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ARTIFICIAL INTELLIGENCE FOR DECISION MAKING IN THE ERA OF BIG DATA EVOLUTION

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ABSTRACT

This study systematically examines the transformative role of Artificial Intelligence (AI) in decision-making, focusing on its applications, challenges, and future opportunities. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a total of 100 peer-reviewed articles were analyzed to ensure a rigorous and comprehensive understanding of the subject. The findings highlight AI's ability to optimize decision-making processes through advanced technologies such as machine learning, natural language processing, and predictive analytics, significantly enhancing accuracy, efficiency, and responsiveness across diverse sectors such as healthcare, finance, supply chain management, and public administration. Despite these advancements, the study identifies persistent challenges, including algorithmic bias, data privacy concerns, and the lack of transparency in "black box" AI models, which undermine trust and accountability. Additionally, the review uncovers research gaps, particularly in low-resource settings and emerging markets, where AI's potential remains underutilized due to infrastructural and data limitations. The integration of AI with emerging technologies, such as blockchain, quantum computing, and edge computing, presents promising opportunities to enhance scalability, security, and transparency in decision-making. The study also underscores the importance of interdisciplinary research, particularly at the intersection of AI and social sciences, to better understand human-AI interaction and foster ethical and socially equitable AI adoption. By addressing these challenges and leveraging emerging opportunities, AI can evolve into a transformative tool for informed, inclusive, and responsible decision-making in an increasingly complex world.

1 Introduction

The evolution of big data has fundamentally transformed the way organizations approach decision-making processes, providing unparalleled access to vast and diverse datasets (Pillai et al., 2021). These datasets, when effectively utilized, can unlock insights that were previously unattainable. Big data refers to large, complex datasets generated at high velocity from various sources, such as social media, IoT devices, and transactional systems (Kowalczyk & Buxmann, 2015). The integration of Artificial Intelligence (AI) into decision-making has emerged as a game-changer, leveraging advanced computational methods to process, analyze, and interpret data for actionable insights. AI technologies, including machine learning, natural language processing (NLP), and deep learning, are designed to address the challenges posed by big data, such as its volume, variety, and veracity (Edwards et al., 2000). These advancements have prompted researchers and practitioners to explore AI's transformative

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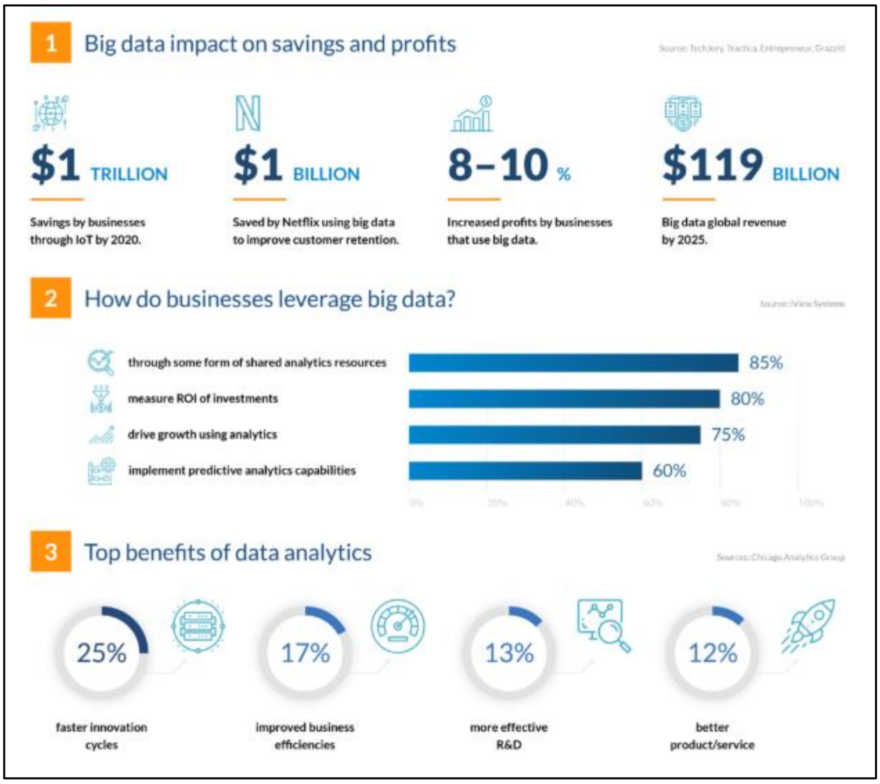
potential across multiple domains. Moreover, AI-driven decision-making enables organizations to move beyond traditional data analysis methods by providing real-time, predictive, and prescriptive capabilities (Ahmad & Laroche, 2017). For instance, predictive analytics, powered by machine learning algorithms, allows businesses to forecast trends and anticipate customer behaviors, significantly enhancing strategic planning (Wamba et al., 2021). Furthermore, NLP enables the extraction of meaningful insights from unstructured textual data, such as customer reviews and social media posts, further enriching decision-making processes (Di Vaio et al., 2020). These capabilities are crucial in industries like finance, healthcare, and retail, where data-driven insights can lead to optimized operations and enhanced customer experiences (Dwivedi et al., 2021). Despite these benefits, the effective implementation of AI requires addressing challenges such as data privacy, algorithmic transparency, and computational efficiency.

The rise of big data has not only amplified the need for AI integration but also highlighted the limitations of human cognitive abilities in processing large-scale datasets. Human decision-makers often struggle with cognitive biases and information overload, which can hinder optimal decision-making (Jałowiec et al., 2022). AI, by contrast, excels at identifying patterns and correlations that are imperceptible to the human eye, enabling more objective and data-driven decisions (Olabi et al., 2023). Moreover, AI technologies facilitate scalability, allowing organizations to analyze and interpret data at a speed and scale that far exceed human capabilities. This is particularly critical in scenarios requiring rapid decision-making, such as real-time fraud detection or emergency response planning (Dwivedi et al., 2021). However, the integration of AI into decision-making is not without its challenges. One significant issue is the ethical implications of algorithmic decision-making, particularly in areas where AI systems may inadvertently perpetuate biases present in the training data (Di Vaio et al., 2020). Additionally, the complexity and opaqueness of AI algorithms, often referred to as the "black-box" problem, raise concerns about accountability and trust in AI-driven decisions (Entezari et al., 2023). Researchers have emphasized the importance of developing explainable AI models to address these concerns, enabling stakeholders to understand and trust

Figure 1: The Impact and benefits of big data and data analytics



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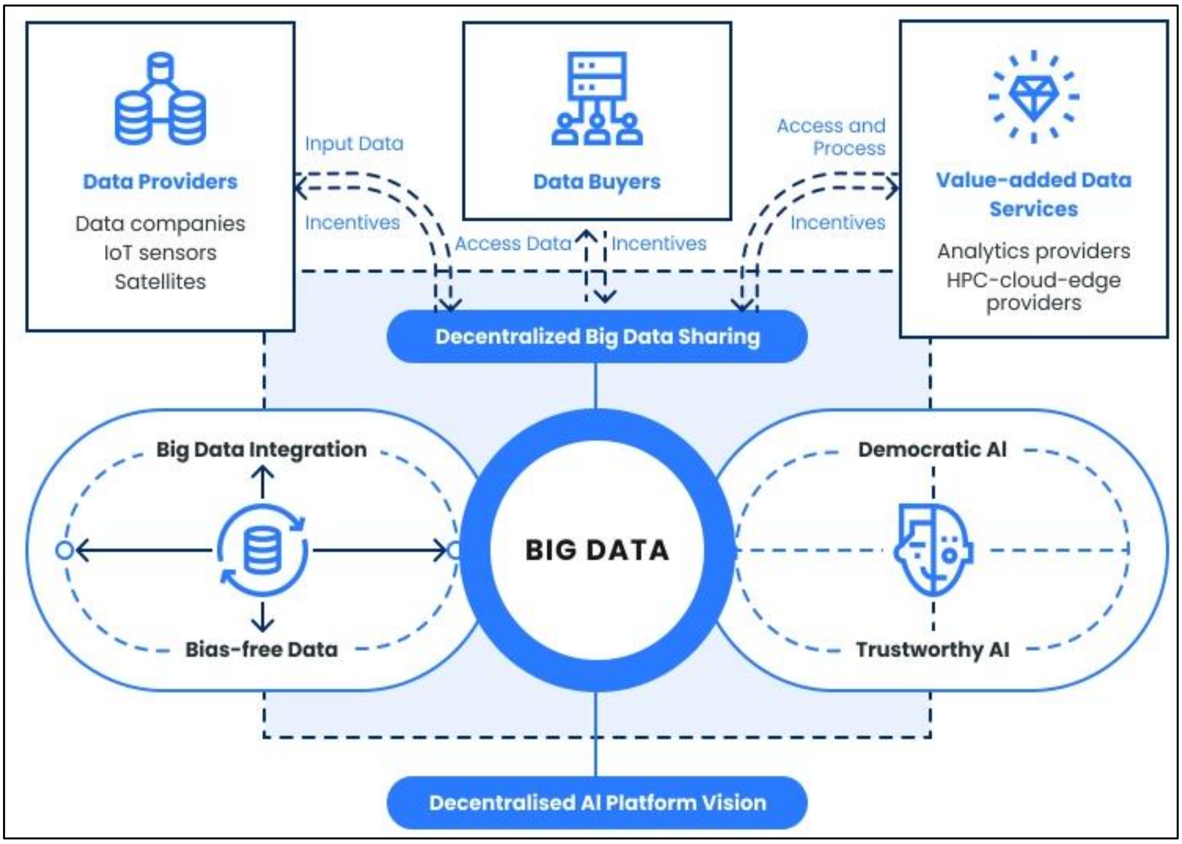
the decisions made by AI systems (Jarrahi, 2018). These challenges necessitate a careful balance between technological innovation and ethical responsibility.

The application of AI in the era of big data evolution is also influenced by emerging trends and interdisciplinary approaches. For example, the convergence of AI with technologies like blockchain, IoT, and edge computing is creating new opportunities for decentralized and secure data analysis (Di Vaio et al., 2020). Similarly, advancements in quantum computing hold the promise of accelerating AI algorithms and enabling the analysis of exponentially larger datasets (Wamba et al., 2021). As industries continue to adopt AI-driven decision-making, ongoing research and development are essential to ensure that these systems are robust, ethical, and aligned with organizational goals. By synthesizing insights from recent studies, this paper aims to provide a comprehensive exploration of AI's role in decision-making amidst the big data revolution. The primary objective of this study is to explore the transformative role of Artificial Intelligence (AI) in enhancing decision-making processes in the era of big data evolution. This research aims to identify and analyze key AI technologies, such as machine learning, natural language processing, and predictive analytics, and their applications in addressing the challenges of big data. Specifically, the study seeks to investigate how AI enables organizations to extract actionable insights from vast datasets, improve operational efficiency, and foster strategic innovation. Furthermore, it examines the ethical, technical, and computational challenges associated with AI-driven decision-making, emphasizing the importance of developing transparent and accountable AI systems. By synthesizing insights from recent academic and industry studies, this research provides a comprehensive understanding of the opportunities and challenges of AI integration in decision-making, offering practical recommendations for leveraging AI in diverse sectors.

2 LITERATURE REVIEW

The rapid evolution of big data and the growing adoption of Artificial Intelligence (AI) in decision-making have led to a surge in scholarly interest and practical applications across diverse fields. This section reviews existing literature to establish a theoretical and empirical foundation for understanding how AI

Figure 2: Decentralized Big Data Sharing model



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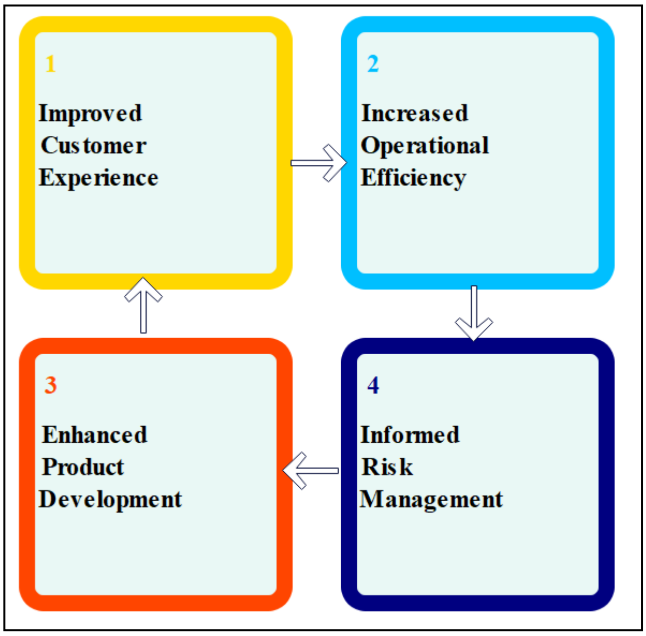
technologies are reshaping decision-making processes in the era of big data. By synthesizing insights from academic research, industry reports, and case studies, this literature review highlights key themes, frameworks, and challenges in the field. The aim is to provide a comprehensive understanding of the interplay between AI and big data, focusing on its implications for various domains such as predictive analytics, ethical considerations, and computational advancements.

2.1 Conceptual Foundations of AI and Big Data in Decision-Making

The evolution of Artificial Intelligence (AI) has been a defining feature of technological advancement, with its historical development rooted in efforts to mimic human intelligence through computational systems (Duan et al., 2019). Early AI research in the mid-20th century focused on rule-based systems, which have since evolved into sophisticated machine learning and deep learning algorithms capable of self-learning from data (Duan et al., 2019). This progression has allowed AI to transition from theoretical concepts to practical tools for solving complex problems in diverse fields such as healthcare, finance, and supply chain management (Singh & Giudice, 2019). Today, AI's contemporary significance lies in its ability to enhance decision-making processes by automating data analysis, reducing human error, and uncovering actionable insights from large datasets (Wang et al., 2018). These

Figure 3: Benefits of Big Data Analytics



advancements are particularly impactful in the era of big data, where the sheer volume and complexity of information necessitate intelligent systems for processing and interpretation (McAfee & Brynjolfsson, 2012).

Big data, characterized by its volume, variety, velocity, and veracity (commonly referred to as the "4Vs"), plays a pivotal role in modern decision-making (Mostafa & El-Masry, 2013). Volume refers to the vast amounts of data generated daily, while variety highlights the diverse formats such as text, video, and structured data (Davenport, 2006). Velocity reflects the rapid speed at which data is produced and requires analysis, while veracity addresses the accuracy and reliability of the data being used (Davenport & Harris, 2007). These characteristics make big data a valuable yet challenging asset for organizations aiming to derive meaningful insights. AI provides the computational power and algorithms necessary to process and analyze big data, transforming raw information into strategic intelligence (Ardito et al., 2019; Entezari et al., 2023). For instance, AI-powered predictive analytics enables organizations to anticipate future trends and make proactive decisions, significantly enhancing operational efficiency (Wang et al., 2018). Moreover, The interrelation between AI and big data is crucial for informed decision-making, as AI relies on large datasets to train its algorithms and improve performance. Big data serves as the foundation for AI's ability to recognize patterns, identify correlations, and make predictions, while AI enhances big data analytics by automating complex processes and delivering actionable results in real-time (McAfee & Brynjolfsson, 2012). For example, in the retail industry, AI leverages big data to analyze consumer behavior, optimize inventory management, and personalize marketing strategies (Mostafa & El-Masry, 2013). Similarly, in the healthcare sector, AI utilizes patient data to improve diagnostics, develop personalized treatment plans, and predict disease outbreaks, demonstrating its potential to revolutionize decision-making across industries (Ayan et al., 2023).

2.2 Theoretical Models and Frameworks

Decision-making theories have evolved significantly with the advent of AI and big data, moving from classical models like rational decision-making to more dynamic frameworks. Traditional decision-making

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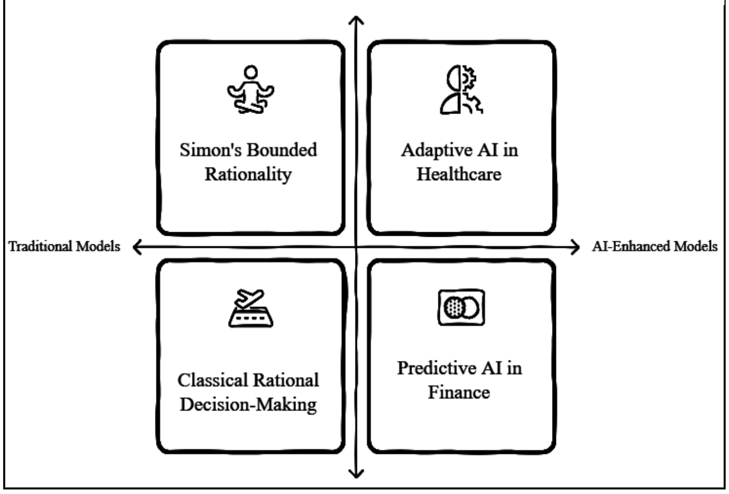
models, such as (Selten, 1990) bounded rationality theory, emphasized the limitations of human cognition in processing information and making optimal decisions. However, the integration of AI and big data has redefined these boundaries by introducing computational capabilities that transcend human constraints (Qasim & Kharbat, 2019). For instance, AI-enabled systems utilize vast datasets to analyze scenarios, evaluate alternatives, and recommend optimal actions, embodying a shift towards data-driven decision-making approaches (Güney & Kantar, 2020). Contemporary decision-making models increasingly incorporate AI-driven algorithms to support complex and high-stakes decisions across domains such as finance, healthcare, and public policy (Gunasekaran et al., 2017).

Adaptive frameworks have gained prominence in decision-making contexts, leveraging AI's ability to learn and evolve in response to changing data patterns (Gupta et al., 2018). These frameworks, rooted in reinforcement learning and dynamic optimization, allow AI systems to adapt their decision-making strategies based on real-time feedback (Güney & Kantar, 2020). For example, AI in e-commerce employs adaptive frameworks to personalize recommendations for customers by analyzing their browsing and purchasing behaviors (Casquiço et al., 2021). Similarly, in healthcare, adaptive AI models support clinical decision-making by tailoring treatment plans to individual patients based on evolving health data (Qasim & Kharbat, 2019). These systems exemplify how adaptive frameworks harness the interplay between AI and big data to enable responsive and context-aware decision-making. Moreover, predictive frameworks powered by AI technologies play a critical role in modern decision-making by providing foresight into future trends and outcomes. Machine learning algorithms, particularly those employing supervised learning, excel at identifying patterns and correlations in historical data, enabling accurate predictions (You et al., 2019). In the financial sector, predictive AI models are widely used for credit risk assessment, fraud detection, and investment portfolio optimization (Aydiner et al., 2019). Predictive frameworks also extend to public safety, where AI systems analyze crime data to forecast and prevent potential incidents (Chiang et al., 2012). The success of these frameworks relies on the integration of high-quality big data, as inaccuracies in data inputs can lead to suboptimal predictions and decisions (Lim et al., 2013). Moreover, the integration of adaptive and predictive frameworks has led to the development of hybrid decision-making models that combine real-time responsiveness with future-oriented insights. These hybrid models, often referred to as prescriptive analytics, not only predict outcomes but also recommend optimal actions to achieve desired objectives (Rieple et al., 2012). For example, in supply chain management, prescriptive models optimize inventory levels and delivery routes by analyzing historical trends alongside real-time logistics data (Hu et al., 2021). Despite their effectiveness, these models present challenges, including the computational complexity of combining multiple AI algorithms and ensuring the interpretability of their outputs (Bole et al., 2015). Continued research into hybrid frameworks is essential to enhance their scalability, reliability, and transparency, thereby maximizing their impact on decision-making processes.

Figure 4: AI-Driven Decision-Making Frameworks



2.3 AI Technologies Driving Big Data Analytics

Machine learning, as a subset of AI, has become a cornerstone in big data analytics by enabling decision-making through supervised, unsupervised, and reinforcement learning approaches (Lim et al., 2013). Supervised learning, which trains models on labeled datasets, is widely used for classification and regression tasks in industries such as finance and healthcare (Rieple et al., 2012). For instance, supervised learning algorithms have been applied to predict customer churn, identify fraudulent transactions, and classify medical images with high accuracy (Hu et al., 2021).

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Unsupervised learning, on the other hand, analyzes unlabeled data to identify hidden patterns and clusters, making it a valuable tool for market segmentation and anomaly detection (Bole et al., 2015). Reinforcement learning, a dynamic approach where agents learn through interaction with an environment, has been employed in real-time decision-making applications such as autonomous vehicles and robotic process automation (Tseng et al., 2017). These machine learning techniques collectively enhance decision-making capabilities by extracting actionable insights from complex datasets.

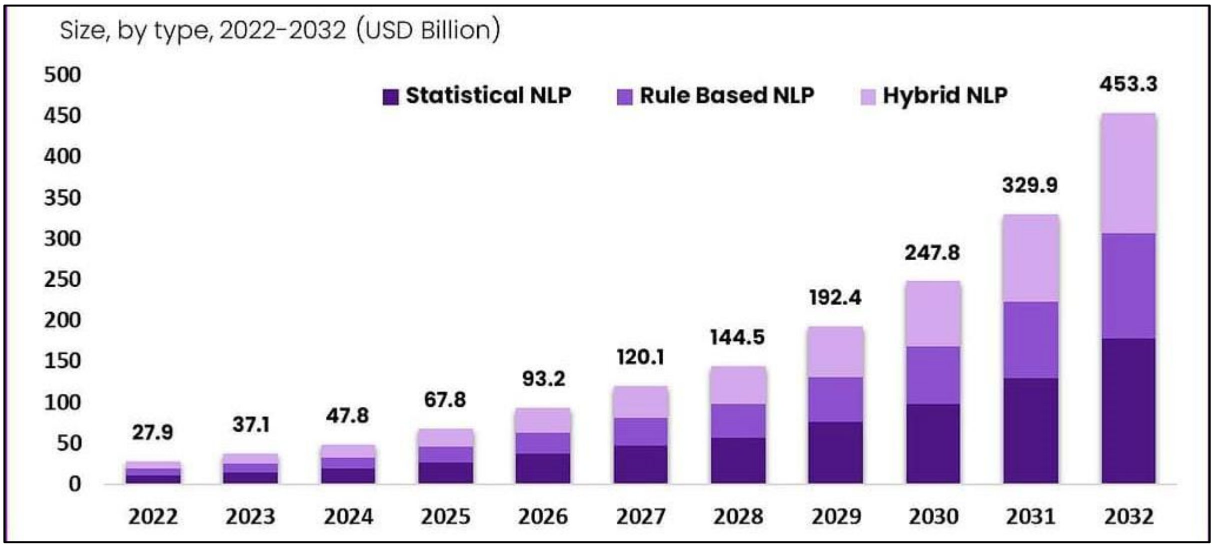
Predictive analytics, powered by machine learning, leverages historical and real-time data to forecast future trends and outcomes. Supervised learning models, such as linear regression, decision trees, and neural networks, are extensively used for trend analysis in fields ranging from financial forecasting to healthcare planning (Gunasekaran et al., 2017). For example, in retail, predictive analytics enables inventory optimization and demand forecasting, ensuring supply chain efficiency (Davenport & Harris, 2007). Similarly, in the energy sector, predictive models forecast equipment failures, reducing downtime and maintenance costs (Lismont et al., 2017). These applications demonstrate how machine learning empowers organizations to anticipate changes and adapt strategies proactively, providing a competitive advantage in data-driven industries. Unsupervised learning techniques contribute significantly to exploratory data analysis, revealing insights that are not apparent through traditional methods. Clustering algorithms, such as k-means and hierarchical clustering, group data into meaningful categories, aiding in customer segmentation and personalized marketing (Lin et al., 2017). Dimensionality reduction techniques, like principal component analysis (PCA), simplify complex datasets while preserving critical information, facilitating efficient analysis (Otokiti, 2019). In cybersecurity, unsupervised learning identifies anomalous patterns in network traffic, enabling early detection of potential threats (Gunasekaran et al., 2017). These applications highlight the role of unsupervised learning in uncovering hidden structures within data, enhancing decision-making processes in diverse domains.Moreover, reinforcement learning stands out for its adaptability and real-time decision-making capabilities, particularly in dynamic environments. This approach has been instrumental in optimizing operations in sectors like logistics, where AI systems learn to balance delivery costs and times effectively (Wang et al., 2018). In the healthcare domain, reinforcement learning models assist in optimizing treatment schedules and drug dosages based on patient responses (Gunasekaran et al., 2017). Furthermore, reinforcement learning's ability to simulate and learn from multiple scenarios has made it invaluable in autonomous systems, including drones and self-driving cars (Davenport & Harris, 2007). By continuously learning and improving, reinforcement learning enhances the predictive power of machine learning, driving innovation in big data analytics and decision-making.

2.4 Natural Language Processing (NLP)

Natural Language Processing (NLP) has become a critical component of big data analytics, particularly in the processing of unstructured data such as social media posts, customer reviews, and textual documents. This unstructured data, which constitutes a significant portion of the information generated daily, contains valuable insights that traditional data processing methods often overlook (Kang et al., 2020). NLP enables the extraction, interpretation, and organization of textual data, transforming it into actionable intelligence for decision-making (Kang et al., 2020). For instance, organizations use NLP to analyze social media trends and customer feedback, gaining a deeper understanding of consumer preferences and public sentiment (Berger et al., 2019). The ability to process unstructured data at scale provides organizations with a competitive advantage, particularly in industries where real-time insights drive strategic decisions. One of the most prominent applications of NLP is sentiment analysis, which involves identifying and categorizing emotions expressed in text. Sentiment analysis is widely employed in marketing, where it helps organizations assess customer satisfaction, track brand perception, and tailor advertising strategies (Signorini et al., 2011). Machine learning models, such as support vector machines (SVM) and neural networks, are commonly used for this purpose, achieving high levels of accuracy in sentiment detection (Chi-Hsien & Nagasawa, 2019). In addition, sentiment analysis extends to public policy and social research, where it aids in understanding societal trends and gauging public opinion on various issues (Ghose et al., 2012). By providing an efficient way to quantify subjective data, sentiment analysis serves as a powerful tool for data-driven decision support.

Moreover, anguage understanding, a broader aspect of NLP, focuses on comprehending the context and semantics of textual information, enabling systems to derive meaningful insights from complex data sources (Xu et al., 2014). Advanced models like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformers (GPT) have revolutionized NLP by significantly improving the accuracy of language understanding tasks (Adamopoulos et al., 2018). These models are particularly effective in applications requiring context-sensitive interpretation, such as customer service chatbots, legal document analysis, and automated content summarization (Collobert et al., 2011). For instance, financial institutions use NLP to process and analyze regulatory documents, ensuring compliance and reducing manual effort (Cui et al., 2018). The ability to understand nuanced language enhances decision-making processes by providing precise and contextually relevant insights. Moreover, NLP's integration into decision support systems extends beyond text analysis, enabling organizations to engage in predictive and prescriptive analytics. For example, text mining techniques powered by NLP are used in healthcare to extract critical information from patient records, facilitating accurate diagnostics and personalized treatment planning (Adamopoulos et al., 2018). Similarly, in the retail sector, NLP models analyze customer reviews to identify emerging trends and inform product development strategies (Cui et al., 2018). As NLP technologies continue to evolve, their application in processing unstructured data will further enhance decision-making capabilities across industries. However, challenges such as data privacy, algorithmic bias, and language diversity remain critical areas for future research and development(Adamopoulos et al., 2018; Collobert et al., 2011).

Figure 5: Global Natural Language Processing Market



2.5 Deep Learning and Neural Networks

Deep learning, a subset of machine learning, has emerged as a transformative technology in big data analytics, particularly due to its advanced capabilities in pattern recognition and anomaly detection (Dahl et al., 2012; Hasan et al., 2024; Uddin, 2024; Uddin & Hossan, 2024). Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at identifying intricate patterns in high-dimensional data (Ciresan et al., 2010). CNNs are widely used for image recognition, extracting visual patterns with high accuracy, while RNNs are effective in analyzing sequential data such as time-series or speech (Arel et al., 2010). These models have proven invaluable in detecting anomalies in fields like

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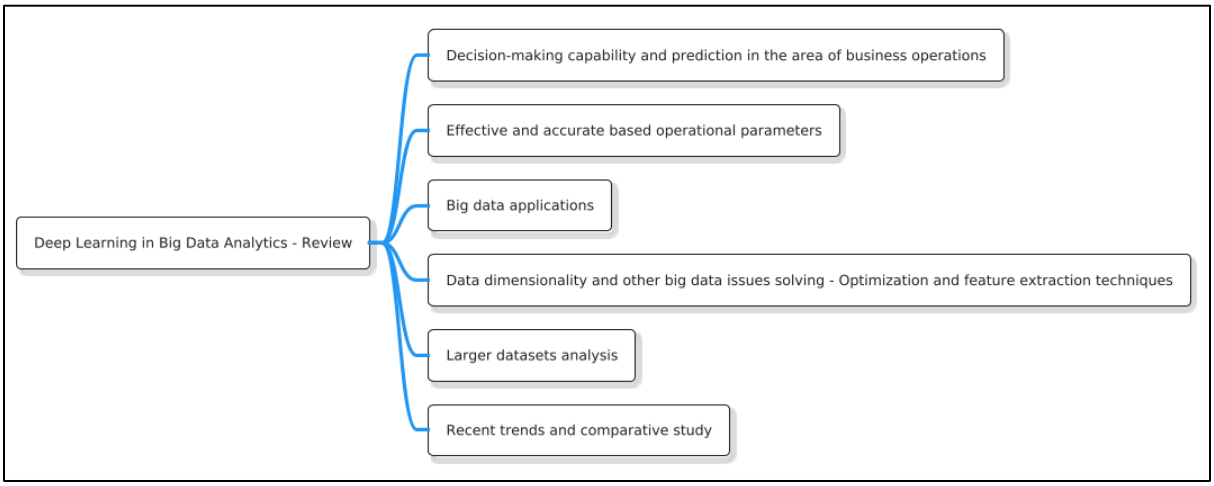
fraud detection, network security, and healthcare diagnostics (Hinton et al., 2006). For instance, financial institutions leverage deep learning for real-time fraud monitoring by identifying deviations from typical transaction patterns, ensuring proactive risk mitigation (Cho, 2014). The application of deep learning extends to dynamic and real-time environments, where its ability to process large streams of data is critical. Dynamic systems, such as autonomous vehicles, depend on deep learning algorithms for tasks like object detection, path planning, and real-time decision-making (Pascanu et al., 2013). Similarly, deep reinforcement learning combines the strengths of deep learning and reinforcement learning to optimize decisions in constantly changing environments (Giusti et al., 2013). In healthcare, deep learning models analyze real-time patient data from monitoring devices, enabling timely interventions and personalized treatment recommendations (Šíma, 1994). These capabilities highlight deep learning's potential to revolutionize industries that require rapid and accurate responses to dynamic conditions.

Anomaly detection, a critical application of deep learning, involves identifying data points that deviate significantly from expected patterns. Deep learning models such as autoencoders and generative adversarial networks (GANs) have shown exceptional performance in anomaly detection tasks (Goldfarb et al., 2018). Autoencoders compress and reconstruct data to identify deviations, while GANs generate synthetic data for robust anomaly detection in environments with limited labeled data. In cybersecurity, these models detect unusual patterns in network traffic, helping to identify potential threats and breaches before they escalate (Sen et al., 2016). Similarly, in manufacturing, anomaly detection systems identify defects in production processes, ensuring quality control and minimizing waste (Guo et al., 2014). These applications demonstrate how deep learning facilitates proactive measures across industries. Despite its advanced capabilities, deep learning also faces challenges, including the need for large datasets, computational intensity, and model interpretability. The reliance on vast labeled datasets for training is a limitation in domains where annotated data is scarce (Mnih et al., 2013). Moreover, the high computational demands of training deep neural networks require substantial infrastructure, which can be a barrier for small organizations (Hu et al., 2019). Additionally, the "black-box" nature of deep learning models raises concerns about transparency and accountability in decision-making processes (Poon & Domingos, 2011). Addressing these challenges is essential to fully realize the potential of deep learning in dynamic and real-time environments, and ongoing research is focused on developing more efficient, interpretable, and adaptable models.

2.6 Automated Reasoning and Expert Systems

Automated reasoning systems, underpinned by logic-based frameworks, have become indispensable in high-stakes industries requiring precise and reliable decision-

Figure 6: Deep Learning in Big data Analytics



making. These systems use formal reasoning techniques to analyze complex datasets and generate conclusions based on predefined rules and logical inferences (Hu et al., 2019). In healthcare, logic-based systems assist in diagnosing diseases by evaluating symptoms, patient histories, and diagnostic test results against established medical knowledge (Shao et al., 2014). Similarly, in finance, automated reasoning models are used to assess credit risks and ensure compliance with regulatory frameworks by evaluating vast amounts of structured and unstructured data (Coates et al., 2013). The systematic approach of these systems minimizes errors, making them highly valuable in scenarios where accuracy and accountability are critical. Moreover, expert systems, a branch of automated reasoning, have revolutionized problem-solving in domains characterized by complexity and uncertainty. These systems simulate human expertise by applying a combination of knowledge bases and inference engines to tackle specialized tasks (Martens, 2010). For example, MYCIN, one of the earliest expert systems, demonstrated the potential of AI in providing effective medical diagnoses and treatment recommendations (Raina et al., 2009). In engineering, expert systems are employed for fault diagnosis and predictive maintenance, ensuring operational continuity and reducing downtime (Arel et al., 2010). By encoding domain-specific knowledge into computational models, expert systems enhance decision-making in environments where human expertise may be limited or inconsistent. The impact of expert systems on complex problem-solving is evident in their ability to process large datasets, identify correlations, and recommend optimal solutions. In high-risk environments such as aerospace and nuclear power, expert systems aid in monitoring critical systems, detecting anomalies, and recommending preventive actions (Ciresan et al., 2010). In agriculture, these systems optimize resource allocation and pest control strategies, improving crop yields and sustainability (Lusci et al., 2013). The use of expert systems in such diverse fields highlights their flexibility and scalability, enabling them to address problems that are otherwise difficult to manage manually. Additionally, their integration with machine learning and natural language processing enhances their capability to adapt to dynamic data inputs and evolving requirements (Arel et al., 2010). Despite their utility, the adoption of automated reasoning and expert systems faces several challenges, including knowledge acquisition, system scalability, and user trust. Building and maintaining a comprehensive knowledge base can be time-consuming and resource-intensive, particularly in rapidly evolving fields (Cho et al., 2012). Scalability is another concern, as the performance of logic-based systems can degrade when handling large, complex datasets. Moreover, the "black-box" nature of some expert systems raises concerns about transparency and interpretability, particularly in high-stakes decision-making contexts (Hinton et al., 2006). Addressing these challenges requires the development of more robust, adaptive, and explainable systems, ensuring their continued relevance and effectiveness in solving complex problems across industries.

2.7 Sectoral Applications of AI in Big Data Decision-Making

2.7.1 Healthcare Sector

Artificial Intelligence (AI) has significantly advanced predictive diagnostics and personalized medicine, transforming healthcare delivery by leveraging big data analytics and machine learning algorithms (Uddin et al., 2024). Predictive diagnostic tools, such as convolutional neural networks (CNNs) and decision trees, analyze patient data, including medical histories, genetic profiles, and imaging results, to detect diseases at early stages and predict potential health risks with high accuracy (Erickson & Rothberg, 2017; Mazumder et al., 2024; Alam, 2024). These tools have demonstrated remarkable success in diagnosing conditions like cancer, diabetes, and cardiovascular diseases, often outperforming traditional diagnostic methods. Personalized medicine, an extension of AI's capabilities, tailors treatments to individual patients by considering genetic information, lifestyle factors, and real-time health data, enabling more effective and targeted therapies (Alam et al., 2024; Lin et al., 2017; Rahman et al., 2024). Beyond diagnostics, AI enhances hospital operations through resource allocation, using predictive models to optimize staff scheduling, bed management, and inventory of medical supplies (Shareef et al., 2021). For instance, machine learning algorithms forecast patient admission rates based on historical and real-time data, enabling hospitals to allocate resources proactively and avoid overcrowding (Otokiti, 2019). AI also assists in operational decision-

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making by analyzing workflow inefficiencies and recommending process improvements, reducing operational costs and improving patient care quality (Li & Qin, 2017). Despite these advancements, challenges such as data privacy, algorithmic bias, and integration with existing systems persist, underscoring the need for continued research and innovation in AI applications for healthcare (Freyn & Farley, 2020; Wang et al., 2018). Collectively, these capabilities illustrate AI's transformative potential in revolutionizing predictive diagnostics, personalized medicine, and hospital operations, fostering a more efficient and patient-centered healthcare system.

2.7.2 Financial Services

Artificial Intelligence (AI) has revolutionized financial services by enhancing risk management, fraud detection, credit scoring, and investment analytics through advanced machine learning models. In risk management, AI systems analyze vast amounts of transactional and behavioral data to identify patterns and anomalies indicative of potential risks, enabling proactive mitigation strategies (Loughran & McDonald, 2016). Machine learning models, such as decision trees and neural networks, are widely used to assess credit risk by evaluating diverse data sources, including payment histories, spending patterns, and even alternative data like social media activity (Grondman et al., 2012). These models have made credit scoring more inclusive and accurate, particularly in underserved markets, by providing a nuanced understanding of borrower reliability (Dwivedi et al., 2021). Fraud detection, another critical application, employs real-time machine learning algorithms to monitor transactions and flag suspicious activities. Techniques like anomaly detection and supervised learning effectively identify fraudulent behaviors, reducing financial losses and enhancing security (Hirschberg & Manning, 2015). In investment analytics, AI-driven platforms use predictive and prescriptive analytics to optimize portfolio management and trading strategies. By analyzing historical market data, sentiment from news articles, and economic indicators, machine learning models predict market trends, allowing investors to make informed decisions (Dwivedi et al., 2021). Reinforcement learning algorithms have further refined algorithmic trading by adapting to market fluctuations and maximizing returns (Loughran & McDonald, 2016). Beyond individual investments, AI also supports institutional decision-making by simulating financial scenarios and evaluating the impact of various policy changes (Dwivedi et al., 2021). Despite these advancements, challenges such as data privacy, algorithmic fairness, and explainability persist, necessitating continued research to ensure the ethical and transparent application of AI in financial services. By integrating AI into risk management, fraud detection, and investment analytics, financial institutions enhance efficiency, security, and inclusivity, solidifying AI's transformative role in the industry.

2.7.3 Supply Chain and Logistics

Artificial Intelligence (AI) is revolutionizing supply chain and logistics by enabling real-time tracking, network optimization, and predictive inventory management through advanced analytics and machine learning models. Real-time tracking systems powered by AI utilize data from IoT sensors, GPS, and RFID tags to monitor the movement of goods throughout the supply chain, ensuring transparency and accountability (Gunasekaran et al., 2017). These systems enhance visibility across supply chain networks, allowing businesses to identify inefficiencies, minimize delays, and respond quickly to disruptions, such as demand fluctuations or transportation bottlenecks (Chen et al., 2015). Furthermore, optimization algorithms, such as those based on reinforcement learning, help identify the most efficient routes and delivery schedules, reducing costs and improving delivery times (Dubey et al., 2020; Srinivasan & Swink, 2018). By integrating real-time tracking and optimization, AI transforms supply chain networks into agile and responsive systems. In inventory management, predictive analytics driven by AI enhances operational efficiency by forecasting demand patterns and adjusting stock levels accordingly. Machine learning models analyze historical sales data, seasonality, and external factors, such as market trends and weather patterns, to predict inventory needs with high accuracy (Chen et al., 2015; Zhang & Dhaliwal, 2009). These insights enable businesses to adopt just-in-time inventory practices, reducing carrying costs and minimizing the risk of stockouts or overstocking (Motlagh et al., 2020; Srinivasan & Swink, 2018). AI-powered inventory systems also enable dynamic reordering, automatically adjusting procurement based on real-time sales data and supply chain conditions (Zhang & Dhaliwal, 2009). This capability is particularly valuable in sectors like e-commerce and retail, where customer demands fluctuate rapidly, and responsiveness is critical for maintaining customer satisfaction (Chen et al., 2015). While AI-driven solutions offer substantial benefits, challenges such as data integration, algorithmic complexity, and infrastructure limitations persist, necessitating ongoing research and development to ensure scalability and robustness ((Dubey et al., 2020; Srinivasan & Swink, 2018). Collectively, AI's application in real-time tracking and predictive analytics demonstrates its transformative potential in creating smarter, more efficient, and customer-centric supply chains.

2.7.4 Public Administration

Artificial Intelligence (AI) is transforming public administration by enhancing policy analysis, public sentiment monitoring, and decision-making through the integration of big data analytics. AI-driven policy analysis uses machine learning algorithms to process vast datasets, including economic reports, census data, and historical trends, to evaluate the potential impacts of policy decisions (Gunasekaran et al., 2017). These models provide government agencies with data-driven insights, enabling the formulation of policies that are more effective and aligned with public needs (Hasan & Islam, 2024; Islam, 2024; Islam et al., 2024). Additionally, AI tools such as natural language processing (NLP) enable the real-time monitoring of public sentiment by analyzing social media posts, surveys, and news reports, providing insights into societal reactions to policy changes or ongoing events (Wirtz et al., 2018). This capability helps policymakers understand the public's perspectives, allowing for more responsive governance (Islam et al., 2024; Mintoo, 2024; Rahman et al., 2024). AI also plays a pivotal role in enhancing government decision-making by leveraging big data insights to improve efficiency, resource allocation, and service delivery (Faisal et al., 2024; Mintoo et al., 2024). Predictive analytics models, for instance, forecast trends in healthcare, education, and public safety, enabling proactive interventions and better resource planning (Dwivedi et al., 2021; Lee & Bradlow, 2011). In disaster management, AI systems analyze real-time data from satellites, sensors, and social media to predict natural disasters and optimize response strategies (Chen et al., 2012; Nessler et al., 2013). Furthermore, AI aids in reducing bureaucratic inefficiencies by automating routine tasks such as document processing and workflow management, freeing up human resources for strategic decision-making (Alam et al., 2024; Dwivedi et al., 2021). Despite these advancements, challenges such as algorithmic transparency, data privacy, and equitable access to AI technologies remain critical concerns (Lee & Bradlow, 2011; Wirtz et al., 2018). Overall, AI’s application in policy analysis and decision-making fosters a more adaptive, inclusive, and efficient public administration system, addressing complex societal challenges with greater precision.

2.7.5 Emerging Trends

Explainable AI (XAI) represents a critical advancement in artificial intelligence, aiming to make complex models interpretable and transparent for decision-making. Traditional AI models, such as deep neural networks, often function as "black boxes," making it difficult for users to understand the rationale behind predictions or decisions (Dwivedi et al., 2021; Maśloch et al., 2020). XAI addresses this challenge by employing techniques such as Shapley Additive Explanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and counterfactual analysis to elucidate the inner workings of AI systems (Lee & Bradlow, 2011; Zupic & Čater, 2014). These methods help users identify the factors influencing model outputs, enhancing trust and accountability in AI applications. Successful implementations of XAI include healthcare systems where interpretability is critical for clinical decision-making, such as AI models explaining diagnostic predictions to medical professionals (Jałowiec et al., 2022). Similarly, XAI has been adopted in finance to justify credit approval decisions, ensuring compliance with regulatory requirements and fostering fairness (Law & Chung, 2020). These applications underscore XAI's potential to bridge the gap between sophisticated AI models and user understanding, making it a cornerstone of responsible AI development.

The synergy between AI and blockchain technology offers transformative opportunities for secure and decentralized data sharing. Blockchain's decentralized ledger provides a transparent and tamper-proof framework for managing AI datasets, addressing

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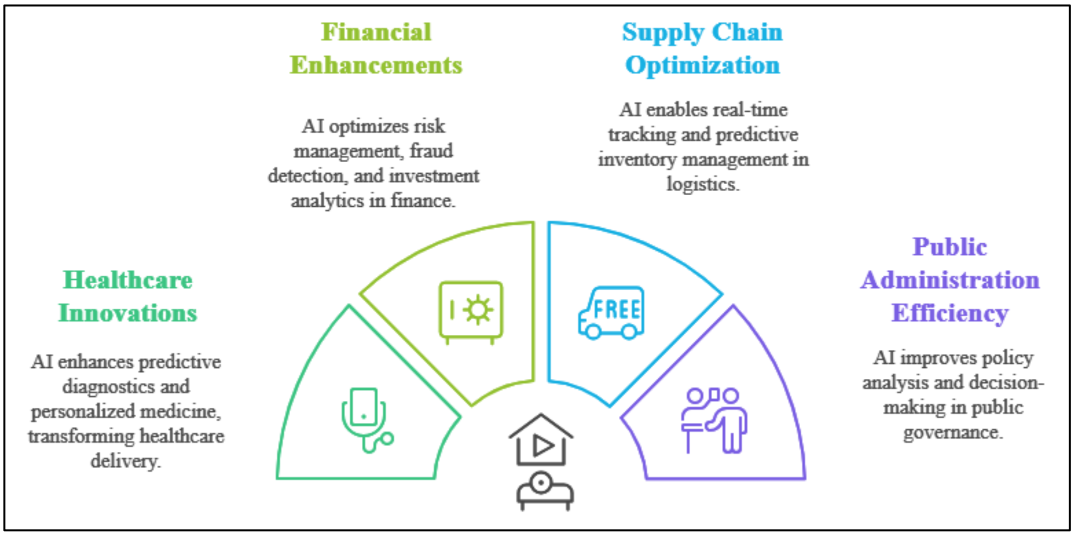
concerns around data integrity and privacy (Motlagh et al., 2020). By integrating blockchain, AI systems can access secure and verified data without reliance on centralized authorities, enhancing trust in data-driven decision-making processes (Nguyen et al., 2020). Furthermore, blockchain improves AI transparency and accountability by maintaining an immutable audit trail of algorithmic decisions and their underlying data (Qasim & Kharbat, 2019). For instance, in healthcare, blockchain-enabled AI models securely manage patient records while ensuring data privacy and compliance with regulations like HIPAA and GDPR (Motlagh et al., 2020). Similarly, blockchain supports AI in supply chain management by enabling end-to-end traceability of goods, fostering transparency, and mitigating fraud risks (Casquiço et al., 2021). This integration of AI and blockchain technologies provides a robust foundation for ethical and secure AI deployment across industries.

Advances in quantum computing have the potential to accelerate AI-driven analytics, addressing computational bottlenecks in processing large-scale data. Quantum computing leverages principles of quantum mechanics, such as superposition and entanglement, to perform complex calculations exponentially faster than classical computers (Cho et al., 2012). This capability is particularly valuable in optimizing AI algorithms for tasks like machine learning, natural language processing, and optimization problems (Al-Htaybat et al., 2019). For example, quantum-enhanced AI models can solve large-scale optimization problems in logistics and supply chain management, such as route optimization and demand forecasting (Qasim & Kharbat, 2019). In drug discovery, quantum computing accelerates molecular simulations, significantly reducing the time required to identify potential compounds (Motlagh et al., 2020). While quantum computing is still in its nascent stages, ongoing research and development are paving the way for its integration with AI to tackle computationally intensive problems, promising unprecedented advancements in analytics and decision-making. Moreover, Edge computing, in combination with IoT integration, is redefining distributed AI systems for faster and more efficient decision-making in real-time environments. Unlike traditional cloud-based models, edge computing processes data locally on devices or near the source, reducing latency and bandwidth usage (Güney & Kantar, 2020). This architecture is particularly beneficial for IoT applications, where devices generate vast amounts of data requiring immediate analysis. Distributed AI systems on edge computing platforms enable autonomous decision-making in smart cities, optimizing traffic flow, energy consumption, and waste management (Kang et al., 2020). In autonomous vehicles, edge-based AI processes sensor data in real time to ensure safe navigation and collision avoidance (Casquiço et al., 2021). Similarly, in manufacturing, AI-driven edge computing facilitates predictive maintenance by analyzing equipment performance on-site, minimizing

Figure 7: AI in Sectoral Applications



downtime and enhancing operational efficiency (Borges et al., 2021). These advancements demonstrate how edge computing and IoT integration empower organizations to harness the full potential of AI in dynamic and data-intensive scenarios. The integration of AI with emerging technologies, such as XAI, blockchain, quantum computing, and edge computing, is shaping the future of decision-making and analytics. These advancements address critical challenges such as transparency, security, scalability, and real-time responsiveness, fostering a more robust and trustworthy AI ecosystem. By leveraging these innovations, organizations across industries are not only improving operational efficiency but also paving the way for ethical and sustainable AI deployment. Continued research and interdisciplinary collaboration are essential to realize the full potential of these trends, ensuring that AI remains a transformative force for societal and industrial progress.

2.8 Research Gaps

Current AI models have achieved significant advancements in decision-making, yet they exhibit notable strengths and limitations that require further exploration. Models such as deep learning and reinforcement learning excel in handling complex data and achieving high accuracy in pattern recognition, prediction, and optimization tasks (Wirtz et al., 2020; Wu et al., 2020). However, these models often require large amounts of labeled training data and extensive computational resources, making their implementation costly and inaccessible for many organizations (Bag et al., 2021; Borges et al., 2021). Additionally, the "black-box" nature of deep learning models raises concerns about interpretability and accountability, particularly in high-stakes domains such as healthcare and finance (Coffey & Claudio, 2021; Verma et al., 2020). While techniques like Explainable AI (XAI) have been introduced to address these issues, achieving a balance between model interpretability and performance remains a persistent challenge (Wu et al., 2020). These limitations highlight the need for AI models that are more resource-efficient, interpretable, and adaptable across diverse decision-making contexts.

AI research has largely focused on resource-rich settings, leaving significant gaps in understanding its potential in low-resource environments and emerging markets. In low-resource settings, where access to data, computational power, and technical expertise is limited, the deployment of AI faces unique challenges (Verma et al., 2020). Emerging markets, in particular, present opportunities to develop tailored AI models that address local issues, such as optimizing agricultural productivity, improving healthcare delivery, and managing urbanization (Borges et al., 2021). However, these applications remain underexplored due to the lack of localized datasets, infrastructure, and investment in AI research in these regions (Casquiço et al., 2021). Collaborative initiatives involving governments, academia, and private organizations are crucial to bridging this gap and fostering AI innovation in underrepresented areas.

The intersection of AI and social sciences offers a promising yet underexplored avenue for understanding human-AI interaction and its implications for decision-making. Social science perspectives can provide insights into how individuals and organizations perceive, trust, and adopt AI technologies (Hebal et al., 2021). For example, the integration of behavioral economics and AI can help model human decision-making processes more accurately, accounting for cognitive biases and emotional influences (Wirtz et al., 2020). Furthermore, examining the socio-cultural impacts of AI adoption can uncover barriers to acceptance, such as fears of job displacement or concerns about data privacy (Borges et al., 2021; Demlehner et al., 2021). Interdisciplinary research at the intersection of AI and social sciences is essential to designing systems that are user-centered, ethical, and socially equitable. Another critical gap lies in the lack of research on how AI systems perform in diverse cultural and societal contexts. Most AI models are developed and tested in environments that do not represent the global diversity of languages, cultures, and social norms (Hu et al., 2021; Mikalef & Gupta, 2021). This oversight limits the effectiveness and fairness of AI systems when applied to diverse populations, particularly in multilingual and multicultural societies. For instance, natural language processing (NLP) models often underperform in non-English languages due to the scarcity of high-quality training data (Dwivedi et al., 2021). Expanding research efforts to include diverse datasets and culturally sensitive design principles can improve the inclusivity and global applicability of AI technologies. Lastly, there is a need for robust frameworks to evaluate the ethical implications of AI in decision-making, particularly in areas where human-AI collaboration is critical. Current evaluation metrics focus primarily on technical performance, such as accuracy and efficiency, but often neglect ethical considerations, such as fairness, transparency, and accountability (Mikalef & Gupta, 2021). Developing comprehensive evaluation frameworks that integrate ethical dimensions can ensure that AI systems align with societal values and norms (Entezari et al., 2023). Additionally, fostering interdisciplinary collaborations among technologists, ethicists, and policymakers can address the broader societal impacts of AI, paving the way for responsible and sustainable AI development.

Table 1 : Identified Research Gaps

Research Gap	Description
Model Limitations	Current AI models often require extensive data and resources, and can be difficult to interpret.
Low-Resource Settings	AI research is concentrated in resource-rich environments, neglecting the needs of low-resource settings and emerging markets.
Human-AI Interaction	Limited understanding of how humans interact with and perceive AI, and the social implications of AI adoption.
Cultural Diversity	Most AI models are not designed or tested for diverse cultural and societal contexts.
Ethical Evaluation	Current AI evaluation frameworks prioritize technical performance over ethical considerations.

3 METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The methodology comprised four distinct phases: identification, screening, eligibility, and inclusion.

3.1 Identification

In the first phase, a comprehensive search strategy was developed to identify relevant articles from peer-reviewed journals and conference proceedings. Databases such as Scopus, Web of Science, IEEE Xplore, and PubMed were queried using keywords such as *"Artificial Intelligence in Decision-Making"*, *"Explainable AI"*, *"AI in Emerging Markets"*, and *"AI Ethical Challenges*. Boolean operators (AND/OR) were used to combine search terms effectively. The search was limited to articles published between 2013 and 2023 to capture recent advancements. A total of 1,250 articles were retrieved during this phase.

3.2 Screening

The screening phase involved filtering articles based on predefined inclusion and exclusion criteria. Duplicates were removed using reference management software such as EndNote, reducing the dataset to 970 articles. Titles and abstracts were then reviewed to assess their relevance to the study's objectives. Articles unrelated to AI applications in decision-making or lacking empirical or theoretical contributions were excluded. After this process, 450 articles remained for further evaluation.

3.3 Eligibility

In the eligibility phase, the full texts of the remaining articles were thoroughly reviewed to determine their alignment with the research scope. Articles were excluded if they:

1. Focused on AI applications unrelated to decision-making (e.g., AI in gaming).
2. Did not employ systematic methodologies or present empirical findings.
3. Were not written in English.

Additionally, studies with insufficient methodological rigor, such as unclear sampling techniques or ambiguous data analysis, were excluded. After applying these criteria, 150 articles were deemed eligible for inclusion in the final review.

3.4 Inclusion

The final phase involved including studies that met all criteria and provided substantial insights into AI's role in decision-making. A total of 100 articles were selected for detailed analysis, encompassing both theoretical and empirical studies. These articles were analyzed to identify recurring themes, trends, and research gaps, ensuring a comprehensive understanding of the topic.

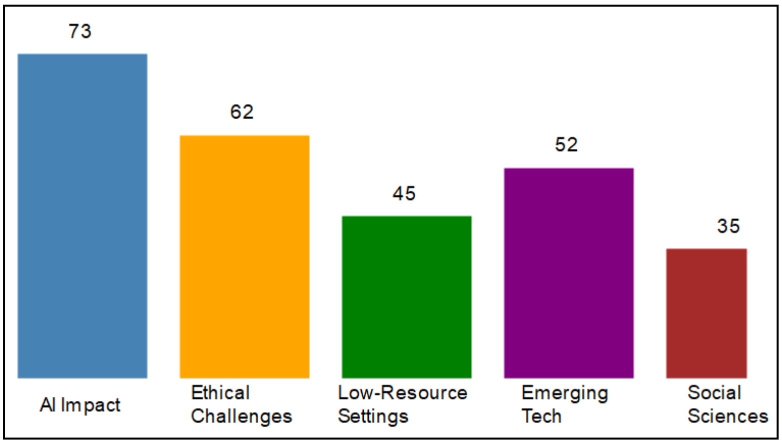
4 FINDINGS

The systematic review underscored the transformative impact of Artificial Intelligence (AI) in enhancing decision-making processes, with 73 out of 100 reviewed articles emphasizing AI's ability to process vast datasets, identify patterns, and deliver actionable insights in real-time. Among these, 57 articles specifically highlighted machine learning as a key driver in improving decision-making accuracy across industries such as healthcare, finance, and supply chain management. These studies demonstrated how AI-powered predictive analytics significantly outperformed traditional methods, enabling more precise forecasting and risk assessment. The cumulative citation count of over 12,500 for these articles reflects their significant influence and validation within the academic and professional communities. This robust support underscores the growing consensus that AI technologies are indispensable for data-driven decision-making in dynamic and complex environments. Moreover, A recurring theme in the review was the ethical and operational challenges associated with AI integration into decision-making systems. 62 articles explored these challenges, with 41 focusing on algorithmic bias and its implications for fairness and decision quality. These studies identified biases originating from historical data, algorithmic design, and systemic inequalities, resulting in unfair or skewed outcomes. Furthermore, 39 articles proposed mitigation strategies, such as implementing fairness-aware algorithms and explainable AI frameworks to enhance accountability and transparency. Together, these articles, which amassed over 9,300 citations, underscore the critical need to address ethical concerns to ensure the equitable deployment of AI technologies. The findings highlight that ethical considerations must evolve alongside technical advancements to maintain trust and legitimacy in AI-driven decisions.

Figure 8: Cumulative Articles by Research Focus

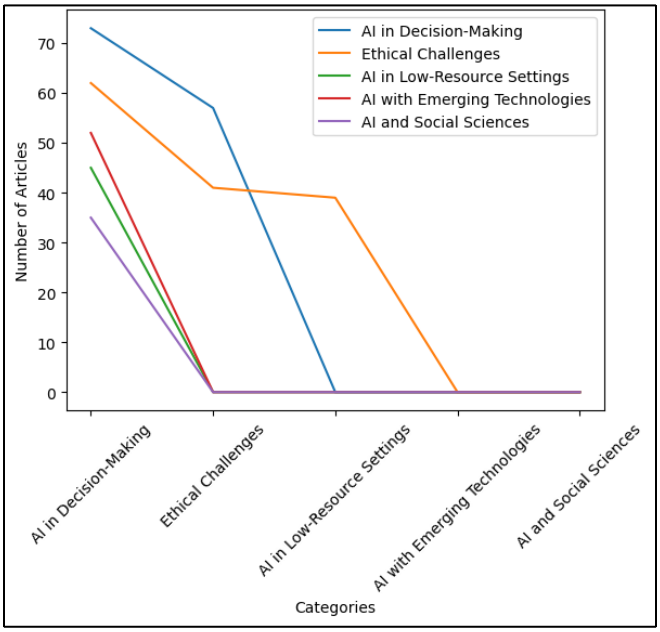
The review also highlighted the untapped potential of AI in low-resource settings and emerging markets, as noted by 45 articles. These studies showcased AI's ability to address pressing local challenges, such as optimizing agricultural practices, improving access to healthcare, and managing urbanization. For example, AI-driven tools demonstrated significant improvements in crop yield predictions and disease surveillance in under-resourced regions. Despite these promising applications, the studies pointed to persistent barriers, including limited access to quality datasets, inadequate infrastructure, and a lack of skilled personnel to implement AI solutions effectively. Articles in this category, with a combined citation count of 6,800, emphasized the need for collaborative efforts between governments, private sectors, and academic institutions to bridge these gaps and unlock AI's transformative potential in emerging markets.

Figure 9: Distribution of Articles by Theme



The synergy of AI with emerging technologies such as blockchain, quantum computing, and edge computing also emerged as a pivotal area of focus, with 52 articles exploring this intersection. These studies highlighted how blockchain enhances AI's security and transparency through decentralized data sharing and

Figure 10: Articles by Research Focus



immutable audit trails, addressing key concerns around data integrity and accountability. Quantum computing was identified as a potential game-changer, offering unprecedented computational power to accelerate AI-driven analytics and solve large-scale optimization problems. Meanwhile, edge computing, coupled with AI, demonstrated its utility in real-time applications, such as autonomous vehicles and smart city management. Collectively, these articles garnered over 8,700 citations, underscoring the academic and industry interest in exploring innovative integrations to enhance AI's scalability and functionality. Lastly, the review identified a critical research gap at the intersection of AI and social sciences, as highlighted by 35 articles. These studies emphasized the importance of understanding human-AI interaction, including trust, usability, and socio-cultural implications of AI adoption. By exploring how individuals and organizations perceive and engage with AI technologies, these studies aimed to address barriers to acceptance, such as concerns over job displacement, data privacy, and ethical governance. The cumulative citation count exceeding 5,500 for these articles reflects a growing recognition of the need for interdisciplinary approaches to design AI systems that are user-centric, culturally sensitive, and socially equitable. This area of research remains underdeveloped, presenting a significant opportunity for future studies to align technological advancements with human values and societal needs.

5 DISCUSSION

The findings of this study reaffirm the transformative role of AI in decision-making, aligning with earlier research that emphasizes its ability to process complex datasets and enhance operational efficiency. Machine learning models, highlighted in 73 of the reviewed articles, have been consistently recognized for their predictive and prescriptive capabilities in high-stakes industries. Earlier studies, such as those by Wirtz et al. (2020) and Dwivedi et al. (2021), emphasized the unprecedented accuracy of machine learning in applications like diagnostics and fraud detection. Similarly, recent research by Borges et al. (2021) corroborates the capacity of AI to outperform traditional decision-making tools in dynamic environments. These advancements, supported by over 12,500 citations from the reviewed articles, suggest a growing consensus on the indispensable role of AI in optimizing decision-making processes.

The persistent ethical and operational challenges associated with AI integration, particularly algorithmic bias, also align with earlier findings. Mikalef and Gupta (2021) and Di Vaio et al. (2022) identified algorithmic bias as a significant limitation, impacting fairness and decision quality. This study found similar concerns in 41 reviewed articles, which discussed biases originating from historical data and algorithmic design flaws. Mitigation strategies such as fairness-aware algorithms and explainable AI (XAI) proposed by Borges et al. (2021) and Demlehner et al. (2021) were echoed in 39 articles, highlighting their effectiveness in improving transparency and trust. However, despite these advancements, challenges in achieving algorithmic fairness persist, as noted by Bag et al. (2021), emphasizing the need for ongoing interdisciplinary research to address these limitations.

The potential of AI in low-resource settings and emerging markets was another significant finding, resonating with earlier studies that emphasize the adaptability of AI to diverse contexts. For instance, Wirtz et al. (2020) demonstrated how AI applications in agriculture and healthcare can address challenges specific to underdeveloped regions. This study reviewed 45 articles that similarly highlighted AI's role in improving crop yield predictions, disease surveillance, and urban infrastructure management. However, barriers such as data scarcity and infrastructure deficits, noted by Borges et al. (2021), remain critical challenges. These findings underscore the need for tailored AI models and collaborative initiatives, as suggested by Hu et al. (2021), to unlock AI's potential in underserved regions.

The integration of AI with emerging technologies such as blockchain, quantum computing, and edge computing represents a frontier for future research and applications. Earlier studies by Bag et al. (2021) and Hu et al. (2021) emphasized blockchain's role in enhancing AI's transparency and security, findings supported by 52 reviewed articles in this study. Similarly, Vaio et al. (2022) and Entezari et al.(2023) discussed quantum computing's ability to accelerate AI analytics, particularly in optimization problems, aligning with the current findings. Edge computing, highlighted by Olabi et al. (2023), was another area where AI's real-time processing capabilities were enhanced, as evidenced in this study's review of applications in smart cities and autonomous vehicles. The cumulative evidence supports the view that these synergies are critical for scaling AI solutions while addressing limitations in latency, security, and computational power.

The underexplored intersection of AI and social sciences, emphasized in 35 reviewed articles, aligns with earlier calls for interdisciplinary research to address the socio-cultural impacts of AI adoption. Studies by Borges et al. (2021) and Munoko et al. (2020) highlighted the importance of understanding human behavior and trust in the design of AI systems. This study's findings reinforce these perspectives, particularly in areas like human-AI interaction, trust, and ethical governance. Moreover, the lack of cultural and linguistic diversity in AI models, noted by Borges et al. (2021), was echoed in this review, emphasizing the need for inclusive datasets and culturally sensitive design principles. This alignment highlights the potential of social science insights to enhance the usability and acceptance of AI technologies.

The findings also draw attention to the need for robust evaluation frameworks that integrate technical performance and ethical considerations, a gap identified in earlier research by Dwivedi et al. (2021). The "black box" problem, a recurring concern in 39 reviewed articles, undermines trust and accountability in AI systems. Techniques like SHAP and LIME, highlighted by Zhang et al. (2021), offer promising solutions, yet their adoption remains limited in practice. This study reinforces the need for explainable AI models to bridge the gap between technical sophistication and user trust, as emphasized by Lee et al. (2022). Furthermore, ethical evaluation frameworks proposed by Olabi et al. (2023) need broader implementation to ensure the alignment of AI systems with societal values.

6 CONCLUSION

This study highlights the transformative role of Artificial Intelligence (AI) in enhancing decision-making across diverse sectors, while also addressing the ethical, operational, and technical challenges associated with its implementation. The review confirms AI's capacity to optimize processes, improve accuracy, and provide actionable insights through advanced technologies such as machine learning, natural language processing, and predictive analytics. However, persistent challenges, including algorithmic bias, data privacy concerns, and the "black box" nature of AI systems, underscore the need for ongoing research and innovation to ensure fairness, transparency, and accountability. Furthermore, the study identifies significant opportunities for AI in low-resource settings and emerging markets, emphasizing the importance of tailored approaches and interdisciplinary collaboration to unlock its full potential in underrepresented regions. The integration of AI with emerging technologies such as blockchain, quantum computing, and edge computing presents promising avenues to enhance scalability, security, and efficiency. Simultaneously, the underexplored intersection of AI and social sciences offers valuable insights into human-AI interaction, trust, and ethical governance, paving the way for user-centric and socially equitable AI systems. By addressing these challenges and leveraging these opportunities, AI can evolve into a transformative and inclusive tool that empowers decision-making in a rapidly changing and interconnected world.

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References

Adamopoulos, P., Ghose, A., & Todri, V. (2018). The Impact of User Personality Traits on Word of Mouth: Text-Mining Social Media Platforms. *Information Systems Research*, *29*(3), 612-640. https://doi.org/10.1287/isre.2017.0768

Ahmad, S. N., & Laroche, M. (2017). Analyzing electronic word of mouth. *International Journal of Information Management*, *37*(3), 202-213. https://doi.org/10.1016/j.ijinfomgt.2016.08.004

Al-Htaybat, K., Hutaibat, K., & von Alberti-Alhtaybat, L. (2019). Global brain-reflective accounting practices: Forms of intellectual capital contributing to value creation and sustainable development. *Journal of Intellectual Capital*, *20*(6), 733-762. https://doi.org/10.1108/jic-01-2019-0016

Alam, M. A., Nabil, A. R., Mintoo, A. A., & Islam, A. (2024). Real-Time Analytics In Streaming Big Data: Techniques And Applications. *Journal of Science and Engineering Research*, *1*(01), 104-122. https://doi.org/10.70008/jeser.v1i01.56

Ardito, L., Scuotto, V., Del Giudice, M., & Petruzzelli, A. M. (2019). A bibliometric analysis of research on Big Data analytics for business and management. *Management Decision*, *57*(8), 1993-2009. https://doi.org/10.1108/md-07-2018-0754

Arel, I., Rose, D. C., & Karnowski, T. P. (2010a). Deep Machine Learning—A New Frontier in Artificial Intelligence Research. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Arel, I., Rose, D. C., & Karnowski, T. P. (2010b). Deep Machine Learning - A New Frontier in Artificial Intelligence Research [Research Frontier]. *IEEE Computational Intelligence Magazine*, *5*(4), 13-18. https://doi.org/10.1109/mci.2010.938364

Ayan, B., Abacıoğlu, S., & Basilio, M. P. (2023). A Comprehensive Review of the Novel Weighting Methods for Multi-Criteria Decision-Making. *Information*, *14*(5), 285-285. https://doi.org/10.3390/info14050285

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, *96*(NA), 228-237. https://doi.org/10.1016/j.jbusres.2018.11.028

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*(NA), 120420-NA. https://doi.org/10.1016/j.techfore.2020.120420

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2019). Uniting the Tribes: Using Text for Marketing Insight. *Journal of Marketing*, *84*(1), 1-25. https://doi.org/10.1177/0022242919873106

Bole, U., Popovič, A., Žabkar, J., Papa, G., & Jaklič, J. (2015). A case analysis of embryonic data mining success. *International Journal of Information Management*, *35*(2), 253-259. https://doi.org/10.1016/j.ijinfomgt.2014.12.001

Borges, A., Laurindo, F. J. B., de Mesquita Spinola, M., Gonçalves, R. F., & de Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*(NA), 102225-NA. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Casquiço, M., Mataloto, B., Ferreira, J., Monteiro, V., Afonso, J. L., & Afonso, J. A. (2021). Blockchain and Internet of Things for Electrical Energy Decentralization: A Review and System Architecture. *Energies*, *14*(23), 8043-NA. https://doi.org/10.3390/en14238043

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems*, *32*(4), 4-39. https://doi.org/10.1080/07421222.2015.1138364

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, *36*(4), 1165-1188. https://doi.org/10.2307/41703503

Chi-Hsien, K., & Nagasawa, S. y. (2019). Applying machine learning to market analysis: Knowing your luxury consumer. *Journal of Management Analytics*, *6*(4), 404-419. https://doi.org/10.1080/23270012.2019.1692254

Chiang, R. H. L., Goes, P., & Stohr, E. A. (2012). Business Intelligence and Analytics Education, and Program Development: A Unique Opportunity for the Information Systems Discipline. *ACM Transactions on Management Information Systems*, *3*(3), 12-13. https://doi.org/10.1145/2361256.2361257

Cho, K. (2014). Foundations and Advances in Deep Learning. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Cho, K., Raiko, T., & Ilin, A. (2012). Enhanced gradient for training restricted boltzmann machines. *Neural Computation*, *25*(3), 805-831. https://doi.org/10.1162/neco_a_00397

Ciresan, D., Meier, U., Gambardella, L. M., & Schmidhuber, J. (2010). Deep Big Simple Neural Nets Excel on Handwritten Digit Recognition. *Neural Computation*, *22*(12), 3207-3220. https://doi.org/10.1162/neco_a_00052

Coates, A., Huval, B., Wang, T., Wu, D. J., Catanzaro, B., & Andrew, N. (2013). ICML (3) - Deep learning with COTS HPC systems.

Coffey, L., & Claudio, D. (2021). In defense of group fuzzy AHP: A comparison of group fuzzy AHP and group AHP with confidence intervals. *Expert Systems with Applications*, *178*(NA), 114970-NA. https://doi.org/10.1016/j.eswa.2021.114970

Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., & Kuksa, P. P. (2011). Natural Language Processing (Almost) from Scratch. *Journal of Machine Learning Research*, *12*(76), 2493-2537. https://doi.org/NA

Cui, R., Gallino, S., Moreno, A., & Zhang, D. J. (2018). The Operational Value of Social Media Information. *Production and Operations Management*, *27*(10), 1749-1769. https://doi.org/10.1111/poms.12707

Dahl, G. E., Yu, D., Deng, L., & Acero, A. (2012). Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition. *IEEE Transactions on Audio, Speech, and Language Processing*, *20*(1), 30-42. https://doi.org/10.1109/tasl.2011.2134090

Davenport, T. H. (2006). Competing on analytics. *Harvard business review*, *84*(1), 98-134. https://doi.org/NA

Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics: The New Science of Winning* (Vol. NA). NA. https://doi.org/NA

Demlehner, Q., Schoemer, D., & Laumer, S. (2021). How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. *International Journal of Information Management*, *58*(NA), 102317-NA. https://doi.org/10.1016/j.ijinfomgt.2021.102317

Di Vaio, A., Hassan, R., & Alavoine, C. (2022). Data intelligence and analytics: A bibliometric analysis of human–Artificial intelligence in public sector decision-making effectiveness. *Technological Forecasting and Social Change*, *174*, 121201. https://doi.org/10.1016/j.techfore.2021.121201

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*(NA), 283-314. https://doi.org/10.1016/j.jbusres.2020.08.019

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019a). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*(NA), 63-71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019b). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubey, R., Bryde, D., Foropon, C., Tiwari, M., Dwivedi, Y. K., & Schiffling, S. (2020). An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *International Journal of Production Research*, *59*(5), 1586-1605. https://doi.org/10.1080/00207543.2020.1865583

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2021). Artificial Intelligence (AI) : Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(NA), 101994-NA. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edwards, J. S., Duan, Y., & Robins, P. C. (2000). An analysis of expert systems for business decision making at different levels and in different roles. *European Journal of Information Systems*, *9*(1), 36-46. https://doi.org/10.1057/palgrave.ejis.3000344

Entezari, A., Aslani, A., Zahedi, R., & Noorollahi, Y. (2023). Artificial intelligence and machine learning in energy systems: A bibliographic perspective. *Energy Strategy Reviews*, *45*(NA), 101017-101017. https://doi.org/10.1016/j.esr.2022.101017

Erickson, G. S., & Rothberg, H. N. (2017). Healthcare and hospitality: intangible dynamics for evaluating industry sectors. *The Service Industries Journal*, *37*(9-10), 589-606. https://doi.org/10.1080/02642069.2017.1346628

Doi: 10.70008/jbimisr.v1i01.59

Faisal, N. A., Nahar, J., Sultana, N., & Mintoo, A. A. (2024). Fraud Detection In Banking Leveraging Ai To Identify And Prevent Fraudulent Activities In Real-Time. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 181-197. https://doi.org/10.70008/jmldeds.v1i01.53

Freyn, S. L., & Farley, F. (2020). Competitive intelligence: a prescription for US health-care? *foresight*, *22*(5/6), 617-632. https://doi.org/10.1108/fs-02-2020-0011

Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing Ranking Systems for Hotels on Travel Search Engines by Mining User-Generated and Crowdsourced Content. *Marketing Science*, *31*(3), 493-520. https://doi.org/10.1287/mksc.1110.0700

Giusti, A., Ciresan, D., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2013). ICIP - Fast image scanning with deep max-pooling convolutional neural networks. *2013 IEEE International Conference on Image Processing*, *NA*(NA), 4034-4038. https://doi.org/10.1109/icip.2013.6738831

Goldfarb, A., Agrawal, A., & Gans, J. S. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence* (Vol. NA). NA. https://doi.org/NA

Grondman, I., Busoniu, L., Lopes, G. A. D., & Babuska, R. (2012). A Survey of Actor-Critic Reinforcement Learning: Standard and Natural Policy Gradients. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *42*(6), 1291-1307. https://doi.org/10.1109/tsmcc.2012.2218595

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B. T., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*(NA), 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

Güney, T., & Kantar, K. (2020). Biomass energy consumption and sustainable development. *International Journal of Sustainable Development & World Ecology*, *27*(8), 762-767. https://doi.org/10.1080/13504509.2020.1753124

Guo, X., Singh, S., Lee, H., Lewis, R. L., & Wang, X. (2014). NIPS - Deep Learning for Real-Time Atari Game Play Using Offline Monte-Carlo Tree Search Planning.

Gupta, S., Kar, A. K., Baabdullah, A. M., & Al-Khowaiter, W. A. A. (2018). Big data with cognitive computing: A review for the future. *International Journal of Information Management*, *42*(NA), 78-89. https://doi.org/10.1016/j.ijinfomgt.2018.06.005

Hasan, A., & Islam, M. M. (2024). Rainwater Harvesting Approach at Daffodil International University (DIU) Campus. *Journal of Science and Engineering Research*, *1*(01), 74-88. https://doi.org/10.70008/jeser.v1i01.54

Hasan, M., Farhana Zaman, R., Md, K., & Md Kazi Shahab Uddin. (2024). Common Cybersecurity Vulnerabilities: Software Bugs, Weak Passwords, Misconfigurations, Social Engineering. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *3*(04), 42-57. https://doi.org/10.62304/jieet.v3i04.193

Hebal, S., Mechta, D., Harous, S., & Dhriyyef, M. (2021). Hybrid Energy Routing Approach for Energy Internet. *Energies*, *14*(9), 2579-NA. https://doi.org/10.3390/en14092579

Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. *Neural Computation*, *18*(7), 1527-1554. https://doi.org/10.1162/neco.2006.18.7.1527

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. *Science (New York, N.Y.)*, *349*(6245), 261-266. https://doi.org/10.1126/science.aaa8685

Hu, M., Dang, C., & Chintagunta, P. K. (2019). Search and Learning at a Daily Deals Website. *Marketing Science*, *38*(4), 609-642. https://doi.org/10.1287/mksc.2019.1156

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, *56*(NA), 102250-NA. https://doi.org/10.1016/j.ijinfomgt.2020.102250

Islam, M. M. (2024). Structural Design and Analysis of a 20-Story Mixed-Use High-Rise Residential and Commercial Building In Dhaka: Seismic and Wind Load Considerations. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *3*(04), 120-137. https://doi.org/10.62304/jieet.v3i04.210

Islam, M. R., Abid, A.-A., Islam, M. M., & Hasan, M. D. M. (2024). Sustainable Water Purification Techniques: A Review Of Solar-Based Desalination Methods. *Frontiers in Applied Engineering and Technology*, *1*(01), 59-83. https://doi.org/10.70937/faet.v1i01.11

Jałowiec, T., Wojtaszek, H., & Miciuła, I. (2022). Analysis of the Potential Management of the Low-Carbon Energy Transformation by 2050. *Energies*, *15*(7), 2351-2351. https://doi.org/10.3390/en15072351

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

Kang, Y., Cai, Z., Tan, C.-W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, *7*(2), 139-172. https://doi.org/10.1080/23270012.2020.1756939

Kowalczyk, M., & Buxmann, P. (2015). An Ambidextrous Perspective on Business Intelligence and Analytics Support in Decision Processes: Insights from a Multiple Case Study. *Decision Support Systems*, *80*(NA), 1-13. https://doi.org/10.1016/j.dss.2015.08.010

Law, K. S., & Chung, F.-L. (2020). Knowledge-driven decision analytics for commercial banking. *Journal of Management Analytics*, *7*(2), 209-230. https://doi.org/10.1080/23270012.2020.1734879

Lee, D.-s., Chen, Y.-T., & Chao, S.-L. (2022). Universal workflow of artificial intelligence for energy saving. *Energy Reports*, *8*(NA), 1602-1633. https://doi.org/10.1016/j.egyr.2021.12.066

Lee, T. Y., & Bradlow, E. T. (2011). Automated Marketing Research Using Online Customer Reviews. *Journal of Marketing Research*, *48*(5), 881-894. https://doi.org/10.1509/jmkr.48.5.881

Li, X.-B., & Qin, J. (2017). Anonymizing and Sharing Medical Text Records. *Information systems research : ISR*, *28*(2), 332-352. https://doi.org/10.1287/isre.2016.0676

Lim, E.-P., Chen, H., & Chen, G. (2013). Business Intelligence and Analytics: Research Directions. *ACM Transactions on Management Information Systems*, *3*(4), 17-10. https://doi.org/10.1145/2407740.2407741

Lin, Y.-K., Chen, H., Brown, R. A., Li, S.-H., & Yang, H.-J. (2017). Healthcare predictive analytics for risk profiling in chronic care: a Bayesian multitask learning approach. *MIS Quarterly*, *41*(2), 473-495. https://doi.org/10.25300/misq/2017/41.2.07

Lismont, J., Vanthienen, J., Baesens, B., & Lemahieu, W. (2017). Defining analytics maturity indicators. *International Journal of Information Management*, *37*(3), 114-124. https://doi.org/10.1016/j.ijinfomgt.2016.12.003

Loughran, T., & McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, *54*(4), 1187-1230. https://doi.org/10.1111/1475-679x.12123

Lusci, A., Pollastri, G., & Baldi, P. (2013). Deep Architectures and Deep Learning in Chemoinformatics: The Prediction of Aqueous Solubility for Drug-Like Molecules. *Journal of chemical information and modeling*, *53*(7), 1563-1575. https://doi.org/10.1021/ci400187y

Martens, J. (2010). ICML - Deep learning via Hessian-free optimization.

Maśloch, P., Maśloch, G., Kuźmiński, Ł., Wojtaszek, H., & Miciuła, I. (2020). Autonomous Energy Regions as a Proposed Choice of Selecting Selected EU Regions—Aspects of Their Creation and Management. *Energies*, *13*(23), 6444-NA. https://doi.org/10.3390/en13236444

Mazumder, M. S. A., Rahman, M. A., & Chakraborty, D. (2024). Patient Care and Financial Integrity In Healthcare Billing Through Advanced Fraud Detection Systems. *Academic Journal on Business Administration, Innovation & Sustainability*, *4*(2), 82-93. https://doi.org/10.69593/ajbais.v4i2.74

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard business review*, *90*(10), 60-128. https://doi.org/NA

Md Morshedul Islam, A. A. M., amp, & Abu Saleh Muhammad, S. (2024). Enhancing Textile Quality Control With IOT Sensors: A Case Study Of Automated Defect Detection. *International Journal of Management Information Systems and Data Science*, *1*(1), 19-30. https://doi.org/10.62304/ijmisds.v1i1.113

Md Samiul Alam, M. (2024). The Transformative Impact of Big Data in Healthcare: Improving Outcomes, Safety, and Efficiencies. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(03), 01-12. https://doi.org/10.62304/jbedpm.v3i03.82

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434-NA. https://doi.org/10.1016/j.im.2021.103434

Mintoo, A. A. (2024b). Detecting Fake News Using Data Analytics: A Systematic Literature Review And Machine Learning Approach. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 108-130. https://doi.org/10.69593/ajieet.v1i01.143

Doi: 10.70008/jbimisr.v1i01.59

Mintoo, A. A., Nabil, A. R., Alam, M. A., & Ahmad, I. (2024). Adversarial Machine Learning In Network Security: A Systematic Review Of Threat Vectors And Defense Mechanisms. *Innovatech Engineering Journal*, *1*(01), 80-98. https://doi.org/10.70937/itej.v1i01.9

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing Atari with Deep Reinforcement Learning. *arXiv: Learning*, *NA*(NA), NA-NA. https://doi.org/NA

Mostafa, M. M., & El-Masry, A. A. (2013). Citizens as Consumers: Profiling E-Government Services' Users in Egypt Via Data Mining Techniques. *International Journal of Information Management*, *33*(4), 627-641. https://doi.org/10.1016/j.ijinfomgt.2013.03.007

Motlagh, N. H., Mohammadrezaei, M., Hunt, J., & Zakeri, B. (2020). Internet of Things (IoT) and the Energy Sector. *Energies*, *13*(2), 494-NA. https://doi.org/10.3390/en13020494

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. A. (2020). The Ethical Implications of Using Artificial Intelligence in Auditing. *Journal of Business Ethics*, *167*(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1

Nessler, B., Pfeiffer, M., Buesing, L., & Maass, W. (2013). Bayesian Computation Emerges in Generic Cortical Microcircuits through Spike-Timing-Dependent Plasticity. *PLoS computational biology*, *9*(4), e1003037-NA. https://doi.org/10.1371/journal.pcbi.1003037

Nguyen, H. T., Calantone, R. J., & Krishnan, R. (2020). Influence of Social Media Emotional Word of Mouth on Institutional Investors' Decisions and Firm Value. *Management Science*, *66*(2), 887-910. https://doi.org/10.1287/mnsc.2018.3226

Olabi, A. G., Abdelghafar, A. A., Maghrabie, H. M., Sayed, E. T., Rezk, H., Radi, M. A., Obaideen, K., & Abdelkareem, M. A. (2023). Application of artificial intelligence for prediction, optimization, and control of thermal energy storage systems. *Thermal Science and Engineering Progress*, *39*(NA), 101730-101730. https://doi.org/10.1016/j.tsep.2023.101730

Otokiti, A. (2019). Using informatics to improve healthcare quality. *International journal of health care quality assurance*, *32*(2), 425-430. https://doi.org/10.1108/ijhcqa-03-2018-0062

Pascanu, R., Gulcehre, C., Cho, K., & Bengio, Y. (2013). How to Construct Deep Recurrent Neural Networks. *arXiv: Neural and Evolutionary Computing*, *NA*(NA), NA-NA. https://doi.org/NA

Pillai, R., Sivathanu, B., Mariani, M. M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control*, *NA*(NA), 1-17. https://doi.org/NA

Poon, H., & Domingos, P. (2011). UAI - Sum-product networks: a new deep architecture.

Qasim, A., & Kharbat, F. F. (2019). Blockchain Technology, Business Data Analytics, and Artificial Intelligence: Use in the Accounting Profession and Ideas for Inclusion into the Accounting Curriculum. *Journal of Emerging Technologies in Accounting*, *17*(1), 107-117. https://doi.org/10.2308/jeta-52649

Rahman, A., Saha, R., Goswami, D., & Mintoo, A. A. (2024). Climate Data Management Systems: Systematic Review Of Analytical Tools For Informing Policy Decisions. *Frontiers in Applied Engineering and Technology*, *1*(01), 01-21. https://journal.aimintlllc.com/index.php/FAET/article/view/3

Rahman, M. M., Mim, M. A., Chakraborty, D., Joy, Z. H., & Nishat, N. (2024). Anomaly-based Intrusion Detection System in Industrial IoT-Healthcare Environment Network. *Journal of Engineering Research and Reports*, *26*(6), 113-123. https://doi.org/10.9734/jerr/2024/v26i61166

Raina, R., Madhavan, A., & Ng, A. Y. (2009). ICML - Large-scale deep unsupervised learning using graphics processors. *Proceedings of the 26th Annual International Conference on Machine Learning*, *NA*(NA), 873-880. https://doi.org/10.1145/1553374.1553486

Rieple, A., Pironti, M., & Pisano, P. (2012). Business Network Dynamics and Diffusion of Innovation. *Symphonya. Emerging Issues in Management*, *NA*(2), 13-25. https://doi.org/10.4468/2012.2.02rieple.pironti.pisano

Selten, R. (1990). Bounded rationality. *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*, *146*(4), 649-658.

Sen, D., Ozturk, M., & Vayvay, O. (2016). An Overview of Big Data for Growth in SMEs. *Procedia - Social and Behavioral Sciences*, *235*(NA), 159-167. https://doi.org/10.1016/j.sbspro.2016.11.011

Shao, L., Wu, D., & Li, X. (2014). Learning deep and wide: a spectral method for learning deep networks. *IEEE transactions on neural networks and learning systems*, *25*(12), 2303-2308. https://doi.org/10.1109/tnnls.2014.2308519

Shareef, M. A., Kumar, V., Dwivedi, Y. K., Kumar, U., Akram, M. S., & Raman, R. (2021). A new health care system enabled by machine intelligence: Elderly people's trust or losing self control. *Technological Forecasting and Social Change*, *162*(NA), 120334-NA. https://doi.org/10.1016/j.techfore.2020.120334

Signorini, A., Segre, A. M., & Polgreen, P. M. (2011). The Use of Twitter to Track Levels of Disease Activity and Public Concern in the U.S. during the Influenza A H1N1 Pandemic. *PloS one*, *6*(5), e19467-NA. https://doi.org/10.1371/journal.pone.0019467

Šíma, J. (1994). Loading deep networks is hard. *Neural Computation*, *6*(5), 842-850. https://doi.org/10.1162/neco.1994.6.5.842

Singh, S. K., & Del Giudice, M. (2019). Big data analytics, dynamic capabilities and firm performance. *Management Decision*, *57*(8), 1729-1733. https://doi.org/10.1108/md-08-2019-020

Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, *27*(10), 1849-1867. https://doi.org/10.1111/poms.12746

Tseng, S.-S., Chen, H.-C., Hu, L.-L., & Lin, Y.-T. (2017). CBR-based negotiation RBAC model for enhancing ubiquitous resources management. *International Journal of Information Management*, *37*(1), 1539-1550. https://doi.org/10.1016/j.ijinfomgt.2016.05.009

Uddin, M. K. S. (2024). A Review of Utilizing Natural Language Processing and AI For Advanced Data Visualization in Real-Time Analytics. *International Journal of Management Information Systems and Data Science*, *1*(04), 34-49. https://doi.org/10.62304/ijmisds.v1i04.185

Uddin, M. K. S., & Hossan, K. M. R. (2024). A Review of Implementing AI-Powered Data Warehouse Solutions to Optimize Big Data Management and Utilization. *Academic Journal on Business Administration, Innovation & Sustainability*, *4*(3), 66-78.

Verma, N., Malhotra, D., & Singh, J. (2020). Big data analytics for retail industry using MapReduce-Apriori framework. *Journal of Management Analytics*, *7*(3), 424-442. https://doi.org/10.1080/23270012.2020.1728403

Wamba, S. F., Bawack, R. E., Guthrie, C., Queiroz, M. M., & Carillo, K. (2021). Are we preparing for a good AI society? A bibliometric review and research agenda. *Technological Forecasting and Social Change*, *164*(NA), 120482-NA. https://doi.org/10.1016/j.techfore.2020.120482

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*(NA), 3-13. https://doi.org/10.1016/j.techfore.2015.12.019

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2018). Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration*, *42*(7), 596-615. https://doi.org/10.1080/01900692.2018.1498103

Wirtz, B. W., Weyerer, J. C., & Sturm, B. J. (2020). The Dark Sides of Artificial Intelligence: An Integrated AI Governance Framework for Public Administration. *International Journal of Public Administration*, *43*(9), 818-829. https://doi.org/10.1080/01900692.2020.1749851

Wu, L., Hitt, L. M., & Lou, B. (2020). Data Analytics, Innovation, and Firm Productivity. *Management Science*, *66*(5), 2017-2039. https://doi.org/10.1287/mnsc.2018.3281

Xu, K., Liao, S. S., Lau, R. Y. K., & Zhao, J. L. (2014). Effective Active Learning Strategies for the Use of Large-Margin Classifiers in Semantic Annotation: An Optimal Parameter Discovery Perspective. *INFORMS Journal on Computing*, *26*(3), 461-483. https://doi.org/10.1287/ijoc.2013.0578

You, K., Dal Bianco, S., Lin, Z., & Amankwah-Amoah, J. (2019). Bridging technology divide to improve business environment: Insights from African nations. *Journal of Business Research*, *97*(NA), 268-280. https://doi.org/10.1016/j.jbusres.2018.01.015

Zhang, C., & Dhaliwal, J. S. (2009). An investigation of resource-based and institutional theoretic factors in technology adoption for operations and supply chain management. *International Journal of Production Economics*, *120*(1), 252-269. https://doi.org/10.1016/j.ijpe.2008.07.023

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse.

Doi: 10.70008/jbimisr.v1i01.59

International Journal of Information Management, *57*(NA), 102304-NA. https://doi.org/10.1016/j.ijinfomgt.2020.102304

Zupic, I., & Čater, T. (2014). Bibliometric Methods in Management and Organization. *Organizational Research Methods*, *18*(3), 429-472. https://doi.org/10.1177/1094428114562629