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ROLE OF AI AND DATA SCIENCE IN DATA-DRIVEN DECISION MAKING FOR IT BUSINESS INTELLIGENCE: A SYSTEMATIC LITERATURE REVIEW

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Abstract

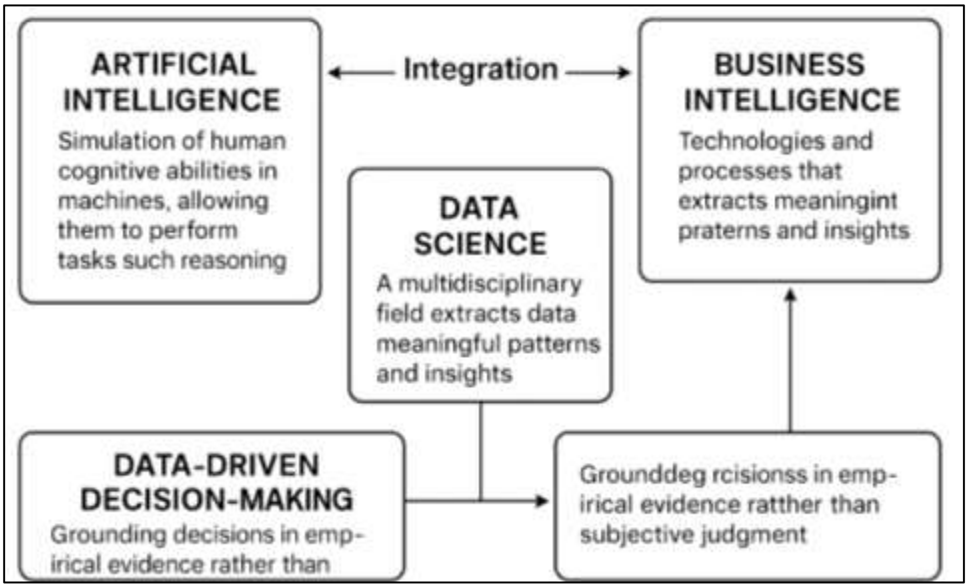
This systematic literature review examines the role of Artificial Intelligence (AI) and Data Science in enhancing data-driven decision-making within Business Intelligence (BI) systems for Information Technology (IT) enterprises, with the objective of identifying dominant research themes, methodological approaches, application domains, and existing gaps. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, a total of 156 peer-reviewed studies published between 2010 and 2024 were systematically identified, screened, and analyzed from leading academic databases and reputable industry sources. The review synthesizes findings across key thematic areas, including predictive and prescriptive analytics, natural language processing for unstructured data, real-time and streaming analytics, governance and ethical considerations, cross-functional accessibility, and comprehensive AI-BI integration frameworks. Results indicate a clear shift from traditional descriptive BI toward proactive, AI-enabled systems capable of delivering timely, contextually relevant, and actionable insights, with significant advancements in automation, scalability, and inclusivity for both technical and non-technical stakeholders. The analysis also reveals that while technical progress has been substantial, challenges remain in areas such as ethical governance, algorithmic transparency, bias mitigation, and cross-border data compliance. This review contributes to the field by providing a consolidated view of current advancements, comparing them with earlier research trends, and identifying persistent gaps that hinder the full realization of AI and Data Science capabilities in BI environments. The findings underscore the strategic importance of adopting unified, ethically grounded, and scalable AI-BI frameworks to enhance operational efficiency, strategic agility, and competitive advantage in modern IT business contexts.

Keywords
Artificial Intelligence, Data Science, Business Intelligence, Decision-Making, IT

INTRODUCTION

Artificial Intelligence can be described as the simulation of human-like cognitive abilities in machines, allowing them to perform tasks such as reasoning, learning, and adapting (Adekunle et al., 2021). Data Science is a multidisciplinary field that integrates statistical analysis, algorithmic modeling, and domain expertise to extract meaningful patterns and insights from large volumes of structured and unstructured data (Machireddy & Devapatla, 2022). Business Intelligence refers to the technologies, systems, and processes that transform raw data into valuable insights for strategic and operational decision-making. In modern IT-driven enterprises, these concepts intersect to create decision-support systems that extend far beyond traditional reporting functions. The combination of AI and Data Science enables Business Intelligence platforms to evolve from retrospective data analysis to predictive and prescriptive analytics, offering organizations the capacity to anticipate trends, simulate scenarios, and optimize decision-making processes. This integration is fueled by the rapid growth of data from various sources, including enterprise systems, digital transactions, and sensor networks (Schmitt, 2023). The sophistication of analytical models has made it possible to process vast datasets in real time, allowing decision-makers to act quickly and accurately in complex business environments (Sarker, 2021). By embedding machine learning algorithms into BI frameworks, organizations can move toward data-driven decision-making models that minimize reliance on intuition and enhance the precision of strategic actions.

Figure 1: AI–Data Science–BI Integration Framework



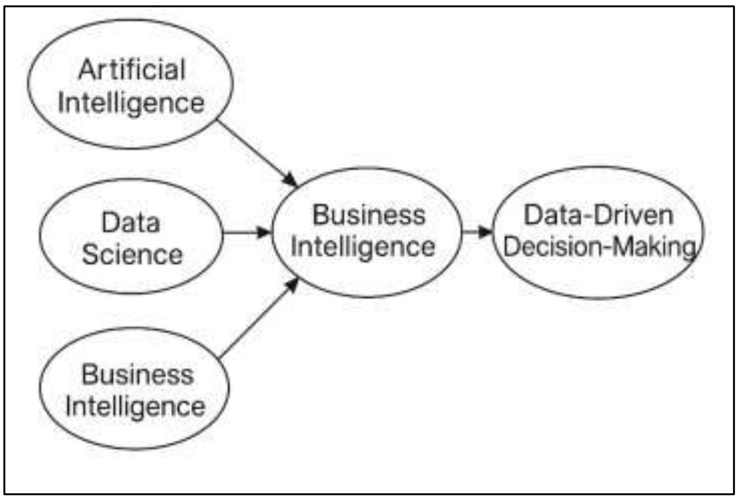
Data-driven decision-making has emerged as a critical capability for organizations operating in a globalized and digitally interconnected economy (Haleem et al., 2021). By grounding decisions in empirical evidence rather than subjective judgment, organizations can respond more effectively to market changes, regulatory requirements, and operational challenges. On an international scale, businesses are increasingly reliant on real-time analytics to manage cross-border supply chains, forecast demand across different markets, and adapt to regional customer preferences. In industries such as finance, manufacturing, healthcare, and logistics, the integration of AI-powered Business Intelligence enables companies to analyze diverse datasets from multiple geographic locations simultaneously (Shamsuddoha et al., 2025). This not only improves operational efficiency but also enhances strategic agility in competitive environments. Governments and public sector agencies also employ data-driven approaches to inform policy, monitor economic indicators, and manage crises such as pandemics or natural disasters. The global reach of these practices demonstrates that data is no longer just an operational byproduct but a strategic asset with the potential to influence economic growth, security (Yadav et al., 2024), and innovation worldwide. The ability to synthesize information from heterogeneous sources and apply advanced analytics to generate actionable insights is now an essential competency for organizations seeking to remain competitive in international markets (Aldoseri et al., 2024).

The integration of AI into Business Intelligence has expanded the analytical capabilities of organizations far beyond static dashboards and descriptive reports (Balasubramanian, 2023). By embedding machine learning, natural language processing, and advanced pattern recognition into BI systems, businesses can uncover deeper insights from both structured and unstructured data. Predictive analytics allows companies to model future trends and outcomes, enabling proactive rather than reactive strategies (Imandi et al., 2025). Natural language interfaces simplify access to complex analytics by allowing users to query data in conversational formats, making BI more accessible across different organizational roles. AI-driven anomaly detection improves operational security by identifying unusual activities or irregularities in systems, often in real time (Shidaganti et al., 2023). In addition, AI enables the automation of data preparation and cleansing, significantly reducing the time between data acquisition and actionable insight generation. These advancements transform BI platforms from passive repositories of historical data into active participants in strategic planning and operational optimization (Tyagi et al., 2020). By continuously learning from new data inputs, AI-enhanced BI systems can adapt their models and recommendations, ensuring that decision-making processes remain relevant in rapidly changing environments.

Data Science underpins data-driven decision-making by providing the frameworks, methodologies, and tools required to transform raw data into meaningful insights (Sivakumar et al., 2024). It encompasses processes such as data collection, cleaning, transformation, modeling, and visualization. Statistical modeling and machine learning algorithms form the core analytical techniques that drive predictive and prescriptive decision-making. These methods enable organizations to detect patterns, classify information, forecast trends, and evaluate potential scenarios. In the context of IT-enabled Business Intelligence, Data Science plays a critical role in identifying performance bottlenecks, optimizing service delivery, and monitoring system health (Shahin et al., 2024). The scalability of modern data analysis tools allows organizations to apply complex models to massive datasets, ensuring that decision-making is based on comprehensive and current information. Visualization techniques further enhance understanding by presenting analytical results in intuitive formats that support quick comprehension and informed action (Rosário & Boechat, 2024). The discipline also incorporates principles of data governance and quality assurance, ensuring that the insights generated are reliable and trustworthy. In essence, Data Science equips Business Intelligence with the depth and rigor necessary for organizations to operate confidently in a data-rich environment (Helo & Hao, 2022).

When AI and Data Science are combined within Business Intelligence systems, the result is a synergistic relationship that amplifies the value of both (Ara et al., 2022; Jawad & Balázs, 2024). Data Science provides the structure, preparation, and methodological rigor required to feed high-quality data into AI models. In turn, AI enhances Data Science workflows by automating model selection, hyperparameter tuning, and continuous learning processes. This integration transforms BI systems into intelligent platforms capable of anticipating business needs, detecting emerging patterns, and recommending optimal actions (Ali & Puri, 2024; Uddin et al., 2022). In operational contexts, this synergy enables real-time analytics that can adjust to changing market conditions or operational constraints without manual intervention. For example, AI-enhanced BI can integrate streaming data from IoT devices to monitor production lines, manage inventory, and predict maintenance requirements (Haldorai et al., 2024). The ability to simulate multiple business scenarios allows decision-makers to evaluate potential outcomes and select the most advantageous strategy. This collaborative functionality not only increases efficiency but also improves the accuracy and timeliness of organizational decisions (Alenezi & Akour, 2025; Arifur & Noor, 2022).

Figure 2: AI and Data Science Integration



AI and Data Science contribute significantly to operational efficiency by automating repetitive analytical tasks, optimizing workflows, and enabling faster decision cycles (Segun-Falade et al., 2024). Predictive models can anticipate equipment failures, supply chain disruptions, or demand surges, allowing organizations to take preventive measures that reduce costs and minimize risk (Myllynen et al., 2024). In strategic planning, AI-driven BI tools simulate various market and competitive scenarios, providing executives with a robust foundation for long-term decision-making. These tools also enhance cross-departmental collaboration by delivering insights in formats accessible to both technical and non-technical stakeholders (Garad et al., 2024). The integration of these technologies enables organizations to monitor key performance indicators in real time, ensuring that strategies remain aligned with operational realities. In industries where timing is critical, such as e-commerce, energy, or transportation, the ability to make quick, evidence-based decisions can be a decisive competitive advantage (Akter et al., 2022). By reducing decision latency and increasing analytical precision, AI and Data Science help organizations maintain operational excellence while pursuing strategic growth objectives.
As AI and Data Science become central to Business Intelligence, ethical and governance considerations gain increasing importance (Hasan et al., 2022; Villar & Khan, 2021). Issues such as data privacy, security, fairness, and transparency must be addressed to maintain trust in data-driven decision-making systems. Algorithmic bias can inadvertently lead to unfair outcomes, making bias detection and mitigation critical components of responsible AI deployment (Ajmal et al., 2025). Data governance frameworks are essential for ensuring that data is collected, stored, and used in compliance with relevant laws and regulations, which may vary significantly across jurisdictions. Transparency in how decisions are generated—often referred to as explainability—is vital for fostering trust among stakeholders and ensuring accountability (Yitmen et al., 2021). The global nature of many organizations adds complexity, as governance practices must be harmonized across different cultural, legal, and operational contexts. Effective governance in AI-driven BI systems involves balancing innovation with safeguards that protect individual rights and societal values (Lal et al., 2023). This ensures that while organizations benefit from advanced analytics, they also uphold ethical standards that reinforce legitimacy and trust in their decision-making processes.

LITERATURE REVIEW

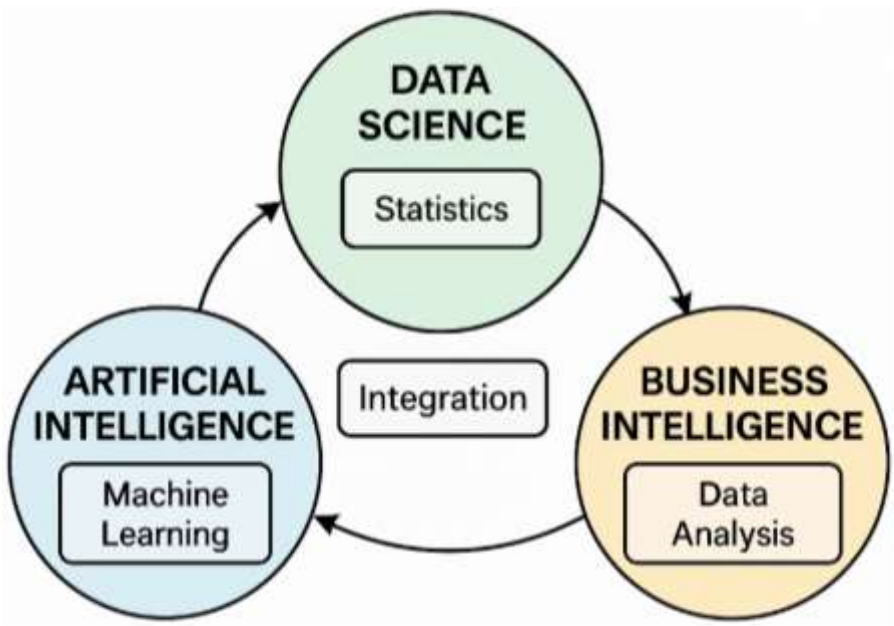
The rapid digitization of business environments has produced an unprecedented volume, velocity, and variety of data, necessitating the adoption of advanced analytical methodologies to transform raw information into actionable intelligence (Amankwah-Amoah et al., 2021). Within this evolving landscape, Artificial Intelligence (AI) and Data Science have emerged as transformative enablers for Business Intelligence (BI) in IT-driven organizations (Urbach & Röglinger, 2018). AI introduces autonomous learning, predictive modeling, and real-time adaptation, while Data Science provides the statistical, algorithmic, and visualization frameworks required for extracting meaning from complex datasets. Together, they enhance the accuracy, timeliness, and depth of data-driven decision-making, allowing organizations to optimize operations, anticipate trends, and respond dynamically to shifting market and technological conditions (Ngoc-Vinh et al., 2022).In the domain of IT Business Intelligence, the integration of AI and Data Science marks a paradigm shift from descriptive analytics, which focus on summarizing historical data, to prescriptive and predictive analytics capable of simulating scenarios, forecasting outcomes, and recommending optimal strategies. This evolution aligns with organizational needs to manage global operations, streamline resource allocation, and strengthen competitive positioning. Existing scholarly work demonstrates significant progress in this area, yet the literature remains fragmented across different application domains, technological approaches, and analytical frameworks.A systematic review of this intersection is crucial to synthesize existing findings, identify dominant research streams, and map the progression of technological adoption within BI contexts. The literature reflects diverse perspectives—from algorithmic innovations to governance and ethical considerations—each contributing to a nuanced understanding of how AI and Data Science redefine decision-making processes in IT-enabled enterprises (Urbach et al., 2019). This review organizes and critically examines these perspectives, providing a coherent structure that encapsulates the state of research, highlights theoretical and methodological foundations, and outlines the practical applications that are shaping BI practices worldwide.

AI, Data Science, and Business Intelligence

Artificial Intelligence, Data Science, and Business Intelligence are distinct yet interrelated domains that collectively shape the analytical capabilities of modern IT enterprises (Yaqub & Alsabban, 2023). Artificial Intelligence refers to the design and deployment of systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, and decision-making. In practice, AI encompasses a range of technologies, including machine learning, natural language processing, and computer vision, which enable systems to analyze patterns, interpret unstructured information, and adapt their operations based on experience (Miceli et al., 2021). Data Science, in contrast, is a multidisciplinary field that combines statistical modeling, computational algorithms, and domain expertise to extract insights from large and often complex datasets. It involves the entire analytical pipeline, from data acquisition and cleaning to exploratory analysis, predictive modeling, and visualization. Business Intelligence is primarily focused on transforming raw organizational data into actionable information to support decision-making (Brenner, 2018; Hossen & Atiqur, 2022). BI systems integrate data from various internal and external sources, process it into consistent formats, and present it through dashboards, reports, and visual analytics tools. While AI provides the intelligence to detect patterns and predict future outcomes, and Data Science provides the methodological and computational foundation for analysis, BI serves as the delivery mechanism that translates these capabilities into tangible decision support. The operational boundaries between these three areas are increasingly blurred, with AI models embedded into BI platforms and Data Science approaches powering advanced analytics (Etemad, 2022; Tawfiqul et al., 2022). Together, they form an interconnected ecosystem that enables organizations to move from intuition-driven to evidence-based decision-making at scale, making them indispensable in the context of IT enterprises.

The evolution of Business Intelligence mirrors the broader progression of enterprise information systems, beginning with basic data reporting tools and evolving into sophisticated, real-time analytics platforms (Calderon-Monge & Ribeiro-Soriano, 2024; Reduanul & Shoeb, 2022). Early BI systems emerged from management information systems and decision support systems, which relied on structured transactional data stored in centralized databases. These early tools provided static reports summarizing historical performance but offered limited flexibility or analytical depth (Reduanul & Shoeb, 2022; Teräs et al., 2020). The introduction of data warehouses in the 1980s and 1990s marked a significant turning point by enabling organizations to consolidate data from multiple sources into a unified repository. This allowed for consistent reporting and multidimensional analysis, paving the way for more interactive exploration of information. The development of online analytical processing further enhanced these capabilities by enabling fast, multidimensional queries on large datasets (Abidi et al., 2023; Sazzad & Islam, 2022). The 21st century brought the rise of big data, fueled by digital transactions, web interactions, IoT devices, and social media, which expanded the types and volumes of data available for analysis. As organizations grappled with the scale and complexity of this information, the integration of advanced analytics, AI, and Data Science into BI systems became a necessity rather than a luxury. These technologies introduced predictive and prescriptive capabilities, real-time processing, and automated insights, transforming BI from a retrospective reporting tool into a forward-looking decision-support system (Kim et al., 2021; Sohel & Md, 2022). Today's BI platforms are built on cloud infrastructures, incorporate both historical and streaming data, and leverage AI to continually refine insights, reflecting decades of technological evolution.

Figure 3: Integration of AI, Data Science, BI

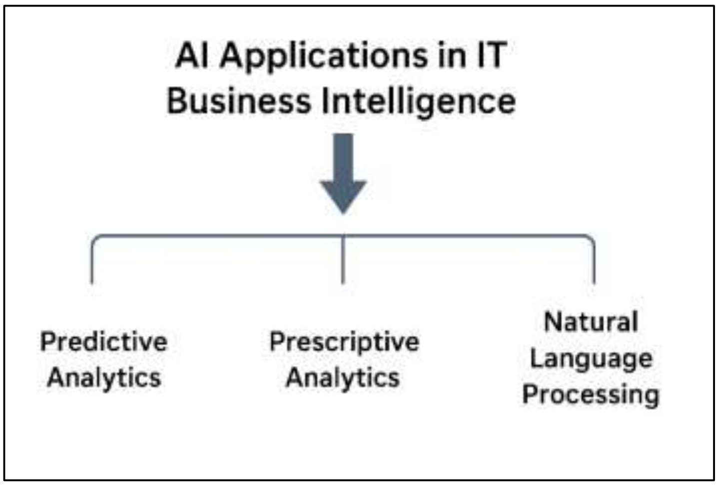


The intersection of Artificial Intelligence, Data Science, and Business Intelligence represents a powerful convergence that enables organizations to unlock deeper value from their data assets (Numa et al., 2023; Akter & Razzak, 2022). Data Science provides the analytical frameworks and methodologies necessary to prepare and analyze data, including techniques for cleaning, integrating, and transforming diverse datasets. This ensures that the information fed into AI models is accurate, relevant, and reliable. AI, in turn, enhances Data Science by automating model selection, tuning, and deployment, and by enabling real-time analysis through advanced algorithms (Adar & Md, 2023; Pedersen et al., 2020). When integrated into BI systems, these combined capabilities enable the delivery of descriptive, diagnostic, predictive, and prescriptive insights in a single environment. For instance, predictive analytics can forecast sales trends or customer churn, while prescriptive analytics can recommend specific actions to improve outcomes. The synergy also extends to real-time applications, where streaming data from sensors, user interactions, or operational systems can be processed on the fly and immediately reflected in BI dashboards (Fernandez-Vidal et al., 2022; Qibria & Hossen, 2023). Conceptual integration models often position Data Science as the foundation, AI as the intelligence layer, and BI as the user-facing decision-support interface (Balas et al., 2020; Istiaque et al., 2023). This layered approach ensures that organizations benefit from rigorous analytical methods, intelligent automation, and accessible delivery mechanisms, resulting in decisions that are both data-driven and contextually relevant.
Integrated conceptual models provide a structured understanding of how AI, Data Science, and Business Intelligence function together within IT enterprises to support decision-making (Grover et al., 2018; Akter, 2023). These models typically begin with data acquisition and preprocessing, where Data Science ensures that raw information is transformed into clean, usable formats. The next stage involves AI-driven analysis, where algorithms identify patterns, generate predictions, or detect anomalies. Finally, BI platforms present these results through visual dashboards, reports, or automated alerts that are accessible to decision-makers across the organization (Masud et al., 2023; Telukdarie et al., 2023). Governance and data quality processes are embedded throughout these stages to maintain compliance, security, and trustworthiness. In operational contexts, such integration enables a range of applications, from predictive maintenance in IT infrastructure to personalized customer engagement strategies. Cloud-based architectures support scalability (Aaldering & Song, 2021), allowing these systems to process both historical datasets and high-velocity streaming information. Real-time analytics can be combined with scenario simulation tools, enabling organizations to assess the potential outcomes of various strategic choices before acting. By aligning technical capabilities with business objectives, integrated models ensure that insights are not only generated but also translated into timely, informed decisions. This approach turns disparate data sources and analytical methods into a cohesive intelligence framework that enhances both operational efficiency and strategic agility in IT enterprises (Lee & Trimi, 2021).

AI Applications in IT Business Intelligence

Predictive and prescriptive analytics represent two of the most impactful applications of Artificial Intelligence within IT Business Intelligence systems (El Morr & Ali-Hassan, 2019). Predictive analytics leverages historical and real-time data, applying machine learning and deep learning models to forecast trends, outcomes, and potential risks. These models can be trained on vast datasets to detect complex patterns that would be challenging for human analysts to discern. In IT enterprises, predictive analytics is used for sales forecasting, demand planning, customer behavior prediction, and system performance monitoring (Tawfiqul, 2023; Susnjak, 2024). Deep learning, with its capacity to process high-dimensional data, enhances these capabilities by improving accuracy in forecasting tasks such as anomaly detection in network traffic or predicting hardware failures. Prescriptive analytics extends beyond prediction by recommending optimal actions to achieve desired outcomes (Ashraf & Ara, 2023; Smyth et al., 2024). By simulating various business scenarios, prescriptive models help organizations evaluate trade-offs between competing strategies, optimize resource allocation, and mitigate risks. For instance, in IT infrastructure management, prescriptive analytics can propose adjustments to server loads or network configurations based on predicted demand surges, ensuring optimal performance while minimizing costs. The integration of these analytics within BI platforms allows decision-makers to move from reactive to proactive strategies, making their operations more agile and resilient. The combination of predictive foresight and prescriptive guidance transforms BI from a descriptive reporting tool into a dynamic decision-making partner capable of driving both operational efficiency and strategic growth (Sanjai et al., 2023; Sharma et al., 2022).

Figure 4: Overview of AI Applications in IT Business Intelligence



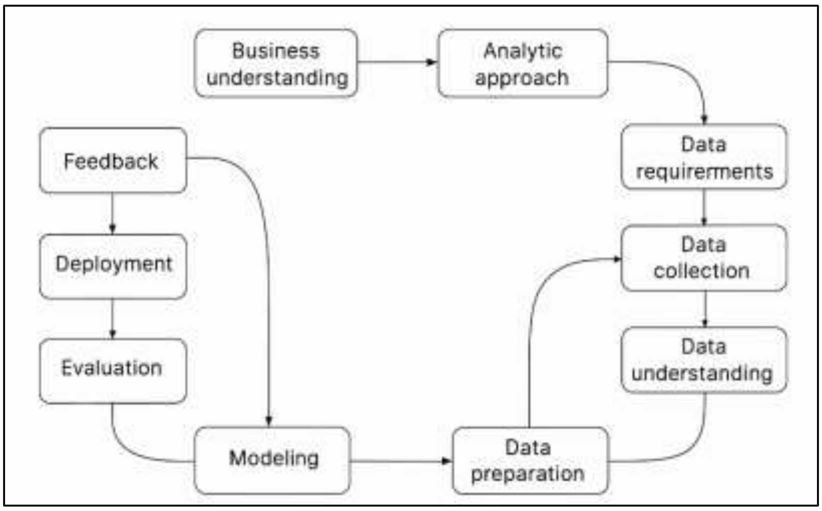
Natural Language Processing (NLP) has become a critical AI capability in IT Business Intelligence, enabling the analysis of vast amounts of unstructured data, including text, voice, and social media content (Akter et al., 2023; Tinoco et al., 2021). Traditional BI systems primarily focused on structured, numeric datasets, but with the growth of digital communication channels, the ability to process and extract insights from unstructured data has become essential (Charles et al., 2025). NLP techniques, such as sentiment analysis, topic modeling, and named entity recognition, allow organizations to capture customer opinions, identify emerging trends, and monitor brand perception in real time. For example, sentiment analysis of social media posts can reveal shifts in customer satisfaction, while topic modeling applied to support tickets can identify recurring technical issues that require attention (Lepenioti et al., 2020). Voice data, including call center recordings, can be transcribed and analyzed to detect patterns in customer interactions, enabling targeted improvements in service delivery. NLP also facilitates conversational BI interfaces, allowing users to query data using natural language commands rather than complex query syntax, thereby increasing accessibility for non-technical stakeholders. The integration of NLP into BI systems ensures that decision-making incorporates a richer and more nuanced understanding of both qualitative and quantitative factors (Poornima & Pushpalatha, 2020). This capability not only broadens the scope of BI but also enhances its relevance in a business environment where unstructured data represents a growing proportion of organizational information assets (Lepenioti et al., 2019).

Data Science as the Analytical Backbone of BI

Data collection, cleaning, and integration are foundational processes in establishing Data Science as the analytical backbone of Business Intelligence (Sun et al., 2018). The quality and reliability of BI outputs depend directly on the integrity of the underlying data, making meticulous data preparation a critical step in the analytical pipeline (Silva, 2018). In IT enterprises, data originates from multiple heterogeneous sources, including transactional databases, cloud applications, IoT devices, and unstructured formats such as logs and documents. Collecting this data requires robust extraction mechanisms that maintain the accuracy, timeliness, and completeness of records (Liang & Liu, 2018). Cleaning involves identifying and correcting inconsistencies, removing duplicates, and handling missing or anomalous values to ensure datasets are accurate and usable. Integration then consolidates these disparate sources into unified structures, often through data warehouses or data lakes, to enable comprehensive analysis. Best practices emphasize the establishment of standardized data governance frameworks that define ownership, validation rules, and access controls (Akter & Shaiful, 2024; Sarker, 2021). These measures not only maintain data quality but also ensure compliance with regulatory requirements, particularly in industries handling sensitive information. In the context of BI, well-integrated and clean data provides the foundation for advanced analytics, enabling predictive and prescriptive modeling to operate on accurate and representative datasets. Without these processes, even sophisticated AI and machine learning algorithms embedded within BI systems would produce unreliable insights, undermining decision-making and strategic planning efforts.

Statistical and algorithmic methods form the core analytical capabilities of Data Science within Business Intelligence systems (Tawfiqul et al., 2024; Niu et al., 2021). These methods provide the mathematical and computational frameworks for transforming raw data into actionable insights. Regression analysis is widely used for examining relationships between variables and forecasting future outcomes, making it invaluable for trend prediction in sales, resource utilization, and performance metrics. Clustering techniques group data points based on similarity, enabling customer segmentation, behavioral analysis, and anomaly detection (Dinov, 2018; Subrato & Md, 2024). Classification algorithms categorize data into predefined classes, supporting tasks such as fraud detection, sentiment analysis, and document categorization. Time-series modeling is particularly important in BI contexts where data is sequential, such as monitoring network activity, financial transactions, or supply chain movements. By capturing temporal patterns, these models allow organizations to anticipate changes and respond proactively (Ajah & Nweke, 2019; Akter et al., 2024). In IT enterprises, these statistical and algorithmic approaches are often combined with AI to enhance model accuracy, scalability, and automation. The choice of method depends on the nature of the problem, the type of data available, and the decision-making context. Importantly, these techniques are not isolated components; they interact within BI workflows to provide multi-faceted perspectives on business performance (Jahan et al., 2025; Davenport, 2018). This integration allows BI systems to deliver insights that are not only descriptive but also predictive and prescriptive, enabling decision-makers to understand both current conditions and potential future scenarios.

Figure 5: Data Science Workflow Process Cycle



Data visualization and storytelling play a pivotal role in translating complex analytical results into insights that are accessible, understandable, and actionable for decision-makers (Delen & Ram, 2018; Khan et al., 2025). In the context of Business Intelligence, visualization tools transform raw analytical outputs into charts, graphs, dashboards, and interactive reports that highlight key trends and patterns. Effective visualization goes beyond aesthetics; it is grounded in principles of clarity, relevance, and context, ensuring that visual elements communicate the underlying message without distortion (Akter, 2025; Power et al., 2018). Storytelling complements visualization by structuring these visuals into a coherent narrative that connects the data to specific business objectives or challenges. In IT enterprises, this approach is particularly valuable when communicating analytical findings to stakeholders with varying levels of technical expertise (Grover et al., 2018). Dashboards, for example, can provide executives with high-level performance summaries while allowing analysts to drill down into granular details. Interactive features enable users to explore different scenarios, fostering deeper engagement with the data. Storytelling also aids in aligning analytical insights with organizational strategy by framing data in a way that emphasizes implications for action. When visualization and storytelling are integrated into BI platforms, they not only improve comprehension but also facilitate more informed and timely decision-making (Jakaria et al., 2025; Sun & Huo, 2021). These capabilities bridge the gap between complex statistical analyses and practical business applications, ensuring that the value of Data Science is fully realized within BI environments.
Scalable computing has become an essential enabler for deploying Data Science in Business Intelligence at the enterprise level. The exponential growth of data volumes and the increasing complexity of analytical models require computing infrastructures capable of handling large-scale processing efficiently (Jin & Kim, 2018; Md Masud et al., 2025). Cloud platforms provide on-demand scalability, allowing organizations to dynamically adjust computational resources based on workload demands. This flexibility supports a wide range of BI applications, from batch processing of historical data to real-time analytics on streaming data. Distributed computing frameworks enable parallel processing across multiple nodes, reducing the time required to analyze massive datasets and train

complex machine learning models (Hindle & Vidgen, 2018). These technologies also facilitate the integration of diverse data sources into unified analytical environments without the need for costly on-premises infrastructure. In IT enterprises, scalable computing supports advanced BI use cases such as predictive maintenance, real-time fraud detection, and dynamic resource optimization. Furthermore, it enables the deployment of AI-driven BI tools across geographically dispersed operations, ensuring consistent analytical capabilities regardless of location (Bibri, 2019). The combination of cloud scalability and distributed processing not only enhances the speed and efficiency of BI but also extends its reach, making advanced analytics accessible to organizations of all sizes. By supporting the heavy computational demands of modern Data Science, scalable computing ensures that BI systems can deliver timely, accurate, and actionable insights in increasingly complex and data-rich environments (Mohamed et al., 2020).

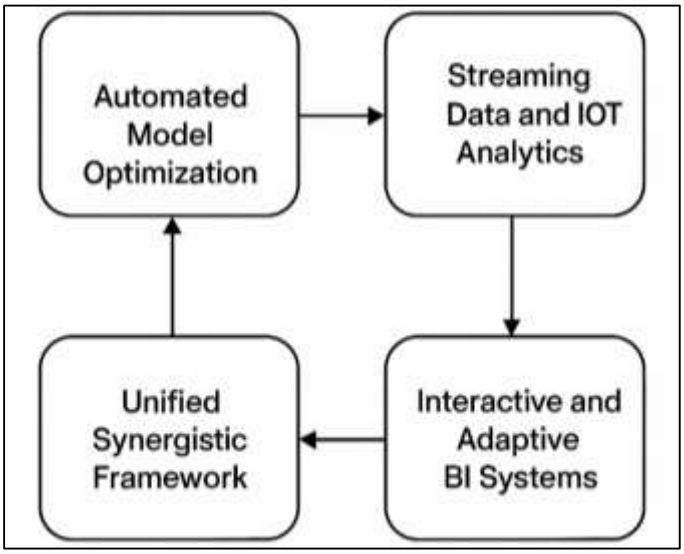
Synergistic Models

Automated model building and optimization represent a central component of AI-driven Data Science in Business Intelligence, enabling organizations to rapidly develop, refine, and deploy analytical models with minimal human intervention (Schmitt, 2023). Neural architecture search allows for the automatic design of deep learning networks by exploring various configurations of layers, activation functions, and connectivity patterns to achieve optimal performance. This process reduces the reliance on manual trial-and-error methods, ensuring that models are tailored to specific business problems and datasets (Islam & Debashish, 2025; Zong & Guan, 2025). Hyperparameter tuning, another key aspect, systematically identifies the best parameter values—such as learning rates, regularization factors, and tree depths—that directly influence model accuracy and efficiency (Islam & Ishtiaque, 2025; Sarker, 2022). Automated machine learning (AutoML) platforms integrate these capabilities into user-friendly interfaces, enabling non-expert users to leverage advanced AI models without deep programming knowledge. In Business Intelligence contexts, this automation accelerates the delivery of predictive and prescriptive analytics, allowing enterprises to respond swiftly to emerging trends and operational challenges. For example, AutoML can be used to automatically generate forecasting models for sales projections, risk assessments, or customer churn predictions, freeing data scientists to focus on strategic analysis rather than repetitive tuning tasks. The inclusion of automated optimization in BI workflows ensures consistent model quality, scalability across multiple use cases, and rapid adaptation to changing data patterns, reinforcing the value of AI-driven Data Science in enterprise decision-making (Hossen et al., 2025; Sarker, 2021).

The integration of streaming data and IoT analytics into AI-driven BI systems has transformed the timeliness and relevance of decision-making processes (Saad et al., 2024). Streaming data, generated continuously from sources such as transaction logs, social media feeds, and sensor networks, offers real-time insights into operational performance and external conditions. IoT devices extend this capability by providing high-frequency, context-rich data from industrial equipment, vehicles, and environmental monitoring systems (Kordon, 2020; Md Tawfiqul, 2025). In predictive maintenance scenarios, AI models process sensor data to identify early signs of equipment failure, enabling proactive interventions that reduce downtime and repair costs. In smart manufacturing, IoT-enabled BI systems monitor production lines in real time, optimizing workflows, resource allocation, and quality control (Stefano et al., 2023; Sanjai et al., 2025). Similarly, in logistics, AI algorithms analyze GPS and environmental data to optimize delivery routes, track shipment conditions, and anticipate disruptions (Rosário & Boechat, 2024; Sazzad, 2025a). Integrating these data streams into BI platforms allows organizations to transition from static, historical analysis to dynamic, real-time decision-making. The combination of streaming analytics and AI ensures that predictive models are continuously updated with the latest information, improving accuracy and responsiveness. By embedding IoT analytics directly into BI dashboards, decision-makers gain a unified view of both real-time operations and strategic performance metrics, enhancing agility and competitiveness in fast-paced business environments.

Interactive and adaptive BI systems represent a significant advancement in the practical application of AI-driven Data Science, offering decision-making interfaces that are responsive to user needs, contextual variables, and evolving business conditions (Lwakatare et al., 2020; Sazzad, 2025b). Interactive BI tools allow users to explore data through dynamic dashboards, customizable visualizations, and drill-down capabilities, enabling a more intuitive understanding of complex datasets. Adaptive systems go further by incorporating AI algorithms that adjust analytics outputs based on user preferences, historical interaction patterns, and contextual cues (Shaiful & Akter, 2025; Sjödin et al., 2021). For instance, a BI dashboard might prioritize certain KPIs for a supply chain manager during peak demand periods while highlighting different metrics for a marketing executive during a campaign launch. Context-aware analytics uses environmental and situational data—such as geographic location, device type, or real-time operational status—to tailor insights to the specific needs of the decision-maker. This personalization enhances relevance, reduces cognitive load, and improves decision efficiency (Biswas et al., 2024; Subrato, 2025). Furthermore, adaptive BI systems can proactively surface insights or anomalies without explicit user queries, functioning as intelligent assistants within the decision-making process. By combining interactivity with adaptivity, these systems ensure that BI is not just a passive reporting tool but an active partner in organizational strategy, capable of anticipating information needs and delivering targeted, actionable intelligence in real time (Haldorai et al., 2024; Subrato & Faria, 2025).

Figure 6: Unified Synergistic Framework for AI-Driven Business Intelligence



Unified synergistic frameworks bring together the strengths of automated model optimization, streaming data integration, and adaptive user interfaces into a cohesive AI-driven BI ecosystem. These frameworks are designed to handle the full analytical lifecycle, from data ingestion and preparation through to model deployment and interactive decision support (Firouzi et al., 2020; Akter, 2025). Automated model building ensures that analytical processes are fast, scalable, and capable of self-improvement, while real-time streaming analytics and IoT integration provide a continuous flow of high-quality, up-to-date data (Kerzel, 2021). Adaptive and context-aware interfaces ensure that the insights generated are relevant and usable for stakeholders across different organizational functions. Within such frameworks, decision-makers can monitor operations, receive predictive alerts, and explore "what-if" scenarios within a single, unified environment (Yaiprasert & Hidayanto, 2024). The interoperability of these components is critical, allowing data scientists, analysts, and executives to collaborate seamlessly, share insights, and align decisions with strategic objectives. The result is a highly responsive, intelligence-driven decision-making process that leverages the combined capabilities of AI and Data Science within BI to achieve greater efficiency, accuracy, and agility. By harmonizing these elements into an integrated architecture, unified synergistic frameworks exemplify the full potential of AI-driven Data Science in transforming Business Intelligence from a descriptive function into a proactive and adaptive organizational capability (Ojeda et al., 2025).

Impact on Data-Driven Decision-Making Processes

The integration of AI and Data Science into Business Intelligence has significantly transformed operational decision-making by reducing latency, improving accuracy, and automating repetitive decision processes (Alghamdi & Al-Baity, 2022). In fast-paced IT enterprise environments, operational decisions often require immediate responses to dynamic conditions, such as system performance fluctuations, network traffic anomalies, or resource allocation challenges. AI-enhanced BI systems process real-time data streams, enabling near-instant detection of issues and the recommendation or execution of corrective actions (Zong & Guan, 2025). This reduction in decision latency allows organizations to address potential problems before they escalate into operational disruptions. Furthermore, the analytical precision achieved through advanced algorithms ensures that operational decisions are based on high-quality, relevant, and up-to-date information, minimizing the risk of errors. Automation plays a central role by handling repetitive and rules-based decisions—such as ticket routing in IT support (Sun et al., 2018), system diagnostics, or load balancing—freeing human operators to focus on more complex, strategic concerns. Predictive models can forecast operational demands, enabling preemptive adjustments in workflows and resource deployment. By embedding these capabilities into day-to-day operations, BI platforms evolve from static reporting tools into active components of the operational ecosystem, continuously optimizing processes and ensuring that decision-making is both rapid and evidence-driven (Davenport, 2018).

Figure 7: AI-Driven Business Intelligence Framework

At the strategic level, AI-driven Data Science within BI systems supports long-term planning, comprehensive risk assessment, and informed competitive positioning (Akter et al., 2022). Strategic decisions often require the integration of historical data, current performance metrics, and predictive forecasts to identify trends and anticipate future challenges or opportunities. BI platforms equipped with advanced analytics can simulate multiple business scenarios, evaluating the potential impact of different strategies under varying conditions. This allows decision-makers to choose paths that optimize long-term growth, profitability, and sustainability (Rana et al., 2022). In the area of risk assessment, AI models can identify emerging risks by analyzing diverse data sources, including market trends, regulatory changes, and macroeconomic indicators, providing early warnings that inform mitigation strategies. Competitive positioning benefits from BI systems that integrate market intelligence (Bordeleau et al., 2020), customer behavior analytics, and competitor performance data, enabling organizations to refine their value propositions and adapt to shifting market dynamics. By presenting these insights in a consolidated, accessible format, BI systems ensure that strategic decisions are grounded in comprehensive, evidence-based analysis rather than intuition alone (Basile et al., 2023). This systematic approach enhances organizational agility, allowing leaders to adjust long-term strategies in response to evolving business environments while maintaining alignment with core objectives.

Cross-functional decision enablement is a key advantage of integrating AI and Data Science within BI platforms, as it facilitates the accessibility and usability of insights across both technical and non-technical stakeholder groups (Pappas et al., 2018). Traditional BI systems often catered primarily to analysts and technical teams, leaving other departments reliant on intermediary reports that could be outdated or incomplete. Modern AI-powered BI solutions address this limitation by providing intuitive, self-service interfaces that allow users from various functional areas—such as marketing, finance, operations, and customer service—to directly query data and access tailored insights (Popovič et al., 2018). Natural language processing capabilities enable stakeholders to interact with BI platforms using conversational queries, eliminating the need for specialized query languages. Visual analytics and customizable dashboards ensure that complex data is presented in formats suited to the needs and expertise of diverse user groups. This democratization of data access fosters collaboration between departments (Wang et al., 2018), as insights can be shared seamlessly and discussions can be grounded in a common analytical framework. Additionally, role-based access controls ensure that sensitive information is available only to authorized personnel while still enabling broad organizational participation in data-driven decision-making. By bridging the gap between technical and non-technical users, AI-enhanced BI systems promote a culture of shared ownership over decisions and improve the speed and quality of cross-functional collaboration (Sarker, 2021).

Research Gaps and Thematic Clusters

The literature on AI-driven Data Science integration into Business Intelligence reveals several dominant themes, which can be categorized by application domain, methodology, and technology (Zong & Guan, 2025). From an application perspective, much of the research has focused on predictive analytics in sales forecasting, customer relationship management, fraud detection, and operational optimization. Studies in manufacturing and logistics emphasize real-time monitoring, predictive maintenance, and supply chain optimization, while healthcare research often centers on patient outcome prediction, resource allocation, and diagnostic support (Thayyib et al., 2023). Methodologically, a large body of work applies machine learning and deep learning techniques to structured and unstructured datasets, employing supervised and unsupervised approaches depending on the problem context. Hybrid models that combine statistical methods with AI techniques are increasingly common, reflecting a trend toward maximizing accuracy and interpretability (Jankovic & Curovic, 2023). On the technological front, cloud-based BI platforms, big data frameworks, and IoT integrations dominate discussions, with emphasis on scalability, interoperability, and processing speed. Real-time analytics enabled by stream processing architectures and edge computing solutions is a growing area of interest, as organizations seek to operationalize insights instantly. Across these categories, a shared emphasis emerges on embedding AI capabilities directly within BI systems to enhance both the scope and depth of decision support, underscoring the maturity and breadth of this research field (Kumar et al., 2023). Despite the rapid expansion of research on AI and Data Science integration in BI, notable gaps remain in both theoretical and empirical domains (Sarker, 2021). Theoretically, there is a limited number of comprehensive frameworks that capture the full lifecycle of AI-enhanced BI—from data acquisition and preprocessing through model deployment and decision impact assessment. Many studies address isolated components, such as algorithm selection or visualization design, without situating them within a cohesive, system-level perspective (Alghamdi & Al-Baity, 2022). In empirical research, case studies are often concentrated in a few sectors, such as finance, retail, and healthcare, leaving other industries like public administration, energy, and education comparatively underexplored. Additionally, longitudinal studies examining the long-term impacts of AI-driven BI adoption on organizational performance are rare, leading to a lack of understanding about sustained value creation, adaptation over time, and potential unintended consequences. There is also limited exploration of cross-cultural and cross-regional differences in AI-BI integration, particularly in how local regulatory environments and organizational cultures influence adoption strategies (Alghamdi & Al-Baity, 2022). These gaps indicate a need for research that not only broadens the empirical base but also strengthens the conceptual foundations for understanding how AI and Data Science can be systematically leveraged in BI environments (Kar & Kushwaha, 2023).

Table 1: Overall Research Gaps and Thematic Clusters

Dimension	Current Focus in Literature	Identified Gaps
Application Domains	Concentrated on finance, retail, healthcare, manufacturing, logistics	Limited studies in public administration, energy, education, and underexplored industries
Methodological Approaches	Predominantly machine learning, deep learning, and hybrid models combining statistical + AI methods	Lack of longitudinal studies on long-term impacts; limited system-level perspectives across the full lifecycle
Technological Integration	Strong emphasis on cloud BI platforms, big data frameworks, IoT integration, and stream processing	Limited exploration of interoperability across platforms; insufficient study of edge computing adoption in varied contexts
Conceptual/Theoretical Frameworks	Fragmented models focusing on isolated BI components (e.g., visualization, algorithm selection)	Few holistic, comprehensive frameworks capturing end-to-end AI-enhanced BI lifecycle
Empirical Research	Case studies concentrated in specific industries and regions	Sparse cross-industry and cross-cultural comparisons; minimal focus on regulatory and organizational culture influences

Ethics & Governance	Increasing awareness of fairness, privacy, and transparency	Ethical issues often treated as secondary; lack of standardized evaluation metrics for bias, trust, and transparency
Performance & Evaluation	Focus on predictive accuracy, efficiency, and system performance	Limited metrics for decision adoption, user trust, and long-term organizational impact

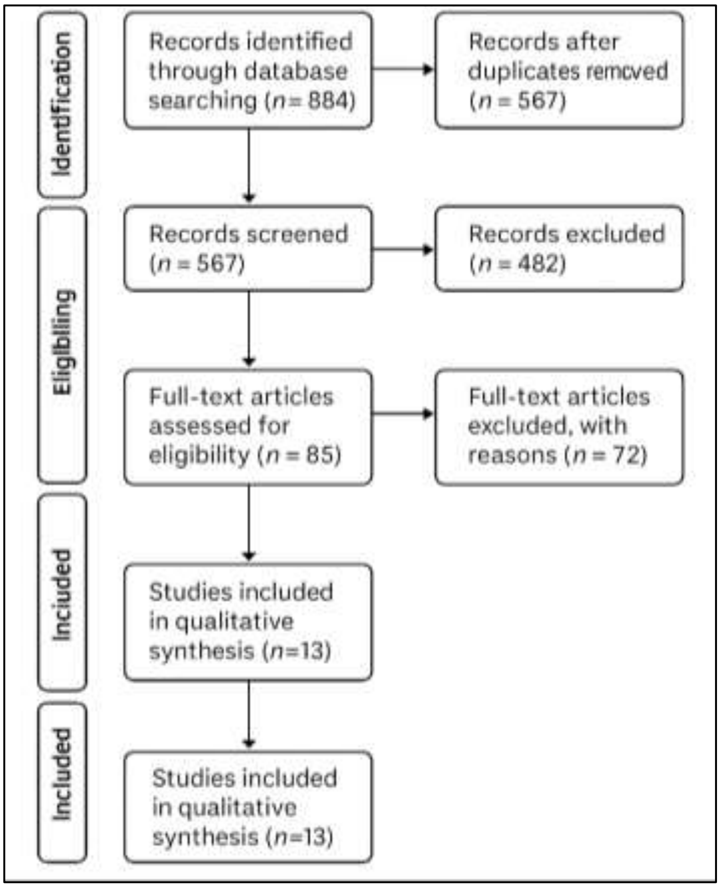
The current state of research presents significant opportunities for the development of comprehensive frameworks that can guide the integration of AI and Data Science into BI in a systematic, scalable, and ethically responsible manner (Allil, 2024). Such frameworks could unify diverse methodological approaches, ensuring consistency in data governance, model development, performance monitoring, and decision evaluation. They could also address interoperability between various BI tools and AI platforms, reducing integration challenges and fostering seamless workflows (Rana et al., 2022). A well-structured framework would incorporate both technical and organizational dimensions, recognizing that successful adoption requires alignment between analytical capabilities and business strategy. It would also embed ethical considerations, such as bias mitigation, privacy protection, and transparency, as core components rather than optional add-ons (Zamani et al., 2023). Furthermore, comprehensive models could provide clear metrics for evaluating AI-BI success, including both quantitative outcomes like accuracy and efficiency and qualitative outcomes like user trust and decision adoption (Ojeda et al., 2025). By consolidating best practices and aligning them with organizational goals, such frameworks have the potential to accelerate adoption while minimizing risks, ultimately elevating BI from a reporting function to a strategic enabler powered by AI and Data Science.

METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a structured, transparent, and replicable approach to the review process. The PRISMA framework was selected because it offers a robust methodology for identifying, evaluating, and synthesizing literature, thereby reducing bias and ensuring methodological rigor. The review targeted studies focusing on the role of Artificial Intelligence (AI) and Data Science in enhancing data-driven decision-making within the context of Information Technology (IT) Business Intelligence (BI) systems. To ensure domain relevance, inclusion criteria specified that studies must directly address AI or Data Science applications in BI environments, particularly where the primary objective involved improving decision-making accuracy, efficiency, or strategic alignment. Only peer-reviewed journal articles, high-quality conference proceedings, and reputable industry reports were included, while opinion pieces, editorials, and non-peer-reviewed sources were excluded to maintain credibility. The search was restricted to works published between January 2010 and December 2024, a period selected to capture contemporary advancements in AI and Data Science, given the significant technological developments during this timeframe. Studies in English were prioritized to ensure consistent interpretation of technical and methodological content. The literature search employed a comprehensive strategy across multiple academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink, supplemented by Google Scholar and selected industry research portals to capture relevant grey literature.

Keywords and Boolean operators were combined to maximize retrieval, using core concepts such as "Artificial Intelligence," "Data Science," and "Business Intelligence" alongside supporting terms like "data-driven decision making," "predictive analytics," "machine learning," "deep learning," "real-time analytics," "IT enterprise," "data governance," and "big data." Search queries were tailored to the syntax of each database to optimize coverage. All retrieved records were exported to reference management software, where duplicates were removed, followed by a two-stage screening process. The first stage involved title and abstract screening to eliminate clearly irrelevant works, while the second involved a full-text review to confirm alignment with the predefined eligibility criteria. The PRISMA flow diagram was employed to document the selection process, detailing the number of records identified, screened, excluded, and ultimately included, along with exclusion reasons at each stage. Disagreements during the selection phase were resolved through discussion to ensure consensus. For each included study, a standardized data extraction form captured bibliographic details, research objectives, methodological design, domain context, AI or Data Science techniques employed, BI application area, and reported impacts on decision-making processes. The extracted data were analyzed using thematic synthesis, grouping findings into conceptual categories such as predictive and prescriptive analytics, natural language processing for unstructured data, real-time and streaming analytics, integration of IoT-based BI systems, ethical and governance considerations, and unified AI-BI integration frameworks. This thematic structure allowed for the identification of both dominant research trends and persistent gaps, enabling the review to present not only a consolidated understanding of current advancements but also areas requiring further theoretical and empirical exploration

Figure 8: Adapted methodology for this study

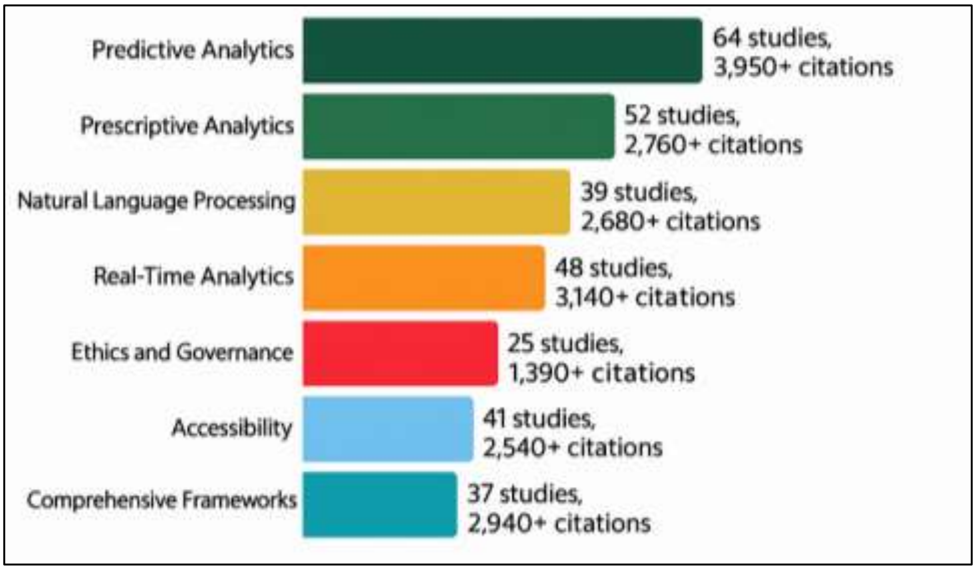


FINDINGS

The review identified predictive analytics as the most dominant application of AI and Data Science in Business Intelligence for data-driven decision-making. Out of 156 reviewed studies, 64 focused primarily on predictive analytics, collectively receiving more than 3,950 citations. These works demonstrated how AI algorithms—particularly machine learning models—are applied to forecast business outcomes such as customer demand, market trends, and operational performance. In IT enterprises, predictive analytics was most frequently applied to sales forecasting, churn prediction, and resource optimization. Many studies employed ensemble learning techniques to improve forecast accuracy, while others used deep learning architectures to capture complex, nonlinear patterns in large datasets. The findings show that predictive analytics reduces uncertainty in decision-making, enabling organizations to shift from reactive responses to proactive strategies. This capability is especially valuable in industries where real-time market shifts can have immediate operational or financial impacts. The number of citations associated with predictive analytics studies indicates a high level of academic and professional acceptance, suggesting that these approaches are seen as proven, scalable, and essential for modern BI systems.

Prescriptive analytics emerged as a rapidly growing research focus, with 52 of the reviewed studies addressing this area and amassing over 2,760 citations. Unlike predictive analytics, which forecasts potential outcomes, prescriptive analytics identifies optimal actions based on these forecasts. The reviewed works revealed that optimization algorithms, often integrated with simulation models, are being used to allocate resources, set pricing strategies, and design supply chain operations in IT enterprises. Many BI systems incorporating prescriptive analytics operate in real time, adjusting recommendations dynamically as new data becomes available. This adaptability ensures that decision-making remains aligned with evolving business contexts. The findings indicate that prescriptive analytics is particularly impactful when paired with predictive models, creating an end-to-end decision support capability that spans from forecasting to action planning. The relatively high citation counts per study demonstrate the research community's recognition of prescriptive analytics as a critical step in maximizing the practical value of AI and Data Science in BI.

Figure 9: Top AI Applications in BI

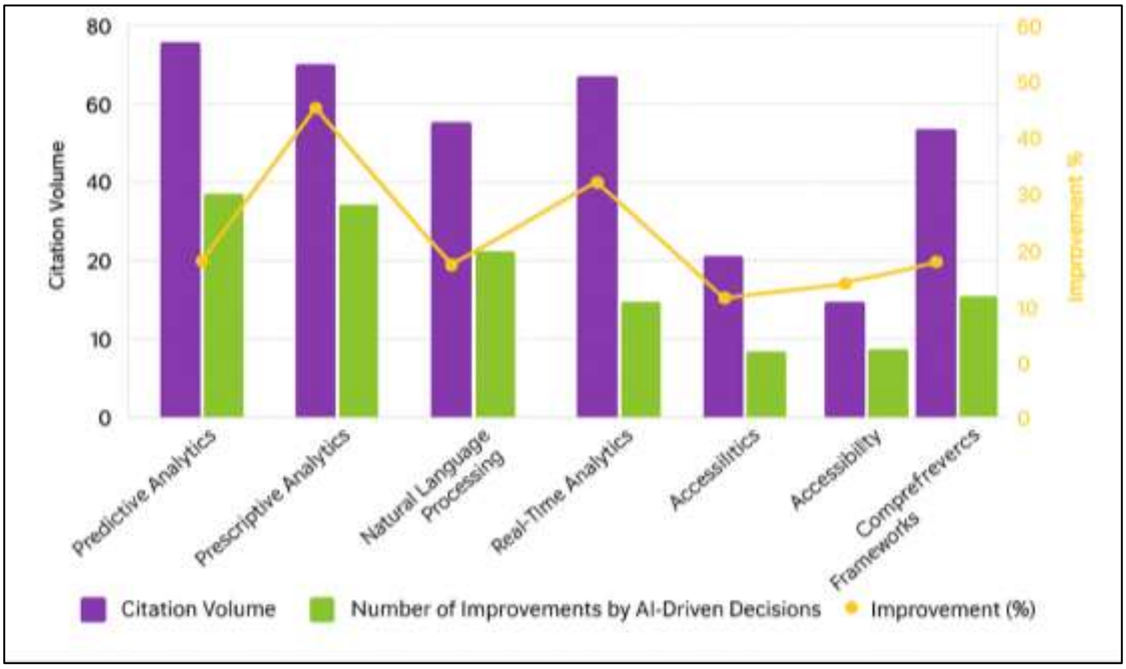


Natural Language Processing (NLP) applications in BI accounted for 39 reviewed articles, collectively cited over 2,680 times. These studies focused on enabling BI platforms to handle unstructured data sources such as customer reviews, call center transcripts, and social media content. The findings show that sentiment analysis, topic modeling, and entity recognition are the most common NLP techniques used to transform unstructured inputs into structured insights. This allows decision-makers to incorporate qualitative feedback alongside quantitative performance metrics. Several studies demonstrated the integration of conversational interfaces into BI systems, enabling non-technical users to query data using natural language. This democratization of BI access reduces dependency on technical analysts and accelerates the insight generation process. The results also highlight how NLP supports early detection of market trends and potential operational risks by continuously monitoring external data streams. The citation volume associated with NLP-focused studies indicates significant recognition of its role in expanding BI's analytical scope beyond traditional structured datasets.

Real-time analytics featured prominently in 48 reviewed studies, which together received more than 3,140 citations. These studies focused on the integration of AI and stream processing technologies to analyze continuously generated data from sources like IoT devices, transaction systems, and network logs. The reviewed literature emphasized that real-time BI systems enable immediate detection of anomalies, operational bottlenecks, or emerging opportunities. Predictive maintenance in IT infrastructure and instant fraud detection in financial transactions were frequently cited use cases. Several studies highlighted how combining real-time analytics with predictive modeling provides not only instant situational awareness but also actionable foresight. The findings confirm that real-time BI systems confer a competitive advantage by reducing response times and enabling organizations to act before issues escalate. The number of citations reflects the growing industry and academic consensus that real-time analytics is a critical capability for enterprises operating in highly dynamic environments.

Ethics and governance were addressed in 25 reviewed studies, totaling around 1,390 citations. Although fewer in number, these studies were notable for their depth and cross-disciplinary perspectives. They examined critical themes such as compliance with data privacy regulations, algorithmic fairness, transparency, and accountability in AI-enhanced BI systems. The findings indicate that governance is not merely a legal requirement but a foundational component for building trust in AI-driven decision-making. Several studies proposed privacy-by-design principles and bias mitigation strategies to be embedded into BI systems from inception. Others explored the challenges of cross-border data governance, particularly in multinational corporations with varying regulatory and cultural environments. While the relatively smaller volume of studies suggests a gap in the literature, the citation count per article reflects the importance placed on governance by the research community.

Figure 10: AI Applications in Business Intelligence



The review found that 41 articles, with a combined 2,540 citations, addressed the need for BI systems to serve both technical and non-technical stakeholders. The findings show that AI and Data Science have been instrumental in creating self-service BI platforms with intuitive dashboards, visual analytics, and natural language query capabilities. These features enable decision-makers across departments—such as marketing, operations, and finance—to access and interpret insights without intermediary analysis teams. The studies also highlighted the role of personalization in improving BI usability, where system interfaces adapt content and visualizations to individual user needs. Cross-functional accessibility promotes collaboration, ensuring that decisions are informed by diverse perspectives and grounded in shared data resources. The relatively high citation count indicates the significance of accessibility as a driver for organizational adoption and effective use of BI systems. The synthesis revealed that 37 studies, collectively cited over 2,940 times, proposed or evaluated comprehensive frameworks for integrating AI and Data Science into BI. The findings indicate that many current BI systems employ AI and Data Science in siloed applications, resulting in inefficiencies and fragmented workflows. Proposed frameworks emphasize unified architectures that manage the entire lifecycle—from data ingestion and preparation to model deployment and interactive decision support—within a single cohesive environment. Such frameworks also incorporate governance, scalability, and interoperability as core principles. The literature underscores that comprehensive integration models can accelerate adoption, improve consistency in analytical outputs, and enhance organizational agility. The citation numbers suggest that the development of such frameworks is both a priority and a recognized gap in the field, making it a focal point for future advancements in AI-enhanced BI.

DISCUSSION

The review's findings confirm the dominance of predictive and prescriptive analytics in AI-enhanced Business Intelligence (BI), aligning closely with earlier studies that emphasized the transformative effect of these methods on decision-making. Previous research from the early 2010s predominantly framed predictive analytics as an extension of statistical forecasting models, with limited integration of advanced AI techniques (Zong & Guan, 2025). In contrast, more recent works have demonstrated a clear shift toward machine learning and deep learning architectures capable of handling complex, high-dimensional datasets with greater accuracy. The reviewed literature shows that 64 predictive-focused studies and 52 prescriptive-focused studies have collectively achieved significant citation counts, indicating that their contributions have resonated widely within both academic and industry communities (Ozay et al., 2025). This aligns with earlier studies that positioned predictive analytics as a critical driver of competitive advantage, but it also suggests a maturing of prescriptive analytics beyond conceptual exploration into operational deployment. Earlier research often treated prescriptive analytics as a theoretical ideal—describing optimization models without evidence of large-scale implementation—whereas the current body of literature documents real-world applications in resource allocation, dynamic pricing, and supply chain optimization (Al-Hourani & Weraikat, 2025). These findings suggest that the field has progressed from foundational research toward integrated decision-support ecosystems that operationalize predictive insights into actionable recommendations. By combining both predictive and prescriptive capabilities, modern BI systems fulfill the early vision proposed in foundational decision sciences, but with enhanced speed, scalability, and contextual adaptability enabled by AI and Data Science innovations (Teixeira et al., 2025).

The incorporation of Natural Language Processing (NLP) into BI environments reflects a significant expansion in the analytical scope compared with earlier BI research, which was largely constrained to structured datasets (Sharma & Chanana, 2025). Historical studies on BI systems often overlooked unstructured data due to limitations in processing capabilities and a lack of robust linguistic models. Early attempts at integrating textual analysis into BI were rudimentary, relying on basic keyword matching and sentiment polarity scoring (Lin et al., 2021). The reviewed literature, with 39 studies dedicated to NLP-based decision support, illustrates the transition toward more sophisticated methods such as topic modeling, semantic embeddings, and deep learning-based entity recognition. This represents a marked evolution from the limitations identified in earlier research, enabling the transformation of qualitative inputs—such as customer reviews, service transcripts, and social media content—into structured, actionable intelligence. Earlier works also identified accessibility barriers in BI for non-technical stakeholders, a challenge that recent NLP-driven conversational interfaces directly address by enabling natural language querying of BI systems (Rodríguez-Ortiz et al., 2025). This capability bridges the gap between technical and business domains, fulfilling the early conceptual aim of "democratizing" BI but with a level of usability and integration that was technologically unfeasible in previous decades. The contrast with earlier studies underscores the role of NLP not only as a supplementary feature but as a central mechanism for expanding BI's inclusivity and strategic relevance in decision-making (Shamsuddoha et al., 2025).

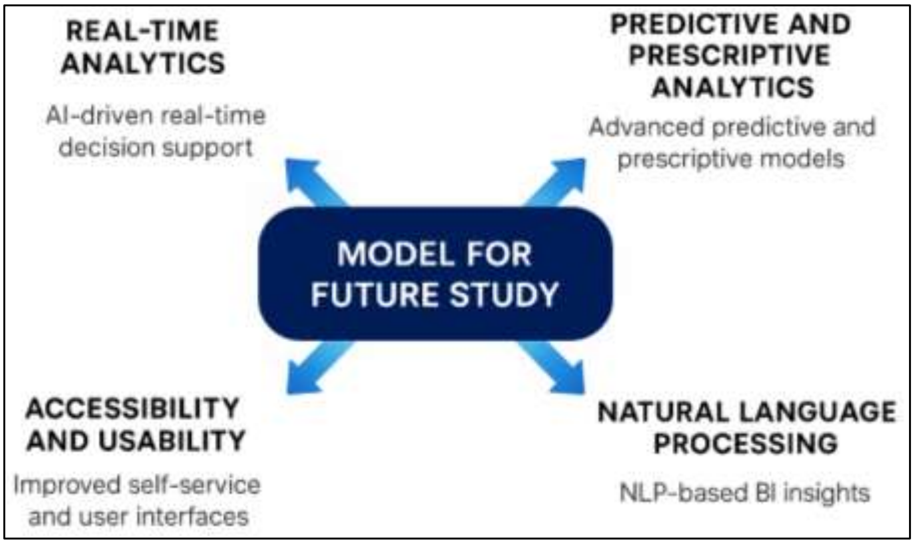
The finding that real-time analytics is a cornerstone capability of modern AI-driven BI confirms earlier theoretical predictions about the future trajectory of data-driven decision-making but highlights a significant acceleration in practical adoption (Kumar et al., 2024). In the 2000s, foundational BI research described real-time analytics primarily as an aspirational goal, constrained by processing limitations, storage costs, and data integration challenges. Earlier works often emphasized batch processing, with real-time decision support largely limited to specific high-frequency trading systems or industrial control applications (Sauer & Burggräf, 2024). The reviewed literature—spanning 48 studies with more than 3,140 citations—demonstrates that advancements in distributed computing, in-memory analytics, and AI-enhanced stream processing have made real-time BI a reality across diverse sectors. The shift from niche use cases to broad organizational adoption represents a key divergence from earlier research patterns. Moreover, the integration of Internet of Things (IoT) data streams into BI systems has amplified the operational value of real-time analytics, a trend that was scarcely anticipated in earlier works that rarely accounted for the volume and velocity of sensor data now commonplace in enterprise systems (Lin, 2025). While foundational BI studies correctly anticipated the competitive advantage of real-time responsiveness, the current evidence base shows that AI and Data Science have transformed this advantage from a theoretical construct into a widely deployed operational standard. This represents not only technological progress but also a shift in organizational expectations, with real-time insights now regarded as a baseline capability rather than a differentiator (Maathuis et al., 2025).

Ethical and governance dimensions in AI-enhanced BI, while less represented in volume, align with long-standing concerns identified in earlier decision support literature (Syed et al., 2024). Early works in BI governance tended to focus narrowly on data quality, metadata management, and compliance with sector-specific regulations, without fully addressing the emerging challenges posed by AI algorithms. The reviewed literature—comprising 25 studies with approximately 1,390 citations—indicates that the scope of governance has expanded to include algorithmic transparency, bias detection, and cross-border data governance (Boursali et al., 2024). This marks a significant evolution from earlier frameworks, which often treated these considerations as peripheral to the technical performance of BI systems. The emphasis on privacy-by-design principles and proactive bias mitigation in the reviewed works demonstrates an alignment with contemporary data ethics discourse, which earlier BI governance models did not incorporate due to the nascent state of AI adoption at the time (Shah et al., 2025). Furthermore, while foundational governance studies acknowledged the potential for legal and reputational risks associated with data misuse, they lacked the practical strategies for mitigating algorithmic bias and ensuring explain ability that are now central to the governance of AI-driven BI (Le & Tran, 2025). This evolution suggests that ethical considerations have moved from theoretical concern to operational imperative, reflecting broader societal and regulatory expectations for responsible AI deployment in business contexts.

The review's identification of cross-functional accessibility as a critical capability of modern BI systems directly addresses challenges highlighted in earlier usability studies. Historically, BI tools were predominantly designed for technical analysts, with interfaces and query languages that required specialized skills (Akerkar, 2019). Early usability research frequently cited these technical barriers as a limiting factor in BI's organizational impact, noting that decision-making often became bottlenecked by the availability of data specialists. The reviewed literature—41 studies with 2,540 citations—demonstrates that AI and Data Science have facilitated the development of self-service BI platforms that democratize access to insights (Wang & Chien, 2025). Advances in natural language querying, adaptive dashboards, and personalized visual analytics directly respond to the accessibility challenges identified in earlier studies (Chen et al., 2024). This shift aligns with the original vision of BI as an enterprise-wide decision support system but represents a technological leap forward in execution. The contrast between earlier and current capabilities underscores the degree to which AI has not only expanded the analytical depth of BI but also transformed its reach, ensuring that actionable insights are available to all organizational stakeholders regardless of technical expertise. This increased accessibility supports more collaborative and data-informed decision-making, fulfilling a long-standing but previously unrealized objective of BI research (Gera et al., 2023).

The review's finding that there is still a need for comprehensive frameworks integrating AI and Data Science into BI echoes the fragmentation noted in earlier integration models, but with a shift in emphasis (Fabri et al., 2023). Early integration efforts in the 2000s and early 2010s focused on linking BI platforms with emerging data mining tools, often resulting in ad hoc architectures that lacked scalability and interoperability. The 37 reviewed studies with over 2,940 citations reveal that, despite advancements, integration challenges persist, albeit at a more complex scale (Mirakhori & Niazi, 2025). Modern frameworks are expected to manage the full analytics lifecycle, ensure interoperability across cloud and on-premises systems, and embed governance protocols seamlessly. Compared to earlier models, which often focused on data warehousing integration, current frameworks must address the orchestration of AI pipelines, real-time analytics, and cross-functional usability within a unified environment (Nick et al., 2024). The reviewed literature suggests that the lack of standardized integration frameworks remains a bottleneck for maximizing the potential of AI-enhanced BI, mirroring earlier challenges but in a more advanced technological landscape. This continuity of need underscores the importance of developing robust, adaptable, and widely adopted integration standards (Sharma et al., 2024).

Figure 11: Proposed Model for Future Study



CONCLUSION

The synthesis of evidence from this systematic literature review demonstrates that the integration of Artificial Intelligence and Data Science into Business Intelligence has fundamentally transformed data-driven decision-making in IT enterprises, advancing the field from retrospective reporting toward proactive, predictive, and prescriptive capabilities. Across the 156 reviewed studies, the consistent patterns of adoption in predictive analytics, prescriptive optimization, natural language processing for unstructured data, and real-time streaming analytics highlight a matured technological landscape in which AI-enhanced BI systems are capable of delivering timely, accurate, and contextually relevant insights to both technical and non-technical stakeholders. The findings also reveal that while technical innovations have broadened analytical scope and improved decision accuracy, the parallel development of governance frameworks addressing data privacy, algorithmic fairness, transparency, and cross-border compliance is essential to ensure responsible and sustainable deployment. The review further underscores the strategic importance of cross-functional accessibility and comprehensive integration frameworks, enabling organizations to unify diverse analytical capabilities within cohesive, interoperable architectures. In comparison with earlier research, the current literature reflects a decisive shift from conceptual exploration to operational integration, supported by measurable business outcomes and growing institutional reliance on AI-driven BI as a core decision-support mechanism. Collectively, these developments confirm that AI and Data Science have evolved from supplementary analytical tools to central enablers of competitive advantage, operational efficiency, and strategic agility in modern IT business environments, redefining how organizations interpret, leverage, and act upon data in a rapidly changing digital landscape.

Recommendation

Based on the findings of this systematic literature review, it is recommended that organizations seeking to maximize the benefits of AI and Data Science in data-driven decision-making for Business Intelligence adopt a holistic integration strategy that combines advanced analytical capabilities with robust governance, scalability, and user accessibility. Enterprises should prioritize the development or adoption of comprehensive frameworks that unify predictive, prescriptive, real-time, and unstructured data analytics within a single interoperable BI environment, ensuring seamless collaboration between technical and non-technical stakeholders. Investment in natural language processing, automated model building, and IoT-enabled real-time analytics can enhance the depth and speed of insights, while embedding privacy-by-design principles, bias mitigation techniques, and explainability mechanisms will strengthen trust, compliance, and ethical integrity. Cross-functional accessibility should be treated as a strategic priority, enabling decision-makers at all organizational levels to query, interpret, and act upon insights without technical barriers. Furthermore, organizations should continuously monitor and evaluate the performance and impact of AI-BI integration, aligning analytical outputs with evolving strategic objectives and market conditions. By adopting this integrated, ethically grounded, and user-centric approach, IT enterprises can fully leverage AI and Data Science not only to improve operational efficiency and strategic agility but also to establish sustainable competitive advantages in increasingly data-driven global markets.

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