ in all samples. The mean estimated indirect effect is about 0.13–0.14, against a design value of $ab = 0.20$; the shortfall is the attenuation produced by measurement error in BDAC and, more consequentially, in the mediator, whose error biases b downward [8]. Figure 1 plots the power curve.

Table 1: Simulated power to detect the indirect effect (bootstrap percentile interval) and mean estimate, 100 datasets per sample size, indicator reliability 0.80

Sample size	*Power for ab > 0*	*Mean estimated ab*	*Design value of ab*
100	0.98	0.141	0.20
200	1.00	0.133	0.20
300	1.00	0.137	0.20
500	1.00	0.132	0.20

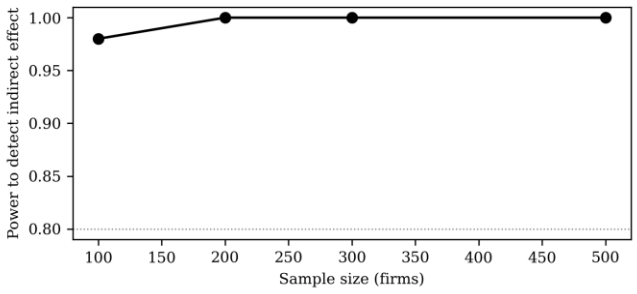


Figure 1: Simulated power to detect the BDAC → DMC → AGIL indirect effect as a function of sample size.

The illustrative dataset at $N = 400$ yields $a = 0.458$, $b = 0.272$, $c' = 0.363$ and $g = 0.096$, with R^2 for agility of 0.33 (Table 2). All signs agree with H1–H5. The direct effect is slightly overestimated because part of the attenuated indirect effect is reattributed to the direct path, and the interaction coefficient is roughly halved because the product of two error-laden scores has reliability well below 0.80. These patterns are the standard consequences of measurement error in mediation and moderation models and are the reason latent-variable estimation is specified for the field study.

Table 2: Coefficients recovered from one simulated dataset (N = 400) compared with design values

Parameter	*Hypothesis*	*Design value*	*Recovered (OLS on composites)*
a (BDAC → DMC)	H1	0.50	0.458
b (DMC → AGIL)	H2	0.40	0.272
c′ (BDAC → AGIL, direct)	H3	0.30	0.363
ab (indirect)	H4	0.20	0.125
g (BDAC × DYN)	H5	0.20	0.096

Implications for the field study

Three design decisions follow. A target of at least 200 usable responses provides ample power for H4 under the hypothesised effect sizes and a margin for smaller true effects. Because the moderation coefficient is attenuated most severely, the power analysis should be repeated for g with smaller assumed values before fixing the sample target, and the interaction should be estimated with latent product terms or with corrections for unreliability. Reporting should include both the attenuated composite-score estimates and the latent-variable estimates so that readers can judge the sensitivity of conclusions to measurement quality.

Discussion

Contribution to theory

The model advances the BDAC literature by specifying decision-making capability as the mechanism through which analytics resources become agility, and by stating the contingency on dynamism as a formal hypothesis. If supported, the mediation implies that analytics investments without accompanying changes in decision processes will yield less agility than expected; if the moderation is supported, it implies that the agility payoff of analytics is concentrated in turbulent environments, consistent with dynamic-capabilities theory [5].

Contribution to method

Simulation-based pre-validation of an empirical model is inexpensive and clarifies, before the costly step of data collection, whether the planned sample and estimator can answer the research questions. It makes the expected attenuation explicit, which guards against over-interpreting small composite-score coefficients, and it provides a natural pre-registration artefact: the harness, the hypothesised effect sizes and the decision rules are fixed in advance.

Managerial relevance

For managers, the model implies that building BDAC is necessary but not sufficient for agility. The decision-making processes that consume analytical outputs must themselves change, and the return on analytics should be expected to vary with the turbulence of the environment. These implications are conditional on the hypotheses being supported in the field.

LIMITATIONS

The simulation assumes linear relationships, normal errors, equal reliability across constructs and no common-method variance; each assumption can be relaxed in the harness, and the field design includes checks for them. The design effect sizes are judgements informed by prior literature rather than estimates, and the power results hold only for those sizes. No field data are reported, and the recovered coefficients in Table 2 are illustrations of estimator behaviour, not findings about organisations.

CONCLUSION

This paper proposed a research model in which big data analytics capability affects organisational agility directly and through data-driven decision-making capability, with environmental dynamism as a moderator, and validated the model's testability by simulation. The indirect effect is detectable with high power at samples of 200 or more, measurement error attenuates mediation and especially moderation estimates in predictable ways, and latent-variable estimation is therefore specified for the field study. The approach offers a template for pre-validating empirical models before data collection.

REFERENCES

[1] Dwivedi, D. (2024). Agentic AI and global governance: Addressing the challenges of regulating autonomous artificial agents across borders in a digitally interconnected world. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 13(11), 2527–2534. https://doi.org/10.15662/IJAREEIE.2024.1311011

[2] Mahajan, R. A., Dey, R., Khan, M., Kanabar, K., & Gupta, S. K. (2025). Real-time vehicular-to-vehicular (V2V) communication and applications for pedestrian safety in AI-optimized VANETs for autonomous vehicles. In H. Maryam, M. M. Malik, I. U. Khan, & S. K. Gupta (Eds.), AI-driven transportation systems: Real-time applications and related technologies (pp. 151–167). Springer. https://doi.org/10.1007/978-3-031-98349-8_8

[3] Talasila, D. (2026). Agentic AI in multi-agent systems: Exploring the coordination, negotiation, and cooperation of autonomous artificial agents in competitive and collaborative digital ecosystems. Journal of Integrative Science and Societal Impact, 2(1), 64–71. https://doi.org/10.29121/JISSI.v2.i1.2026.43

[4] Aggarwal, A. (2018). Application of federated learning in medical IoT devices for preserving patient privacy and preventing data breaches through decentralized cyber defense models. International Journal of Innovative Research in Computer and Communication Engineering, 6(3), 2654–2660. https://doi.org/10.15680/IJIRCCE.2018.0603167

[5] Chatrath, A. (2018). The impact of containerization on DevSecOps: Security considerations for Docker, Kubernetes, and microservices architectures in continuous deployment pipelines. International Journal of Advanced Research in Education and Technology, 5(6). https://doi.org/10.15680/IJARETY.2018.0506019

[6] Khan, S. (2023). AI-driven speech and voice analytics in CRM platforms: A study on intelligent call center automation, emotion recognition, and service personalization. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 6(2), 510–517. https://doi.org/10.15680/IJMRSET.2023.0602035

[7] Mahadasu, S. S. (2019). Performance-aware VNF placement for distributed 5G core networks over heterogeneous edge and cloud infrastructure. International Journal of Engineering Science and Advanced Technology, 19(10), 5–11. https://doi.org/10.64771/ijesat.2019.v19.i10.pp3849

[8] Bhaskara Raju Rallabandi. (2022). DETERMINISTIC STABILITY ANALYSIS FOR PRODUCTION-LINE CONTROL OVER PRIVATE 5G. American Journal of AI Cyber Computing Management, 2(4), 33–37. https://doi.org/10.64751/ajaccm.2022.v2.n4.pp33-37

[9] Bhanushali, B. (2018). Risk-based approaches in anti-money laundering for balancing regulatory compliance costs and maximizing detection of high-risk financial activities. International Journal of Innovative Research in Computer and Communication Engineering, 6(11),

9006–9014. https://doi.org/10.15680/IJIRCCE.2018.0611081

[10] Jain, J., Jain, A., Srivastava, S. K., Verma, C., Raboaca, M. S., & Illés, Z. (2022). Improved security of e-healthcare images using hybridized robust zero-watermarking and hyper-chaotic system along with RSA. Mathematics, 10(7), 1071.

[11] Devulapalli, N. (2025). Machine learning in database security: Leveraging anomaly detection, intrusion detection, and predictive analytics for proactive threat prevention. International Journal of Innovative Research in Science, Engineering and Technology, 14(2), 1685–1692. https://doi.org/10.15680/IJIRSET.2025.1402105

[12] Gupta, A. (2025). Blockchain-enhanced cloud security: Exploring decentralized trust models, data integrity verification, and secure cloud auditing mechanisms. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 14(1). https://doi.org/10.15662/IJAREEIE.2025.1401019

[13] Bhaskara Raju Rallabandi. (2024). DIGITAL TWIN–DRIVEN 6G CAMPUS NETWORKS: INTELLIGENT FAULT RECOVERY AND ENERGY OPTIMIZATION. American Journal of AI Cyber Computing Management, 4(3), 30–34. https://doi.org/10.64751/ajaccm.2024.v4.n3.pp30-34

[14] Anchala, S. (2019). Database security challenges in cross-border data flows: Analysing compliance, privacy, and risk in international data transfers. International Journal of Advanced Research in Education and Technology, 6(3), 831–838. https://doi.org/10.15680/IJARETY.2019.0603016

[15] Aggarwal, A. (2018). Implementation of cloud security automation in continuous integration pipelines for accelerating DevSecOps adoption and minimizing manual misconfigurations through security-as-code. International Journal of Innovative Research in Science, Engineering and Technology, 7(11). https://doi.org/10.15680/IJIRSET.2018.0711083

[16] Ahuja, R. (2025). The risks and opportunities of generative AI in cyber security: Investigating the dual-use nature of generative models for phishing, malware development, and defence through synthetic data and automated threat detection. International Journal of Innovative Research in Computer and Communication Engineering, 13(2), 1758–1767. https://doi.org/10.15680/IJIRCCE.2025.1302059

[17] Kanabar, K., Dey, R., Mahajan, R., Jadhav, P. V., Khan, M., & Ghantasala, G. S. P. (2026). The benefits of web and blockchain in decision-making for Industry 4.0. In S. K. Singh, R. B. Jadeja, A. Khanna, P. K. Dutta, & B. Virdee (Eds.), Security paradigms in 6G smart cities and IoT ecosystems: Navigating the future (pp. 289–304). CRC Press. https://doi.org/10.1201/9781003564645-18

[18] Chatrath, A. (2019). A multi-layered DevSecOps framework: Integrating secure coding, automated testing, vulnerability scanning, and incident response into end-to-end software development lifecycles. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 8(3). https://doi.org/10.15662/IJAREEIE.2019.0803102

[19] Bhaskara Raju Rallabandi. (2023). NATIVE OBSERVABILITY FOR PRIVATE 5G: A REFERENCE ARCHITECTURE ON COMBINATION OF NWDAF, SMO, AND EDGE ANALYTICS. American Journal of AI Cyber Computing Management, 3(1), 24–28. https://doi.org/10.64751/ajaccm.2023.v3.n1.pp24-28

[20] Gupta, A. (2025). Agentic AI for national security and defense: An analytical study on autonomous agents in surveillance, strategic decision-making, and military operations with a focus on ethical and legal boundaries. Journal of Digital Security and Forensics, 2(1), 163–175. https://doi.org/10.29121/digisecforensics.v2.i1.2025.84

[21] Bhanushali, B. (2019). Integration of biometric authentication with AML systems for strengthening know-your-customer (KYC) processes and reducing identity fraud in financial institutions. International Journal of Advanced Research in Education and Technology, 6(5), 853–860. https://doi.org/10.15680/IJARETY.2019.0605019

[22] Kumar, S., Sharma, K., Kumar, P. A., Jain, A., Bhagat, S. K., & Singh, P. (2024, September). An improved particle swarm approach for energy-aware location-aided routing in mobile ad-hoc network. In 2024 7th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 7, pp. 1119–1124). IEEE.

[23] Gupta, A. (2026). Bias, fairness, and inclusivity in generative AI systems: A critical examination of algorithmic bias, representation gaps, and the challenges of ensuring equity in AI-generated outputs. Journal of Integrative Science and Societal Impact, 2(1), 23–30. https://doi.org/10.29121/JISSI.v2.i1.2026.38

[24] Chatrath, A. (2019). DevSecOps in Agile and Lean development: Examining the alignment of security, speed, and scalability in rapid iteration and continuous delivery environments. International Journal of Multidisciplinary and Scientific Emerging Research, 7(3), 1506–1513. https://doi.org/10.15662/IJMSERH.2019.0703046

[25] Mahadasu, S. S. (2021). Telemetry-assisted mobility management for 5G standalone networks with distributed edge user-plane functions. International Journal of Engineering Research and Science & Technology, 17(1), 141–145. https://doi.org/10.62643/ijerst.2019.v17.n1.4406

[26] Jaiswal, I. A., & Khan, S. (2025). Leveraging cloud-based projects (AWS) for microservices architecture. Universal Research Reports, 12(1), 195–202.



[27] Ahuja, R. (2024). Deployment of content security policies in front-end frameworks for blocking cross-site scripting and clickjacking through declarative access restrictions. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 7(11), 17234–17242. https://doi.org/10.15680/IJMRSET.2024.0711132

[28] Khan, S. (2023). AI-powered innovations in cross-border merchant payment systems: Exploring the role of artificial intelligence in enhancing speed, transparency, and trust in international financial transactions. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 12(5), 1217–1224. https://doi.org/10.15662/IJAREEIE.2023.1205026

[29] Anchala, S. (2018). Adoption of infrastructure as code security validation in cloud-native environments for reducing configuration drifts and compliance violations through automated template scanning. International Journal of Innovative Research in Science, Engineering and Technology, 7(10), 8305–8313. https://doi.org/10.15680/IJIRSET.2018.0710087

[30] Bhanushali, B. (2019). Graph-based network analysis for identifying complex money laundering typologies, detecting suspicious transaction chains, and tracing illicit financial flows. International Journal of Multidisciplinary and Scientific Emerging Research, 7(4), 2007–2014. https://doi.org/10.15662/IJMSERH.2019.0704047

[31] Kumar, S., Ghai, D., Jain, A., Tripathi, S. L., & Rani, S. (Eds.). (2023). Multimodal biometric and machine learning technologies: Applications for computer vision. John Wiley & Sons.

[32] Aggarwal, A. (2018). Implementation of quantum cryptography in financial transactions for enhancing data confidentiality and resisting future quantum attacks through secure key distribution mechanisms. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 7(7), 3196–3204. https://doi.org/10.15662/IJAREEIE.2018.0707016

[33] Khan, S. (2025). The role of artificial intelligence in cyber security: Leveraging machine learning and predictive analytics for intrusion detection, threat intelligence, and autonomous defense mechanisms. The Research Journal, 11(3), 1–7.

[34] Jain, A. (2024, December). Energy-efficient signal processing architectures for IoT networks design. In 2024 International Conference on Emerging Technologies and Innovation for Sustainability (EmergIN) (pp. 362–367). IEEE.

[35] Devulapalli, N. (2026). A comparative study of predictive AI and agentic AI: Examining key differences in autonomy, goal orientation, human interaction, and system accountability. Journal of Integrative Science and Societal Impact, 2(1), 80–87. https://doi.org/10.29121/JISSI.v2.i1.2026.45

[36] Talasila, D. (2024). Implementation of secure DevOps pipelines in cloud-native applications for ensuring code integrity and reducing vulnerability exposure through automated security integration. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 13(11), 2535–2543. https://doi.org/10.15662/IJAREEIE.2024.1311012

[37] Burnout in Global Healthcare Systems: Psychosocial Determinants, Regional Realities, and Behavioral Optimization Pathways. [Author/source details missing in supplied list]

[38] Rangappa, A. S. (2025). Agentic AI and cyber security: Autonomous threat hunting, intrusion detection, and adaptive defense mechanisms in a world of increasingly sophisticated cyber attacks. Journal of Digital Security and Forensics, 2(1), 128–138. https://doi.org/10.29121/digisecforensics.v2.i1.2025.86

[39] Dwivedi, D. (2026). Agentic AI and the future of artificial general intelligence: A study on how goal-oriented autonomous agents contribute to the development of more human-like intelligence, reasoning, and decision-making abilities. Journal of Integrative Science and Societal Impact, 2(1), 72–79. https://doi.org/10.29121/JISSI.v2.i1.2026.44

[40] Devulapalli, N. (2024). Agentic AI in finance and economics: The role of autonomous agents in fraud detection, algorithmic trading, credit risk assessment, and ethical governance of automated financial systems. International Journal of Multidisciplinary and Scientific Emerging Research, 12(4), 1958–1964. https://doi.org/10.15662/IJMSERH.2024.1204057

[41] Dwivedi, D. (2025). A comparative study of public, private, and hybrid cloud security architectures: Evaluating trade-offs in scalability, privacy, cost, and risk management. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 8(1), 485–493. https://doi.org/10.15680/IJMRSET.2025.0801069

[42] Anchala, S. (2018). Deployment of container image scanning in DevSecOps pipelines for mitigating open-source vulnerabilities and ensuring runtime safety through CVE-based detection mechanisms. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 7(3), 1546–1554. https://doi.org/10.15662/IJAREEIE.2018.0703058

[43] Rangappa, A. S. (2024). Application of AI-augmented log analysis in Dev Sec Ops monitoring for accelerating incident response and root cause analysis through pattern recognition and auto-correlation. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 7(10), 16135–16142. https://doi.org/10.15680/IJMRSET.2024.0710081

[44] Talasila, D. (2025). Adoption of dynamic application security testing (DAST) in DevOps lifecycles for identifying runtime vulnerabilities and business logic flaws through continuous fuzzing and penetration testing. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 8(2), 1192–1200. https://doi.org/10.15680/IJMRSET.2025.0802092

[45] Mahadasu, S. S. (2022). GitOps-based continuous delivery of cloud-native 5G network functions with automated configuration validation. International Journal of Data Science and IoT Management System, 1(1), 50–56. https://doi.org/10.64751/ijdim.2022.v1.n1.1286

[46] Ahuja, R. (2026). Adoption of secure session management in multi-device applications for mitigating session hijacking and replay attacks through token rotation and expiry controls. Journal of Integrative Science and Societal Impact, 2(1), 101–108. https://doi.org/10.29121/JISSI.v2.i1.2026.49

[47] Mahadasu, S. S. (2020). Cloud-native life cycle management of virtualized RAN functions using Kubernetes operators and policy-driven automation. International Journal of Engineering Science and Advanced Technology, 20(4), 21–26. https://doi.org/10.64771/ijesat.2020.v20.i04.pp3846

[48] Bhaskara Raju Rallabandi. (2022). SUB-MICROSECOND 5G SYNC FOR RELIABLE FACTORY ROBOT CONTROL. American Journal of Management and IOT Medical Computing, 1(1), 34–39. https://doi.org/10.64751/ajmimc.2022.v1.n1.pp34-39

[49] Rangappa, A. S. (2026). The architecture of agentic AI systems: A technical study on planning, memory, goal-oriented reasoning, and environment interaction for building robust autonomous agents. Journal of Integrative Science and Societal Impact, 2(1), 39–46. https://doi.org/10.29121/9shxnt36

[50] Mahajan, R., Kanabar, K., Dey, R., Jadhav, P. V., Khan, M., & Karimullah, S. (2026). Blockchain complementary model: A new way of devouring smart data by driverless vehicles for next-generation communication. In S. K. Singh, R. B. Jadeja, A. Khanna, P. K. Dutta, & B. Virdee (Eds.), Security paradigms in 6G smart cities and IoT ecosystems: Navigating the future (pp. 115–126). CRC Press. https://doi.org/10.1201/9781003564645-8

[51] Agrawal, N. K., Kumar, S., Bisht, G. S., Srivastav, A., Bansla, V., & Jain, A. (2024, May). Development of a novel quality of service aware video streaming on demand system for the Internet of Thing enabled MANET. In 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE) (pp. 80–85). IEEE.