AI-Driven Transformation of Traditional Data Analytics and Business Intelligence in Computer Science

A. O. Akinlolu[1*], E. R. Jimoh[2], C. B Ujah- Ogbuagu[3] and A. A. Tewogbade[4]

[1]Department of Mathematical and Computer Sciences, Fountain University Osogbo, Nigeria.
[2] Department of Computer Science, Ajayi Crowther University, Oyo, Oyo State.
[3] AI Research Group-Department of Science & Technology, Centre for Strategic Research, National Defence College, Nigeria.
[4]Department of Computer Science, Osun University, Osogbo, Osun State.
[*]Corresponding Author: jimohebunayo@gmail.com

ABSTRACT: The rapid advancement of Artificial Intelligence (AI) is transforming data analytics and Business Intelligence (BI) across multiple domains of computer science. Traditional analytics and BI tools have long been instrumental for processing structured data and generating reports; however, they often struggle with large-scale, unstructured, or highly complex datasets. This study examines how integrating AI technologies such as machine learning, natural language processing, and deep learning enhances the analytical capabilities, adaptability, and decision-making potential of traditional BI systems. Through comparative analysis and real-world case studies, the research explores technical strategies for embedding AI within existing analytics frameworks and evaluates their effectiveness in improving automation, insight generation, and responsiveness. The integration of AI supports the development of intelligent, adaptive systems capable of detecting anomalies, uncovering hidden patterns, and enabling predictive and prescriptive analytics. The findings offer practical methodologies and design principles to guide organizations and researchers in creating next-generation intelligent data systems aligned with the evolving demands of computer science.

KEYWORDS: Artificial Intelligence, Data Analytics, Business Intelligence, Machine Learning

I. INTRODUCTION

The rapid digital transformation of recent years has made data central to organizational strategy. Traditional data analytics and Business Intelligence (BI) systems rely on data warehousing, structured datasets, predefined metrics, and manually developed dashboards to produce descriptive insights. Historically, these tools have supported performance monitoring and decision-making; however, increasing data volume, velocity, and variety now expose their limitations. Legacy BI systems depend on batch processing, static reporting, and manual intervention, making them unsuitable for real-time analytics or handling unstructured and high-dimensional data. They lack predictive and prescriptive capabilities, and their dashboards cannot dynamically adapt to evolving data patterns, resulting in delayed and less actionable insights. Artificial Intelligence including machine learning, deep learning, and natural language processing offers a transformative solution. AI-driven analytics learn from large, complex datasets, detect anomalies, and generate real-time, actionable insights. By enabling predictive and prescriptive decision-making, AI shifts BI from static and retrospective to intelligent, adaptive, and automated analytics. This study addresses the

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

challenge of effectively integrating AI into existing BI infrastructures. While AI adoption is increasing, organizations still struggle with architectural compatibility, model deployment, and workflow interoperability. Current research often isolates AI or BI perspectives, resulting in a fragmented understanding of their convergence. This paper fills that gap by examining traditional BI limitations, analyzing how AI technologies enhance BI capabilities, and exploring implementation strategies such as pipeline modifications and architectural redesign. Through comparative analysis and case studies, it evaluates the performance and adaptability of AI-augmented BI systems. The study contributes a unified framework, evidence-based insights, and practical design principles to support the development of intelligent, next generation analytics systems across computer science and industry.

II. LITERATURE REVIEW

A. Evolution of Data Analytics and Business Intelligence (BI)

Business Intelligence (BI) began as a tool for consolidating and reporting structured transactional data to support historical performance monitoring. Early BI relied on data warehousing, ETL processes, and static reporting. Over time, it evolved into dashboarding and self-service analytics. More recently, BI has transitioned toward real-time analytics, interactive visualization, and cloud-based architectures, expanding from descriptive reporting to predictive and prescriptive analytics in response to technological advancement and changing business needs.

B. AI Techniques in Modern Analytics

AI is now integral to modern analytics. Machine Learning (ML), using supervised and unsupervised methods such as regression, decision trees, and clustering, supports forecasting, segmentation, and anomaly detection. Automated Machine Learning (AutoML) further streamlines model development by automating tasks such as feature engineering and hyperparameter tuning, improving accessibility for non-experts. Deep Learning (DL) expands capabilities with neural architectures (CNNs, RNNs, transformers) that excel in processing high-dimensional and unstructured data. NLP enhances BI by enabling natural language querying, automated report generation, and context-aware insight extraction using transformer-based models and LLMs.

(a). AI-Enhanced BI in Prior Research

Research on integrating Artificial Intelligence (AI) into Business Intelligence (BI) has accelerated since the late 2010s, encompassing conceptual reviews, empirical studies, and industry case studies. A key strand of work synthesizes augmented analytics platforms, comparing traditional BI and AIenhanced BI across the analytics lifecycle—data preparation, modeling, visualization, and insight generation. Alghamdi et al. (2022) highlight that AI accelerates insight generation and reduces manual effort, but persistent limitations remain in governance, explainability, and the need for domain expertise. Automation in model-building pipelines, particularly through Automated Machine Learning (AutoML), represents another major area. AutoML systems lower barriers to predictive modeling by automating feature engineering, model selection, and hyperparameter tuning. Rosário et al. (2024) show that embedding AutoML into BI environments enables nonexperts to build competitive models efficiently. However, trade-offs include reduced transparency, potential overfitting, and the need for robust monitoring in production (Rosário & Boechat, 2024).

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

Natural Language interfaces (NLI) and narrative generation form a third research focus, allowing non-technical users to query data and receive textual or visual insights. Visualization-oriented NLIs (V-NLI) improve accessibility and speed of exploratory analysis, though challenges remain in context understanding, ambiguity resolution, and cross-domain generalization (Shen et al., 2022). Domain-specific case studies further demonstrate AI's operational impact. In healthcare and finance, ML-driven anomaly and fraud detection outperform traditional rule-based BI systems, improving detection rates and reducing time-to-action. Vendor reports on tools like Oracle Fusion Analytics show gains in analyst productivity and faster decision cycles (du Preez et al., 2024). Non-technical considerations—governance, user trust, and ethics—are also emphasized. Without metadata, lineage, and explainable models, AI-augmented BI risks biased insights and reduced trust. Responsible deployment requires human-in-the-loop review, monitoring for drift, and explainability measures (Alghamdi & Al-Baity, 2022). Despite clear benefits, methodological limitations persist: many studies are domain-specific with proprietary datasets, evaluations often focus on narrow performance metrics rather than holistic business outcomes, and few provide end-to-end architectural frameworks for integrating AI into legacy BI. These gaps help explain why enterprise-scale adoption remains uneven (Alghamdi & Al-Baity, 2022).

(b). Challenges and Research Gaps in Modernizing Business Intelligence

Modernizing Business Intelligence (BI) systems through AI integration presents several challenges. Legacy system integration remains a significant barrier, as embedding AI capabilities within existing BI infrastructures is often complex and resource-intensive (Oluwaferanmi, 2025). The effectiveness of AI-driven analytics also depends heavily on data quality and governance; robust metadata management, and compliance mechanisms are essential to ensure reliable performance (Bernardo et al., 2024). Organizations frequently face skill gaps, as shortages of expertise in AI technologies and domain-specific analytics can slow adoption and hinder implementation (Hweka, 2025). Moreover, AI models carry inherent risks of bias and ethical concerns, necessitating frameworks for explainability, fairness, and accountability (Chebrolu, 2025). Operational scalability poses a challenge: transitioning AI prototypes into production-ready BI solutions remains a complex and resource-demanding process (Dissanayake et al., 2025).

Despite these challenges, current literature reveals notable research gaps that must be addressed to advance AI-driven BI. First, there is a lack of integrated architectural frameworks that support endto-end AI embedding within BI systems (Chebrolu, 2025). Comparative evaluations across traditional and AI-driven BI models using standardized performance metrics are limited, reducing evidence-based insights into AI's practical benefits (Antonyraj, 2025). Guidance on lifecycle management, governance, and model explainability in BI contexts remains insufficient (Bernardo, 2024). In addition, deeper understanding is needed regarding human–AI collaboration, particularly in relation to decision accountability, user trust, and effective interaction with intelligent analytics tools (Syed, 2021). Addressing these challenges and research gaps is critical to developing scalable, ethical, and operationally robust AI-driven BI systems capable of supporting data-driven decision making in complex organizational environments.

III. AI-DRIVEN TRANSFORMATION OF BUSINESS INTELLIGENCE

A. Traditional BI Architecture and Limitations

Traditional BI systems are typically structured around multi-tier data warehouse architectures involving source systems e.g., ERP, CRM, staging/ETL processes, data warehouses or marts, OLAP

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

servers, and dashboards. This setup enables consistent reporting, strong governance, and historical trend analysis using structured data. BI tools from vendors such as Oracle, Microsoft, and SAP provide reliable infrastructure and are widely adopted across regulated industries for tasks such as compliance reporting, financial analysis, and sales tracking (Sahara & Aamer, 2022; Hashem et al., 2025). However, traditional BI has notable constraints in modern data environments. ETL processes require high manual intervention and struggle with dynamically evolving datasets. Static dashboards limit exploratory analysis and suffer from delayed insights due to batch processing (Harini, 2023). Scalability is restricted by vertical scaling and infrastructure costs (Tadi, 2022). Legacy systems offer limited support for real-time analytics, high-velocity data, or unstructured formats such as logs, emails, and multimedia (Majid et al., 2024). Additionally, vertical system expansion is usually expensive and time-consuming (Gautam & Kumar, 2023). These limitations make traditional BI unsuitable for real-time decision-making, high-volume ingestion, or advanced predictive modeling.

B. AI Technologies Transforming BI

Artificial Intelligence introduces capabilities that extend BI beyond descriptive analysis to predictive, prescriptive, and adaptive analytics:

(a). Machine Learning (ML): Enables forecasting (sales prediction, churn analysis), segmentation, and anomaly detection using supervised and unsupervised learning. Reinforcement learning supports decision optimization (inventory, pricing).

(b). Deep Learning (DL): CNNs and RNNs processes high-dimensional and unstructured data, supporting image-based quality control, document analysis, and time-series forecasting.

(c). Natural Language Processing (NLP): Allows conversational querying "show top-selling products", automated report generation, and sentiment analytics. Large Language Models (LLMs) improve contextual insight delivery and accessibility.

C. AI-Augmented BI Architecture

AI-augmented BI introduces a dedicated AI layer between data storage and BI front-end interfaces. Key components as shown in Figure 1 include:

(i) Data Sources: structured (transactional systems) and unstructured (logs, sensor data).
(ii) Preprocessing: batch and real-time pipelines enhanced by AI-based anomaly detection.
(iii) Hybrid Storage: data lakes and warehouses.
(iv) AI Layer: ML/DL models for predictive analytics and automated insights.
(v) BI Interface: enhanced with AI narratives, recommendations, and NLP querying.

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

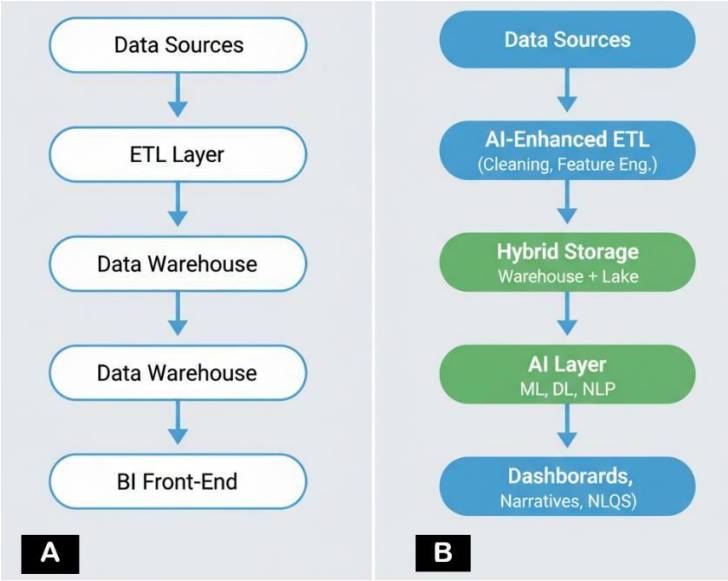


Figure 1: Architectural Diagram Comparing (a) Traditional BI and (b) AI-Augmented BI

D. Data Pipeline Adaptations and AI Integration in BI

Integrating AI into Business Intelligence (BI) systems necessitates modifications to existing data pipelines to ensure high-quality inputs and operationally reliable insights. Key adjustments include automated anomaly detection and data quality scoring, as well as advanced feature engineering and extraction techniques, such as generating embeddings for text or image data. Workflow orchestration tools, including Airflow, Prefect, or Kubeflow, coordinate both real-time and batch processes, ensuring seamless data flow across the analytics lifecycle. AI models can then be embedded into BI platforms in multiple ways. Real-time scoring can be delivered through model-serving APIs, such as REST or gRPC, while native BI integrations like predictive models in Power BI or AI-driven recommendations in Tableau allow analysts to leverage AI insights directly within familiar dashboards. Hybrid approaches are also common, where models are developed using frameworks like Python or TensorFlow and integrated into BI tools via automated pipelines. This embedding strategy augments existing BI systems rather than replacing them, preserving continuity while enabling predictive and prescriptive capabilities that enhance decision-making.

E. Automation, Reporting, and Infrastructure Considerations in AI-Driven BI

AI significantly enhances reporting and visualization in modern Business Intelligence (BI) systems. It enables dynamic dashboards that update in real time, automated narrative generation through natural language processing, intelligent alerts for deviations in key metrics, and natural language interaction for self-service analytics. These capabilities reduce manual effort, improve organizational responsiveness, and allow decision-makers to access actionable insights more efficiently. Implementing AI-driven BI also requires careful attention to infrastructure and scalability. Robust compute resources, including cloud-based GPU clusters for model training and scalable CPU/GPU configurations for inference, are essential. Hybrid storage solutions combining data lakes and warehouses support diverse data types, while elastic cloud architectures ensure responsiveness under high data volumes. Effective orchestration and monitoring are critical for

workflow automation and maintaining model performance, and strong security measures including data lineage tracking and compliance with regulations such as GDPR and HIPAA.

IV. COMPARATIVE ANALYSIS AND REAL-WORLD APPLICATIONS

Evaluation Metrics and Comparative Analysis

Integrating Artificial Intelligence (AI) into Business Intelligence (BI) frameworks transforms system performance, enhances user experience, and expands analytical capabilities. A comparative analysis of traditional and AI-driven BI across key evaluation metrics is summarized in Table 1, while Figure 2 provides a conceptual illustration of these differences.

Table 1: Comparative Performance Analysis

Metric	Traditional BI	AI-Driven BI	Comments
Accuracy	Historical data only, descriptive reports	Predictive & prescriptive models, pattern recognition	AI models allow forecasting and anomaly detection beyond descriptive analysis
Speed / Latency	Batch processing (daily/weekly)	Near real-time insights via automated pipelines	AI enables continuous updates and faster decision-making
Adaptability	Fixed schema, limited unstructured data support	Handles structured, semi structured, and unstructured data	AI models can learn from new sources and adapt dynamically
Insight Quality	Surface-level trends and aggregates	Deep patterns, actionable recommendations	AI enhances value by combining predictive and prescriptive insights
Automation	Manual ETL, dashboard updates	Automated preprocessing, model inference, reporting	Reduces human effort and operational overhead
Scalability	Vertical scaling, limited by hardware	Cloud-native, distributed, elastic	AI-driven pipelines scale efficiently with large datasets

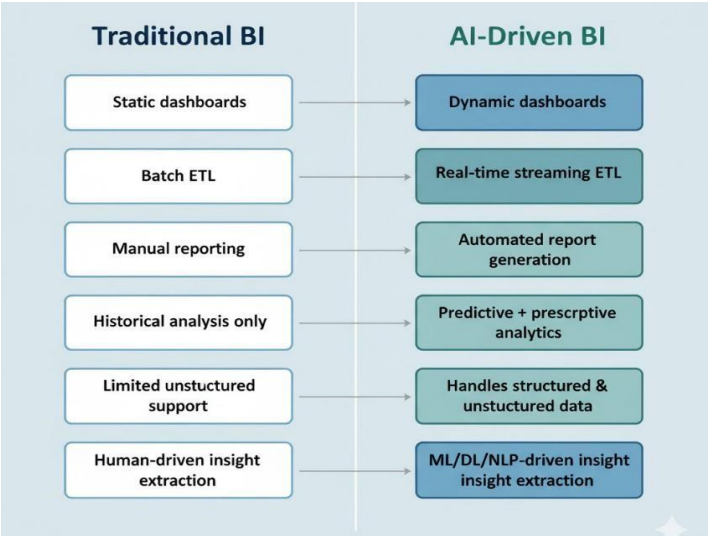


Figure 2: Key Functional Transformation from Traditional to AI-Driven BI

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

F. Benefits, Limitations, and Automation in AI-Driven BI

Traditional Business Intelligence (BI) systems offer mature governance, reliability, and strong support for structured data in stable environments. They are relatively easy to manage due to established tools and skillsets. However, conventional BI lacks predictive capabilities, struggles with unstructured or high-velocity data, and depends on batch ETL processes that introduce latency, limiting real-time responsiveness. In contrast, AI-driven BI enhances analytical intelligence by providing predictive and prescriptive insights, real-time analytics, and automation across the data lifecycle. Key automation features include anomaly detection and automated handling of missing data, AutoML-driven modeling and scoring, dynamic dashboards with real-time alerts, natural language querying, and narrative generation. Figure 3 illustrates the workflow automation processes enabled by AI in modern BI systems. These capabilities shift organizations from reactive analysis to proactive, insight-driven strategies. Despite these advantages, AI-driven BI poses challenges, including higher infrastructure demands, increased complexity in model governance, and the need for specialized expertise in AI and data science. Balancing these benefits and limitations is essential for organizations aiming to leverage AI effectively while maintaining operational reliability and governance.

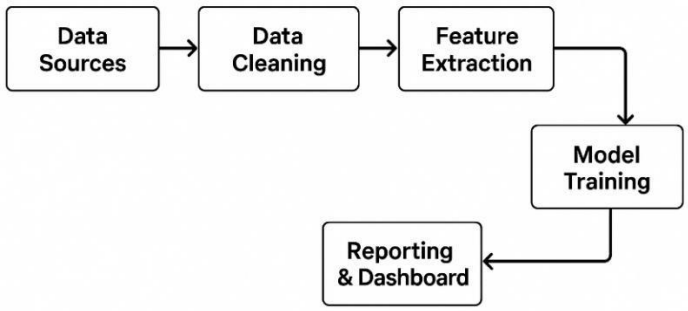


Figure 3: Workflow Automation in AI-Driven BI

G. Case Studies

Real-world applications of AI in Business Intelligence (BI) across finance, healthcare, and cybersecurity illustrate its transformative potential. In finance, JPMorgan Chase leverages AI to enhance fraud detection and anti–money laundering operations by generating synthetic transaction data for training machine learning models, improving anomaly detection, and enabling proactive risk management (Shirvanporzour, 2025). In healthcare, Mount Sinai Health System applies machine learning to predict 30-day readmissions in heart-failure patients with an AUC of 0.78 and 83.2% accuracy, integrating these predictions into BI dashboards to guide preemptive interventions (Shameer et al., 2017). NLP models such as Bio Clinical BERT further improve emergency department admission forecasts, optimizing resource allocation (Patel et al., 2024).

In cybersecurity, Darktrace's Cyber AI Analyst employs unsupervised learning and anomaly detection to continuously monitor networks, identify suspicious activity, and generate "incident graphs" that trace multi-stage attacks, enabling faster, more actionable threat response (Brandao, 2025). Across these sectors, AI enhances BI by delivering predictive and prescriptive insights, reducing manual workload, and providing timely intelligence. Key challenges include data quality and integration, unstructured data preprocessing, AI skills gaps, infrastructure demands for realtime

scoring, and governance requirements such as fairness, interpretability, and regulatory compliance (Shirvanporzour, 2025).

Lessons from these implementations highlight that AI-driven BI is most effective when augmenting existing systems, underpinned by high-quality data preparation. Natural-language interfaces and narrative reporting improve adoption among non-technical users, while robust governance, explainability, and continuous feedback loops ensure models remain trustworthy and aligned with organizational objectives.

H. Design Principles and Best Practices for AI-Driven BI Systems

Next-generation Business Intelligence (BI) systems should be designed with modular and scalable architectures that support hybrid data management, combining data warehouses for structured datasets with data lakes for unstructured or high-volume sources. Real-time analytics, continuous feedback loops, and component-level upgradability are essential to ensure adaptability and minimize operational disruption. Model selection should align with data types and analytical tasks: ML models such as random forests and gradient boosting are suited for structured predictive tasks, while deep learning architectures including CNNs, RNNs, and transformers excel with unstructured data. Effective data governance, including quality assurance, lineage tracking, and compliance through standardized metadata, is critical. Interpretability techniques, such as SHAP, LIME, and attention mechanisms, support transparency and user trust in AI-driven recommendations.

Ethical considerations and risk management are integral to intelligent BI systems. Bias mitigation requires systematic auditing and validation, while privacy and security must be ensured through encryption, anonymization, and access controls. Regulatory compliance with standards such as GDPR and HIPAA, alongside monitoring for model drift, manipulation, or system failure, reinforces system resilience and reliability. Best practices for implementation emphasize phased pilot projects to manage integration risk, user-centered design for intuitive interfaces and natural language interaction, and continuous monitoring of model accuracy, latency, fairness, and operational performance. Leveraging cloud-native, scalable infrastructure and fostering cross functional collaboration among data scientists, BI professionals, IT engineers, and compliance officers further enhances the successful deployment of AI-driven BI systems. Collectively, these principles ensure that intelligent BI platforms are adaptive, trustworthy, and capable of supporting informed, proactive decision-making in complex organizational environments.

Integrating Artificial Intelligence (AI) into Business Intelligence (BI) overcomes the limitations of traditional analytics, which rely on manual data preparation, static dashboards, and batch reporting. AI-driven BI automates repetitive tasks, supports predictive and prescriptive insights, and enables dynamic, real-time dashboards. Predictive models forecast trends, anomaly detection identifies irregularities, and NLP interfaces allow non-technical users to query complex data, shifting organizations from reactive reporting to proactive decision-making. From a computer science perspective, AI adoption drives hybrid architectures for structured and unstructured data, fosters research in scalable ML pipelines, real-time streaming, and high-performance computing, and raises the need for explainable, fair, and trustworthy AI. It also challenges conventional software engineering practices, requiring new approaches to model lifecycle management, automated testing, and continuous monitoring. Organizational readiness and culture critically influence adoption. Data literacy, leadership support, and training programs are essential, while resistance, fear of job displacement, and reliance on intuition can impede implementation. Future trends include cloud native and edge-computing BI, explainable AI, hybrid modeling, AutoML, and stronger ethical and

Volume 1, Issue 5, 2025: Special Issue for Nigerian Society of Data Analytics and Business Intelligence Experts NSDABIE) first International Conference. https://doi.org/10.5281/zenodo.17918742

regulatory frameworks, enabling organizations to anticipate changes, optimize operations, and sustain competitive advantage.

V. CONCLUSION

AI-driven Business Intelligence (BI) is poised to evolve toward more autonomous, transparent, and context-aware systems. Emerging developments include edge computing for processing high velocity data closer to its source, explainable and fair AI models to ensure trustworthy insights, conversational analytics powered by large language models, and hybrid architectures that combine symbolic reasoning with machine learning for deeper analytical understanding and better alignment with human decision-making. The integration of AI fundamentally transforms BI by enabling predictive and prescriptive analytics, automating workflows, and accommodating diverse data types. Evidence from case studies demonstrates enhanced decision-making, improved operational efficiency, and the ability to overcome the limitations of traditional BI systems. While challenges remain such as rapid technological change, ethical considerations, and governance requirements AI-driven BI provides a framework for designing intelligent, adaptive, and transparent systems. This convergence represents a paradigm shift, empowering organizations to generate actionable insights and leverage data effectively in increasingly complex and data-intensive environments.

REFERENCES

[1] Antonyraj, V. A. (2025). The Impact of Artificial Intelligence and Data Analytics on Finance: Transforming Financial Technologies. *In The Impact of Artificial Intelligence on Finance: Transforming Financial Technologies* (pp. 159–188). Springer Nature Switzerland.

[2] Bernardo, B. M. V., São Mamede, H., Barroso, J. M. P., & dos Santos, V. M. P. D. (2024). Data governance & quality management Innovation and breakthroughs across different fields. *Journal of Innovation & Knowledge, 9*(4), 100598.

[3] Brandao, P. R. (2025). Exploring the Role of Artificial Intelligence in Detecting Advanced Persistent Threats. *Computers*.

[4] Chebrolu, S. K. (2025). AI-powered business intelligence: A systematic literature review on the future of decision-making in enterprises. *SSRN 5183746*.

[5] Dissanayake, D., Navarathna, R., Ekanayake, P., & Rajadurai, S. (2025). A survey of evaluating AutoML and automated feature engineering tools in modern data science. In *Proceedings of ICEIS* (pp. 218–225).

[6] Du Preez, A., Bhattacharya, S., Beling, P., & Bowen, E. (2024). Fraud detection in healthcare claims using machine learning: A systematic review. *Artificial Intelligence in Medicine*, 103061.

[7] Gautam, M., & Kumar, Y. (2023). Power BI Dashboard for Analysis of Success and Failures of APIs and Average Time Taken by API to Process.

[8] Harini, C. (2023, February 21). Understanding the Basics of Data Warehouse and its Structure. *Analytics Vidhya*. https://www.analyticsvidhya.com/blog/2023/02/understanding-the-basics-ofdata-warehouse-and-its-structure/

[9] Hashem, O. M., Rahouma, K., & Abd El Hameed, N. S. (2025). Enhancing Quality Factors in Data Warehousing Through Study and Improvement. *Journal of Advanced Engineering Trends, 44*(1), 187–193.

[10] Hweka, M. L. (2025). Implementing Business Intelligence: Challenges and Solutions for Organizations. *SSRN 5424514*.

[11] Oluwaferanmi, J. K. A. (2025). Automating ETL Pipelines Using Artificial Intelligence: Transforming Legacy Data Integration Systems into Intelligent Data Workflows.
[12] Patel, D., Timsina, P., Gorenstein, L., Glicksberg, B. S., Raut, G., Cheetirala, S. N., ... & Zimlichman, E. (2024). Traditional machine learning, deep learning, and BERT approaches for predicting hospitalizations from nurse triage notes. *JMIR AI, 3*(1), e52190.
[13] Rosário, A. T., & Boechat, A. C. (2024). How Automated Machine Learning Can Improve Business. *Applied Sciences, 14*(19), 8749.
[14] Sahara, C. R., & Aamer, A. M. (2022). Real-time data integration of an IoT-based smart warehouse: A case study. *International Journal of Pervasive Computing and Communications, 18*(5), 622–644.
[15] Shameer, K., Johnson, K. W., Yahi, A., Miotto, R., Li, L. I., Ricks, D., ... & Dudley, J. T. (2017). Predictive modeling of hospital readmission rates using EMR-wide machine learning. *Pacific Symposium on Biocomputing, 22*, 276–287.
[16] Shen, L., Shen, E., Luo, Y., Yang, X., Hu, X., Zhang, X., ... & Wang, J. (2022). Towards natural language interfaces for data visualization: A survey. *IEEE Transactions on Visualization and Computer Graphics, 29*(6), 3121–3144.
[17] Shirvanporzour, A. (2025). Artificial Intelligence in Banking Risk Management and Anti-Money Laundering: A Comprehensive Review. *SSRN 5161209*.
[18] Syed, S., & Nampally, R. C. R. (2021). Empowering users: The role of AI in enhancing self-service BI for data-driven decision making. *Educational Administration: Theory and Practice*.
[19] Tadi, V. (2022). Performance and Scalability in Data Warehousing: Comparing Snowflake's Cloud-Native Architecture with Traditional On-Premises Solutions Under Varying Workloadsa