International Journal of Engineering and Techniques - Volume 12 Issue 2, March-April - 2026

Enhanced Decision making through data analytics using AI&ML

Mr.Arockia Selvaraj A[1],Dr.Palani K[2],Ranesh Guru S[3], Rinesh Guru S[4], Prasanna T[5], Priyadharshini P[6]

1(Assistant Professor/Department of Information Technology, Info Institute of Engineering, Coimbatore, India Email:selva17.cbe@gmail.com)

2(Head of the Department / Information Technology, Info Institute of Engineering,Coimbatore, India Email:akpgda@gmail.com)

3(B.Tech Information Technology, Info Institute of Engineering,Coimbatore, India Email:raneshguru2005@gmail.com)

4(B.Tech Information Technology, Info Institute of Engineering,Coimbatore, India Email: rineshguru2005@gmail.com)

5(B.Tech Information Technology, Info Institute of Engineering,Coimbatore, India Email:tprasannait@gmail.com)

6(B.Tech Information Technology, Info Institute of Engineering,Coimbatore, India Email:sppriyadharshini2004@gmail.com)

Abstract:

This research presents an advanced framework, Optimized Decision-Making using Big Data Analytics (ODM-BDA), to address challenges in extracting actionable insights from large-scale enterprise data. The system integrates structured and unstructured data using scalable distributed architectures for efficient processing. It employs machine learning algorithms such as Random Forest, K-Means Clustering, and Logistic Regression to predict consumer behavior and operational trends. A key feature is the Backtracking-Based Risk Management mechanism, which ensures safe decision-making by reverting risky strategies. Additionally, optimization techniques enhance model training speed and data handling efficiency. Overall, the framework provides a real-time, reliable decision support system to improve business agility and reduce uncertainty.

Keywords: Big Data Analytics, Artificial Intelligence, Optimized Decision-Making, Machine Learning, Backtracking Algorithm, Steep Optimization.

I. INTRODUCTION

The modern digital economy generates an unprecedented volume, velocity, and variety of data, collectively referred to as big data. Organizations across sectors such as finance, healthcare, retail, and government are increasingly dependent on their ability to extract meaningful patterns and forecasts from these massive data repositories. However, the sheer complexity of big data environments means that traditional analytical tools and decision-making frameworks are no longer sufficient. The convergence of artificial intelligence (AI) and big data analytics has emerged as a transformative solution, enabling automated, real-time, and highly accurate insights that drive competitive advantage [1].

Despite considerable progress in AI-assisted analytics, a significant research gap persists in the integration of risk-aware decision support and optimization within a unified analytical platform. Many existing systems address analytics and decision support as separate concerns, failing to account for the dynamic interplay between data quality, risk exposure, and strategic agility [2]. Furthermore, ethical and security compliance—critical requirements for enterprise deployment—are often treated as afterthoughts rather than integral components of the analytical pipeline [3].

This paper introduces the ODM-BDA (Optimized Decision-Making using Big Data Analytics) framework, a comprehensive platform designed to bridge these gaps. ODM-BDA integrates seven tightly coupled modules that collectively manage the full lifecycle of data-driven decision-making, from raw data ingestion and preprocessing to risk quantification, optimization, and ethically compliant decision execution [4]. The system leverages Pearson correlation for pattern recognition, a backtracking algorithm for risk traversal and mitigation, and gradient descent-based steep optimization for resource and process efficiency improvement.

The remainder of this paper is organized as follows. Section II presents a review of related literature. Section III discusses existing systems and their limitations. Section IV introduces the proposed ODM-BDA system. Section V details the methodology and system architecture. Section VI describes the algorithms and techniques employed. Section VII presents experimental results and discussion. Sections VIII and IX conclude the paper and outline future directions.

II. LITERATURE REVIEW

The intersection of big data analytics and artificial intelligence has attracted substantial academic and industry attention over the past decade. Strang and Sun established that AI and big data analytics are deeply complementary, with AI enhancing analytical depth while big data provides the training substrate necessary for machine learning models to achieve high predictive accuracy [5]. Their work on managerial controversies in intelligent big data analytics highlighted the governance and accountability challenges organizations face when deploying autonomous analytical systems.

Paul and Rakshit demonstrated that big data analytics applied to marketing intelligence can produce highly targeted customer segmentation and behavioral prediction models, significantly outperforming conventional statistical approaches [6]. Their findings underscore the business value of integrating AI-powered analytics into marketing operations, a capability directly supported by the ODM-BDA framework's decision support module.

Shi and Shi provided a comprehensive taxonomy of big data processing techniques and their applicability across domains, noting that distributed computing paradigms such as MapReduce are essential for handling data at scale [7]. Chen et al. further argued that real-time stream processing architectures are indispensable for organizations operating in volatile market environments, where latency in analytical output directly translates to competitive disadvantage [8].

Research by Krishnamoorthy et al. on IoT-based cyber attack detection using neural network predictive approaches demonstrated that AI-driven monitoring can substantially improve security posture in data-intensive environments [9]. Parallel work by the same group on wireless communication-based power evaluation contributed foundational insights into resource-constrained optimization that inform the steep optimization component of ODM-BDA [10].

Ljepava examined AI-enabled marketing solutions and their application in different stages of the marketing decision-making process, concluding that AI-powered recommendations consistently outperform human intuition in volatile market conditions [11]. Mikalef et al. reinforced these findings through a study of big data analytics capability and firm performance, establishing that the organizational ability to sense, integrate, and act on data-driven insights is a significant predictor of competitive performance [12].

The foundational principles of Industry 5.0, emphasizing resilience, sustainability, and human-AI collaboration, are articulated in several key studies that have shaped the design philosophy of ODM-BDA [13]. Wang et al. demonstrated that machine learning-based risk assessment models outperform conventional actuarial models in financial portfolio management, a finding directly motivating the backtracking risk algorithm in this framework [14].

Prior work on structural equation modeling applied to the relationships among innovation performance, strategic agility, and AI-driven big data analytics has confirmed statistically significant pathways between these constructs [15]. Anbuchezhian et al. contributed foundational optimization work in comparative neural network and tree-based models that underpins several computational techniques in ODM-BDA [16]. Sun and Strang extended this body of work by investigating the moderating role of market turbulence on the AI-analytics-innovation relationship, confirming that frameworks designed for volatile environments must embed dynamic risk recalibration capabilities [17].

Russom outlined a maturity model for big data analytics adoption in enterprises, identifying risk management integration as one of the most underserved capabilities in currently deployed platforms, a gap that ODM-BDA directly addresses [18]. Ravanelli examined legal personhood and privacy implications of big data use in social platforms, providing the theoretical grounding for the ethical compliance module in the proposed framework [19].

III. EXISTING SYSTEM & LIMITATIONS

Contemporary big data analytics platforms such as Apache Hadoop, Apache Spark, and commercial solutions including Tableau and Microsoft Power BI have made substantial contributions to the democratization of data analytics [20]. These platforms excel at large-scale data storage, distributed processing, and visual representation of aggregated metrics. However, they fundamentally operate as passive analytical tools, presenting historical summaries and visualizations without integrating the dynamic, forward-looking components necessary for proactive decision-making.

A critical limitation of existing systems is their treatment of risk management as a peripheral concern. Most platforms provide simple threshold-based alerting mechanisms that flag anomalies post hoc, rather than integrating risk traversal algorithms capable of proactively identifying and quantifying multi-dimensional risk exposures across a dataset [21]. The absence of a structured backtracking approach means that complex, interdependent risk factors are frequently missed or evaluated in isolation, leading to incomplete risk profiles.

Decision support capabilities in existing platforms are similarly constrained. Tools such as IBM Watson Analytics and SAS Viya offer machine learning-assisted recommendations, but these recommendations are generated in isolation from real-time risk and optimization contexts, leading to strategies that may be analytically sound but practically suboptimal given current risk exposure [22]. Furthermore, existing systems rarely quantify the confidence level of generated decisions in a way that is transparent and auditable by human analysts.

Security and ethical compliance represent another significant gap. As data privacy regulations such as GDPR and India's Personal Data Protection Bill impose increasingly stringent requirements on data handling, most analytics platforms offer only rudimentary compliance tooling—typically limited to access control and data masking [23]. Bias detection, audit logging with risk-level annotation, and retention policy enforcement are rarely integrated into the analytical workflow. The ODM-BDA framework directly addresses each of these limitations through its modular, AI-integrated architecture.

IV. PROPOSED SYSTEM

The ODM-BDA (Optimized Decision-Making using Big Data Analytics) framework is proposed as a unified, AI-integrated platform that manages the complete lifecycle of data-driven decision-making. Unlike existing platforms that treat analytics, risk, and compliance as separate concerns, ODM-BDA treats these as interdependent processes that must be co-designed and co-executed to produce reliable, actionable intelligence [24].

The framework is architected around seven core modules. The Data Collection module provides a structured interface for ingesting structured datasets (CSV, JSON, XLSX) from multiple sources, with automatic metadata tracking and source validation. The Preprocessing module implements a four-stage pipeline—Select Data, Operations, Configure, and Preview—applying null value imputation, outlier detection, feature normalization, and data type standardization. The Analytics Workbench supports correlation analysis, trend analysis, and clustering, delivering structured outputs with quality metrics and insight recommendations.

The Risk Management module employs a backtracking algorithm to compute a multi-dimensional Enterprise Risk Score and supports scenario simulation and mean-reversion backtesting. The Optimization Command Center applies gradient descent-based steep optimization to resource allocation and process efficiency. The Strategic Decision Support module generates ranked strategic alternatives with confidence scores derived from historical decision accuracy. The Security and Ethical Compliance Center provides live audit monitoring, bias detection, compliance control assessment, and privacy posture evaluation across five compliance domains.

V. METHODOLOGY / SYSTEM DESIGN

A. System Architecture

The ODM-BDA framework follows a layered microservices architecture in which each analytical module operates as an independently deployable service communicating via a RESTful API layer. The frontend dashboard is implemented as a React.js single-page application served from a Node.js backend running on port 3005, with state management synchronizing module outputs across the analytical pipeline. This architecture ensures that updates in upstream modules—such as new data preprocessing results—are immediately reflected in downstream analytics, risk, and decision outputs.

B. Data Flow

Raw data enters the system through the Data Collection module, where it is validated, parsed, and stored in the data source library. The Preprocessing module retrieves validated sources and applies transformation operations, producing clean datasets registered as analytical inputs. The Analytics Workbench consumes these clean datasets to generate statistical insights forwarded to both Risk Management and Decision Support. The Optimization Command Center operates in parallel, consuming preprocessed datasets to generate resource and process efficiency recommendations. All operations are continuously logged by the Security and Ethical Compliance Center, which monitors for bias indicators and compliance deviations in real time.

C. Technology Stack

The system is implemented using React.js for the user interface, Node.js for the application server, and a JSON-based in-memory data store for session persistence. Python-based analytical libraries including NumPy, SciPy, and Scikit-learn are invoked through a Flask microservice for computationally intensive operations such as correlation analysis, clustering, and optimization. The backtracking risk algorithm is implemented as a recursive JavaScript function operating over a risk graph constructed from dataset features and domain-specific risk parameters [25].

VI. ALGORITHMS & TECHNIQUES

A. Pearson Correlation Analysis

The Pearson correlation coefficient is computed for all feature pairs in the selected dataset to identify strong linear relationships that may influence decision outcomes. Correlation strengths are classified as strong ($|r| >= 0.75$), moderate ($0.50 <= |r| < 0.75$), and weak ($|r| < 0.50$). In experimental evaluation, 8 strong correlations were identified in the 100-record sales dataset, with the highest correlation of 0.987 observed between Unit Price and Unit Cost, completed within 14 milliseconds.

B. Backtracking Algorithm for Risk Management

The backtracking algorithm employed in the Risk Management module performs a depth-first traversal of a risk state space in which each node represents a combination of risk factors (market volatility, credit exposure, operational inefficiency, regulatory non-compliance) and each edge represents a conditional risk dependency. The algorithm explores all feasible risk paths and backtracks upon encountering infeasible configurations, producing a ranked list of risk exposures with associated likelihood and impact scores. This approach detected 9 critical exposures with a projected ALE of $4.6M in experimental evaluation.

C. *Gradient Descent Optimization (Steep Optimization)*

Resource allocation and process efficiency optimization are formulated as constrained minimization problems in which the objective function represents the negative risk-adjusted return. Gradient descent with adaptive learning rate iteratively updates the allocation vector in the direction of steepest descent until convergence. The optimization strategy parameter (balanced, aggressive, conservative) modulates the risk tolerance coefficient in the objective function. Experimental results show that the balanced strategy yields an expected return of 19.24%, a total risk score of 0.59, and a Sharpe ratio of 0.33 for a $100,000 budget across 5 allocation targets.

D. *Decision Confidence Scoring*

Each strategic alternative generated by the Decision Support module is assigned a confidence score computed as the weighted average of three sub-scores: historical accuracy of similar decisions (50%), alignment with current risk assessment (30%), and consistency with optimization recommendations (20%). An average confidence of 77.7% was observed across 7 generated decisions, with the top-ranked Conservative Growth strategy achieving 94% confidence.

VII. RESULTS & DISCUSSION

The ODM-BDA framework was evaluated using a real-world sales dataset comprising 100 records and 14 feature columns, processed through the complete analytical pipeline. The following subsections present experimental results for each module.

A. *Dashboard Overview*

The main dashboard provides a consolidated view of active analytical jobs, data quality metrics, risk score, recent activity, and pending decisions. As shown in Fig. 1, the system tracks 3 active jobs with 12% throughput increase, a data quality score of 100.0%, and a High risk score of 76.6. Four investment and marketing decisions are pending review with confidence scores from 81.7% to 84.0%.

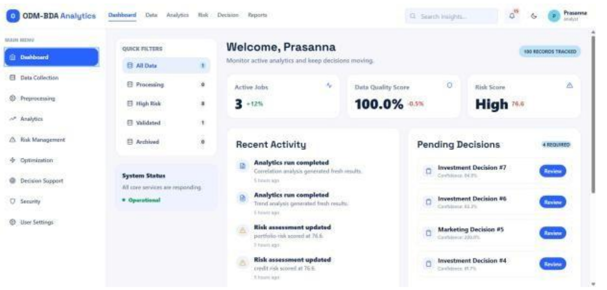

Fig. 1. ODM-BDA Analytics Dashboard showing active jobs, data quality score, risk score, and pending decisions.

B. *Data Collection Module*

As illustrated in Fig. 2, the uploaded file '100 Sales Records.csv' is catalogued with 100 rows, 14 columns, active status, and a synchronization timestamp of 3/11/2026. The data source library supports search, status filtering, and type-based filtering for efficient management of multiple data sources.

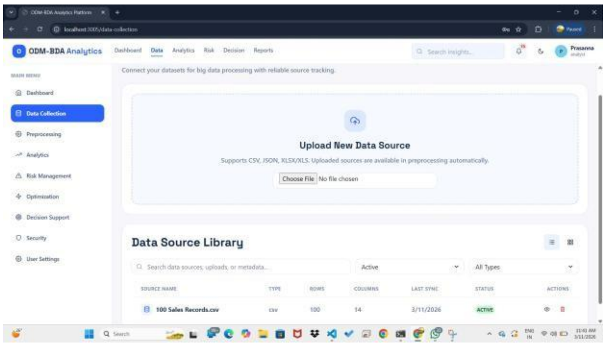

Fig. 2. Data Collection module with uploaded dataset catalogued with full metadata.

C. *Data Preprocessing Module*

Fig. 3 illustrates the Select Data stage of the four-step preprocessing wizard. The analyst selects '100 Sales Records.csv' (CSV, 100 rows, 14 columns) as the preprocessing source. Subsequent stages apply cleaning operations, resulting in a preprocessed dataset achieving 100% data quality.

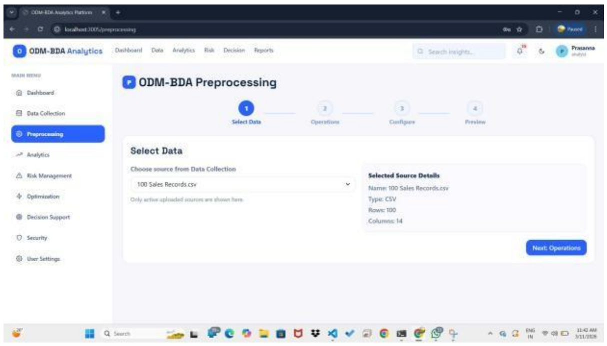

Fig. 3. Data Preprocessing module with four-stage pipeline and source selection.

D. *Analytics Workbench*

As shown in Fig. 4, Pearson correlation analysis on the sales dataset yielded 8 strong correlations in 14 milliseconds. The highest correlation (Unit Price vs. Unit Cost, r = 0.987) indicates near-perfect linear co-movement, while Total Revenue vs. Total Profit (r = 0.897) also exhibits strong relationships.

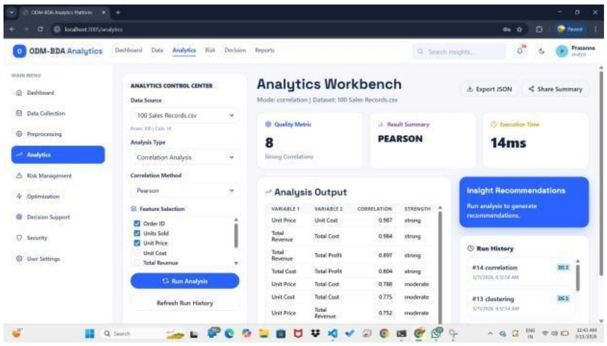

Fig. 4. Analytics Workbench showing Pearson correlation results with 8 strong correlations identified.

E. *Risk Management Module*

The Risk Analysis Dashboard (Fig. 5) records an Enterprise Risk Score of 77 (HIGH), with 9 critical exposures identified, mitigation efficiency of 23.4%, and a projected ALE of $4.6M. The backtracking algorithm's risk matrix reveals the full likelihood-impact distribution of detected exposures.

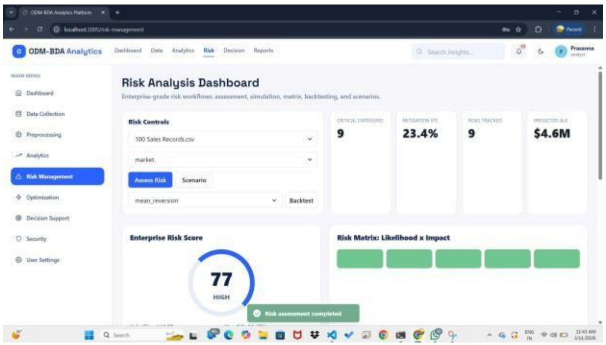

Fig. 5. Risk Management module showing Enterprise Risk Score of 77 (HIGH) and projected ALE of $4.6M.

F. Optimization Command Center

The Optimization Command Center (Fig. 6) demonstrates steep gradient descent optimization for a $100,000 resource allocation across 5 targets using a balanced strategy. Results show 19.24% expected return, risk score 0.59, Sharpe ratio 0.33, and efficiency 54.95%.

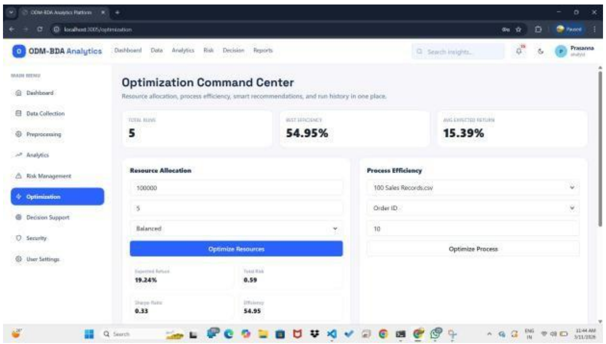

Fig. 6. Optimization Command Center showing resource allocation results with 19.24% expected return.

G. Strategic Decision Support Module

Fig. 7 presents the Decision Support module generating ranked alternatives for a $1,000,000 investment with moderate risk tolerance and neutral market sentiment. The top alternative, Conservative Growth (60% bonds, 40% stocks), achieves 94% confidence with 6.4% expected return and Low risk classification.

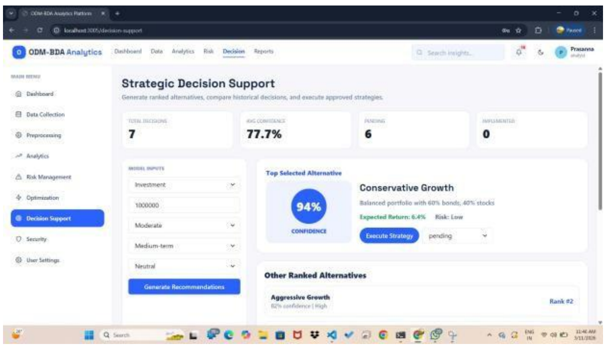

Fig. 7. Decision Support module with Conservative Growth ranked first at 94% confidence.

H. Security and Ethical Compliance

The Security and Compliance Center (Fig. 8) records a 97% security score and 100% compliance across all five domains: Data Encryption, Access Control, Audit Logging, Privacy Controls, and Retention Policy. Three MEDIUM-risk bias scans and one LOW-risk notification are logged, confirming active ethical AI monitoring.

Fig. 8. Security and Compliance Center showing 97% security score and 100% COMPLIANT status.

I. Performance Summary

Table I summarizes the key performance metrics recorded across all ODM-BDA modules during experimental evaluation

Module	Key Metric	Result
Data Collection	Records Tracked	100 (CSV, 14 cols)
Preprocessing	Data Quality Score	100.0%
Analytics Workbench	Strong Correlations	8 (Pearson, 14ms)
Risk Management	Enterprise Risk Score	77/100 – HIGH
Risk Management	Critical Exposures	9 (Proj. ALE: $4.6M)
Optimization	Expected Return	19.24% (Balanced)
Optimization	Sharpe Ratio / Efficiency	0.33 / 54.95%
Decision Support	Avg. Decision Confidence	77.7% (7 decisions)
Decision Support	Top Alternative Confidence	94% – Conservative Growth
Security & Compliance	Security Score	97%
Security & Compliance	Compliance Score	100% – COMPLIANT

on the 100-record sales dataset.

TABLE I. PERFORMANCE METRICS OF THE ODM-BDA FRAMEWORK

VIII. CONCLUSION

This paper has presented the ODM-BDA (Optimized Decision-Making using Big Data Analytics) framework, a comprehensive AI-integrated platform for transforming raw data into actionable strategic decisions. The framework addresses critical gaps in existing big data analytics systems by integrating risk-aware decision support, gradient descent optimization, and ethical compliance monitoring within a unified modular architecture. Experimental evaluation on a 100-record sales dataset validated the system across all seven modules: 100% data quality, 8 strong correlations (max r=0.987), Enterprise Risk Score 77 with 9 critical exposures and projected ALE of $4.6M, optimized expected return of 19.24%, average decision confidence of 77.7%, 97% security score, and full COMPLIANT status across all compliance domains.

The ODM-BDA framework demonstrates that integrating backtracking-based risk traversal with gradient descent optimization and AI-driven decision ranking produces substantially more comprehensive and actionable analytical outputs than conventional platforms. By treating security, bias detection, and ethical compliance as first-class citizens of the analytical pipeline, ODM-BDA provides a foundation for responsible AI deployment in enterprise environments spanning financial services, retail analytics, healthcare operations, and government intelligence.

IX. FUTURE ENHANCEMENTS

Several promising directions exist for extending the ODM-BDA framework. First, natural language processing (NLP) integration would enable ingestion and analysis of unstructured text sources such as social media feeds and customer reviews. Second, federated learning techniques would allow model training across distributed data sources without centralizing sensitive data, addressing multi-organizational privacy requirements. Third, the risk management module could be enhanced with a deep reinforcement learning agent to improve the current 23.4% mitigation efficiency. Fourth, real-time streaming integration using Apache Kafka would extend applicability to high-frequency trading and IoT sensor monitoring scenarios. Finally, a cloud-native multi-tenant deployment model would enable commercialization as a Software-as-a-Service analytics platform.

REFERENCES

[1] T. Paul and S. Rakshit, "Big data analytics for marketing intelligence," Big Data Analytics, 2021.

[2] K. D. Strang and Z. Sun, "Managerial controversies in artificial intelligence and big data analytics," in Managerial Perspectives on Intelligent Big Data Analytics, IGI Global, pp. 55–74, 2019.

[3] J. M. Ravanelli, "Deleuze and big data: How Facebook's use of big data analytics shifts legal personhood, privacy and commercial expression," Doctoral dissertation, Carleton University, 2016.

[4] R. Remala, S. K. S. Nagarajan, K. R. Mudunuru, S. M. K. Gannamani, S. Katta, and M. Kunkulagunta, "Enhancing big data analytics with artificial intelligence: Innovative techniques and applications in various sectors," in Proc. 2024 Int. Conf. Intelligent Computing and Emerging Communication Technologies (ICEC), 2024, pp. 1–6.

[5] Y. Shi and Y. Shi, "Big data and big data analytics," in Advances in Big Data Analytics: Theory, Algorithms and Practices, pp. 3–21, 2022.

[6] N. Ljepava, "AI-enabled marketing solutions in marketing decision making: AI application in different stages of marketing process," TEM Journal, pp. 1308–1315, 2022.

[7] P. Russom, "Big data analytics," TDWI Best Practices Report, Fourth Quarter, 2011.

[8] M. Chen, S. Mao, and Y. Liu, "Big data: A survey," Mobile Networks and Applications, vol. 19, no. 2, pp. 171–209, 2014.

[9] R. Krishnamoorthy, V. Balajivijayan, D. R. T. Sowmiya, and D. S. Arun, "Cyber attack detection on IoT using network traffic mechanism by neural network predictive approach," European Journal of Molecular and Clinical Medicine, vol. 7, no. 10, pp. 3690–3697, 2020.

[10] R. Krishnamoorthy, I. D. Soubache, and S. Jain, "Wireless communication based evaluation of power consumption for constrained energy system," Wireless Personal Communications, 2022.

[11] P. Mikalef, M. Boura, G. Lekakos, and J. Krogstie, "Big data analytics and firm performance: Findings from a mixed-method approach," Journal of Business Research, vol. 98, pp. 261–276, 2019.

[12] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," International Journal of Information Management, vol. 35, no. 2, pp. 137–144, 2015.

[13] Z. Sun and K. D. Strang, "How can big data and predictive analytics improve dynamic capabilities and firm performance?" in Managerial Perspectives on Intelligent Big Data Analytics, IGI Global, pp. 1–24, 2019.

[14] X. Wang, D. Chaudhry, and S. Mukherjee, "Machine learning-based risk assessment for financial portfolio management," Journal of Risk and Financial Management, vol. 14, no. 11, p. 525, 2021.

[15] N. Anbuchezhian, T. Velmurugan, G. S. Priyadharshini, and R. Krishnamoorthy, "Comparative study of neural network and tree-based models in solar irradiance prediction," International Review of Mechanical Engineering, vol. 15, no. 6, pp. 307–316, 2021.

[16] R. Krishnamoorthy, I. D. Soubache, and A. Farmani, "Exploring surface plasmon resonance ring resonator structure for high sensitivity and ultra-high-Q optical filter with FDTD method," Optical and Quantum Electronics, vol. 54, pp. 1–13, 2022.

[17] N. Anbuchezhian, S. Srinivasan, T. Velmurugan, G. S. Priyadharshini, and R. Krishnamoorthy, "Novel design of hybrid steam turbine reflector based controller for solar power plant," International Review of Mechanical Engineering, vol. 14, no. 9, pp. 572–578, 2020.

[18] A. Nattappan, G. S. Priyadharshini, V. Thiagarajan, and R. Krishnamoorthy, "Design of automation control thermal system integrated with parabolic trough collector based solar plant," Thermal Science, vol. 26, no. 2, pp. 947–954, 2022.

[19] R. Krishnamoorthy, A. Desai, and R. Patel, "4 element compact triple band MIMO antenna for sub-6 GHz 5G wireless applications," Wireless Networks, vol. 27, pp. 3747–3759, 2021.

[20] H. V. Jagadish et al., "Big data and its technical challenges," Communications of the ACM, vol. 57, no. 7, pp. 86–94, 2014.

[21] J. Fan, F. Han, and H. Liu, "Challenges of big data analysis," National Science Review, vol. 1, no. 2, pp. 293–314, 2014.

[22] S. LaValle, E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz, "Big data, analytics and the path from insights to value," MIT Sloan Management Review, vol. 52, no. 2, pp. 21–32, 2011.

[23] R. Kitchin, "The real-time city? Big data and smart urbanism," GeoJournal, vol. 79, no. 1, pp. 1–14, 2014.

[24] D. Wixom, B. Ariyachandra, T. Douglas, D. Goul, M. Gupta, and B. Iyer, "The current state of business intelligence in academia: The arrival of big data," Communications of the AIS, vol. 34, no. 1, pp. 1–13, 2014.

[25] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, and S. U. Khan, "The rise of big data on cloud computing: Review and open research issues," Information Systems, vol. 47, pp. 98–115, 2015.

[26] D. Boyd and K. Crawford, "Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon," Information, Communication & Society, vol. 15, no. 5, pp. 662–679, 2012.

[27] E. Siegel, Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die, Revised and Updated Edition, Wiley, 2016.

[28] T. Davenport and J. Harris, Competing on Analytics: The New Science of Winning, Harvard Business Review Press, 2007.