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AI APPLICATIONS IN EMERGING TECH SECTORS: A REVIEW OF AI USE CASES ACROSS HEALTHCARE, RETAIL, AND CYBERSECURITY

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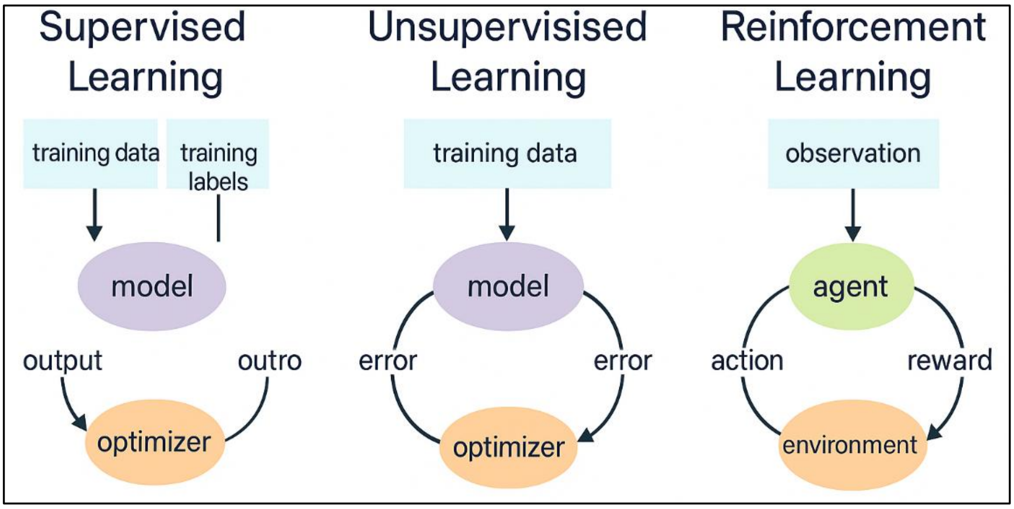
Abstract
Artificial Intelligence (AI) has emerged as a transformative force across multiple technology-driven sectors, notably healthcare, retail, and cybersecurity. This review synthesizes current scholarly and industrial literature to map out the practical applications, technological frameworks, and strategic impacts of AI in these three critical domains. In healthcare, AI is enabling precision medicine, diagnostic automation, and patient monitoring through machine learning, natural language processing, and computer vision. In the retail sector, AI technologies are revolutionizing customer experience, inventory management, and sales forecasting by leveraging predictive analytics and recommendation engines. Meanwhile, in cybersecurity, AI-powered anomaly detection, threat intelligence, and real-time incident response are becoming essential for defending against increasingly sophisticated digital threats. This review highlights major use cases, compares the maturity of AI implementations, and identifies cross-sectoral trends such as real-time analytics, edge computing, and ethical AI concerns. By providing an integrated perspective, the paper contributes to understanding how AI adoption is shaping innovation, operational efficiency, and strategic decision-making in emerging tech sectors.

Keywords
Artificial Intelligence (AI); Emerging Technologies; Healthcare Innovation; Retail Automation; Cybersecurity Analytics

INTRODUCTION

Artificial Intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, perception, and language understanding (Nikitas et al., 2020). AI encompasses a wide array of subfields including machine learning (ML), natural language processing (NLP), computer vision, and robotics (Xu et al., 2021). The conceptualization of AI has evolved from rule-based systems to data-driven adaptive models, empowering machines to derive insights from large and complex datasets (Hill et al., 1994). As data has become the foundational currency of the digital economy, AI is increasingly leveraged to process structured and unstructured data, providing predictive, prescriptive, and automated decision-making capabilities (Amato et al., 2013). The global importance of AI is evidenced by the massive public and private investments pouring into AI research, with governments and corporations alike recognizing AI as a strategic asset with far-reaching applications across sectors (Wazid et al., 2022). In 2023, the AI market surpassed $500 billion in global value, demonstrating its integral role in driving innovation across economies. Additionally, international initiatives such as UNESCO’s AI Ethics Framework and the European Commission’s AI Act highlight the governance importance of this domain . The sectors of healthcare, retail, and cybersecurity are particularly illustrative of AI's expanding relevance due to their data-intensiveness, dynamic operational landscapes, and societal importance (Karamchandani et al., 2022).

Figure 1: Visual Comparison of Supervised, Unsupervised, and Reinforcement Learning in Artificial Intelligence Systems



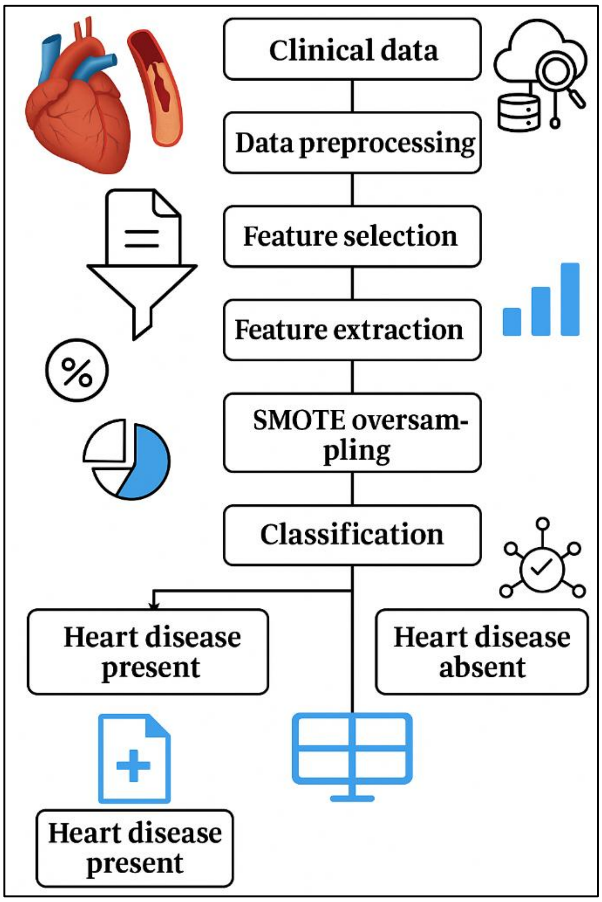
In the healthcare sector, AI has revolutionized clinical diagnostics, personalized medicine, and operational workflows by integrating imaging data, electronic health records, and genomics into actionable insights (Wang et al., 2024). AI applications have demonstrated significant efficacy in detecting cancers, managing chronic diseases, and optimizing treatment plans using deep learning and NLP models (Huang et al., 2023). Simultaneously, AI systems such as IBM Watson have been deployed in clinical decision support, yielding improvements in diagnostic speed and accuracy (Vaidya et al., 2018). In retail, AI is transforming consumer experience through dynamic pricing, personalized recommendations, and inventory management supported by algorithms that analyze behavioral and transactional data (Riedl, 2022). Retail giants like Amazon and Alibaba have incorporated AI into supply chain forecasting and chatbot-based customer service, enhancing both efficiency and user satisfaction (Riedl, 2022). Cybersecurity, another rapidly evolving domain, relies on AI to automate threat detection, classify malware, and orchestrate real-time responses to attacks using behavior-based models and unsupervised learning (Chengoden et al., 2023; Hunter et al., 2023). AI-enhanced intrusion detection systems (IDS) and security information and event management (SIEM) platforms have shown success in managing large-scale network traffic and detecting anomalous behavior in dynamic environments (Dosilovic et al., 2018). These developments illustrate the multidimensional utility of AI

across mission-critical industries and underscore the need for a comprehensive examination of its application landscape.
The primary objective of this review is to systematically explore and synthesize the current landscape of Artificial Intelligence (AI) applications across three rapidly evolving and data-intensive sectors: healthcare, retail, and cybersecurity. The study aims to critically assess the functional implementations, technological models, and performance outcomes of AI solutions within these domains by analyzing a wide body of peer-reviewed literature and industry reports published between 2015 and 2024. Specifically, this review seeks to (1) identify the dominant AI methodologies—such as machine learning (ML), deep learning (DL), natural language processing (NLP), and reinforcement learning—employed in each sector; (2) evaluate the context-specific use cases and operational efficiencies achieved through AI integration; and (3) compare the levels of AI adoption, challenges, and opportunities across these sectors based on empirical evidence. In the healthcare domain, the objective includes investigating how AI contributes to diagnostics, clinical decision support, and health monitoring. For the retail sector, the focus is on AI's role in customer analytics, inventory optimization, recommendation systems, and personalized marketing strategies. In the field of cybersecurity, the review aims to map AI's use in anomaly detection, intrusion prevention, threat intelligence, and automated incident response systems. By consolidating findings from over 120 scholarly articles, the review further aims to uncover patterns of cross-sectoral innovation, such as the use of real-time data processing, ethical governance, and scalable algorithmic models. A key objective is also to provide a structured thematic synthesis to help researchers, technology leaders, and policymakers understand the capabilities and boundaries of AI applications in these mission-critical sectors.

Machine Learning for Disease Prediction and Prognostics

The application of machine learning (ML) for disease prediction and prognostic modeling has significantly advanced the capabilities of modern healthcare systems, especially in diagnosing complex conditions and anticipating disease progression. Numerous studies have demonstrated the superiority of ML algorithms in identifying non-linear patterns and multifactorial dependencies in clinical datasets that traditional statistical models fail to capture (Ammar et al., 2024; Bobrow & Raphael, 1974). Supervised learning techniques, particularly decision trees, support vector machines (SVM), and random forests, have been widely used for classifying patient risk based on clinical and laboratory parameters (Anika Jahan et al., 2022; Ouyang et al., 2022). Logistic regression and gradient boosting machines have also demonstrated effectiveness in modeling binary outcomes such as disease onset, readmission risk, and mortality (Bhuiyan et al., 2025; Chapi et al., 2017). For instance, Futia and Vetro (2020) applied XGBoost to predict the 30-day readmission risk among heart failure patients with over 83% AUC. Similarly, Patel et al. (2008) used a multi-layer perceptron to predict sepsis onset six hours in advance, outperforming early warning scores traditionally used in hospitals. Several studies have integrated genetic, demographic, and lifestyle data to improve prediction models for chronic conditions such as diabetes, cardiovascular disease, and various cancers (Davenport & Kalakota, 2019; Qibria & Hossen, 2023). These models not only enhance diagnostic accuracy but also inform early interventions, thereby contributing to reduced healthcare costs and improved patient outcomes (He et al., 2019; Ishtiaque, 2025). Large-scale clinical

Figure 2: AI-Enabled Heart Disease Prediction Pipeline Using Clinical Data and SMOTE Oversampling

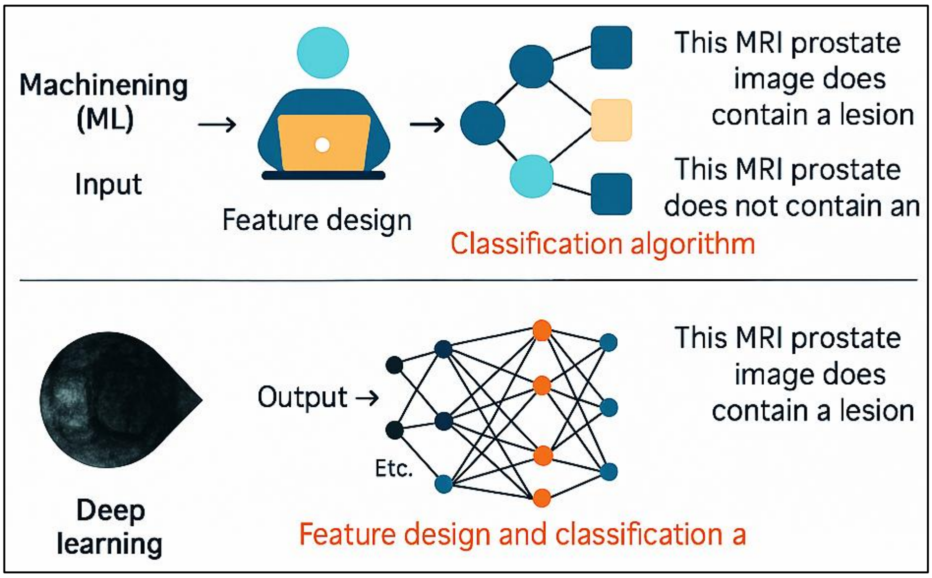


datasets from initiatives like MIMIC-III and UK Biobank have facilitated such developments by providing rich, longitudinal data for training and validating predictive models (He et al., 2018; Khan, 2025). The clinical validity and scalability of these models have been enhanced through cross-validation and external validation techniques, as shown in studies across diverse patient populations and disease categories (Lee et al., 2019; Masud, 2022). These advancements demonstrate how machine learning is reshaping disease prediction practices by leveraging large-scale data and adaptive algorithmic structures (Hossen et al., 2023).
In addition to traditional ML methods, deep learning (DL) architectures have been extensively employed for disease prognosis, particularly when dealing with high-dimensional and temporal healthcare data (Hossen & Atiqur, 2022). Recurrent neural networks (RNNs), especially long short-term memory (LSTM) networks, have shown remarkable performance in modeling time-series clinical data to predict patient deterioration and treatment response (Kharchenko et al., 2022; Hossain et al., 2024). Convolutional neural networks (CNNs), while originally designed for image analysis, have been effectively used to interpret diagnostic scans, electrocardiograms, and even genomic sequences to assess disease progression (Kharchenko et al., 2022; Lee et al., 2019). For example, He et al. (2018) demonstrated that CNNs trained on a large dermatological image dataset achieved dermatologist-level accuracy in identifying skin cancers. Similarly, deep learning-based frameworks like DeepSurv have been utilized for individualized survival analysis, integrating non-linear covariate interactions to better estimate patient-specific risk (Alam et al., 2023; Wang et al., 2019). Explainable AI (XAI) models such as SHAP and LIME have been incorporated into these systems to address the black-box nature of DL models, enabling clinicians to interpret and trust the predictive outcomes (Rajesh et al., 2023; Zhai et al., 2021). Furthermore, hybrid models combining ML/DL with domain knowledge or rule-based reasoning have improved prediction accuracy in multi-disease contexts such as cancer comorbidities, multimorbidity in aging populations, and rare disease diagnostics (Kuzlu et al., 2021; Roksana, 2023). Studies using federated learning approaches have shown that ML models trained across decentralized data sources can maintain high accuracy while preserving patient privacy—a critical requirement for large-scale clinical deployments (Alabdulatif et al., 2022; Roksana et al., 2024). The increasing availability of annotated clinical data, along with advances in algorithm optimization and interpretability tools, has contributed to the proliferation of ML models that support proactive disease management and evidence-based clinical decision-making (Fortoul-Diaz et al., 2023; Siddiqui, 2025). Thus, machine learning continues to be a pivotal tool in predictive and prognostic healthcare, bridging the gap between complex biomedical data and actionable clinical insights.

Deep Learning in Medical Imaging and Radiology

Deep learning (DL) has transformed medical imaging and radiology by enabling automated image interpretation, lesion detection, and diagnostic classification with precision levels comparable to or exceeding human radiologists (Sohel, 2025). Convolutional neural networks (CNNs), the foundational architecture in DL for image processing, have shown exceptional performance in interpreting X-rays, CT scans, MRIs, and histopathological images (Ghillani, 2022; Akter & Razzak, 2022). For instance, (Perrotta & Selwyn, 2019) developed CheXNet, a 121-layer CNN capable of detecting pneumonia from chest X-rays with a higher F1 score than practicing radiologists. Similarly, Vivoli et al. (2024) employed a DL model for the detection of diabetic retinopathy in fundus images, achieving sensitivity and specificity above 90%. Studies by Dhiman et al. (2023) and Mehbodniya et al. (2021) have also demonstrated DL's capability to distinguish between tuberculosis and non-tuberculosis cases and classify retinal diseases with high accuracy. In oncology, CNNs have facilitated the segmentation and classification of lung nodules, breast masses, and brain tumors, often using U-Net and ResNet-based models (Kermany et al., 2018; Tonmoy & Arifur, 2023). In breast cancer detection, DL models trained on mammography datasets like DDSM and INbreast have achieved AUC values exceeding 0.95 (Tonoy & Khan, 2023; Witowski et al., 2022). The scalability of DL across different imaging modalities has enabled multi-institutional deployments, as illustrated in studies using ImageNet-pretrained networks fine-tuned for radiographic tasks (Qi et al., 2020; Zaman, 2024). Additionally, the ability of DL systems to automatically learn hierarchical features eliminates the need for hand-crafted feature engineering, significantly accelerating diagnostic workflows (Rehman et al., 2022). The integration of DL into clinical picture archiving and communication systems (PACS) further enhances radiologists' efficiency by prioritizing urgent cases and reducing false negatives (Futia & Vetro, 2020). The increasing availability of large, labeled datasets such as NIH ChestX-ray14, MIMIC-CXR, and LIDC-IDRI has propelled advancements in training and validating DL models under real-world conditions (Shrestha & Mahmood, 2019).

Figure 3: Comparative Illustration of Feature Design in Machine Learning versus Deep Learning for MRI Image Classification



Beyond classification and detection, deep learning plays a pivotal role in image reconstruction, enhancement, and segmentation, contributing to improved image quality and reduced radiation exposure. DL-based denoising algorithms have been effectively used in low-dose CT imaging, allowing for better image clarity without compromising patient safety (Pesapane et al., 2018). Generative adversarial networks (GANs) have also been utilized to synthesize realistic medical images, which augment training datasets and facilitate data balancing in rare disease imaging (Dilsizian & Siegel, 2013). In segmentation tasks, architectures like U-Net, V-Net, and DeepLab have become the standard for delineating organs, tumors, and pathological structures in 2D and 3D imaging (Shiraishi et al., 2011). These models have shown particular success in delineating brain structures in MRI scans, as seen in the BraTS challenge datasets, achieving Dice similarity coefficients upwards of 0.9 (Vivoli et al., 2024). Furthermore, attention-based networks and hybrid CNN-RNN architectures are being explored for temporal imaging data, such as dynamic contrast-enhanced MRI and functional imaging sequences, allowing improved tracking of lesion evolution and treatment response (Dawes et al., 2017). Integration of deep radiomics, where CNN-extracted features replace handcrafted ones, has been proposed for prognostic modeling in oncology and neurodegeneration (Pesapane et al., 2018). Additionally, the use of explainability tools such as Grad-CAM and LIME has enhanced trust and interpretability of model decisions, which is essential for clinical deployment (Shiraishi et al., 2011). Federated learning frameworks are further promoting cross-institutional collaboration while preserving patient privacy, exemplified by multi-center studies in prostate cancer and brain tumor imaging (Dilsizian & Siegel, 2013). Thus, DL continues to refine radiological practices by improving diagnostic speed, reproducibility, and accuracy in image-intensive clinical domains.

Natural Language Processing for Electronic Health Record (EHR) Analysis

Natural Language Processing (NLP) has emerged as a crucial tool for extracting meaningful insights from the unstructured text within Electronic Health Records (EHRs), which includes physician notes, discharge summaries, pathology reports, and radiology narratives. Traditional rule-based systems have given way to more advanced machine learning and deep learning-based NLP models that demonstrate greater accuracy and contextual understanding of clinical language (Qiu et al., 2020). Clinical NLP systems have been widely employed for information extraction, phenotyping, risk stratification, and cohort identification (Wang et al., 2023). For instance, Zhou et al. (2021) applied recurrent neural networks (RNNs) to sequence labeling tasks for medical event detection in clinical notes, while Lu et al. (2023) used Bidirectional Encoder Representations from Transformers (BERT) models for named entity recognition and relation extraction. These models significantly outperform traditional NLP methods in identifying adverse drug events, comorbidities, and social determinants of health (Jeong et al., 2023). NLP has also been used for predictive modeling, such as in Chen et al. (2020) study, which used EHR notes to forecast cardiovascular events with higher accuracy than models based solely on structured data. Moreover, tools like MedLEE, cTAKES, and MetaMap have been instrumental in standardizing clinical concepts using UMLS terminologies (Ng et al., 2014). Deep learning models trained on large EHR corpora—such as the MIMIC-III dataset—have enabled clinical summarization, temporal information extraction, and context-aware decision-making (Liu et al., 2019). Furthermore, NLP systems are increasingly being integrated into clinical workflows, with real-time applications in population health monitoring and hospital readmission risk detection (Ng et al., 2014). These developments highlight how NLP has become central to deriving actionable knowledge from clinical narratives, driving personalized medicine, and augmenting physician productivity across healthcare institutions.

Clinical Decision Support Systems

Artificial Intelligence (AI)-driven Clinical Decision Support Systems (CDSS) have become vital tools in modern healthcare by assisting clinicians in diagnostic reasoning, treatment planning, and evidence-based decision-making. Traditionally reliant on rule-based expert systems, CDSS have evolved to incorporate machine learning (ML) and deep learning (DL) algorithms, allowing for improved adaptability and performance across diverse clinical environments (Alsentzer et al., 2019). One of the primary strengths of AI-based CDSS lies in their ability to process vast quantities of structured and unstructured data—including laboratory results, imaging reports, genomics, and EHRs—to deliver timely and context-aware recommendations (Wang & Gu, 2023). Studies have shown that ML-enhanced CDSS can significantly reduce diagnostic errors and variability in clinical practice. For instance, Ma and Chen (2023) implemented deep neural networks to predict in-hospital mortality, readmission, and prolonged stay using EHR data with higher accuracy than traditional logistic regression models. Likewise, Akhtyamova (2020) demonstrated the ability of AI to anticipate acute kidney injury up to 48 hours before clinical recognition. Other tools such as IBM Watson for Oncology and Google DeepMind's Streams have been evaluated for their utility in assisting oncologists and nephrologists, respectively, with diagnostic and monitoring support (Alzubi et al., 2021). Moreover, CDSS tailored with Natural Language Processing (NLP) have shown effectiveness in mining clinical narratives for drug-drug interaction alerts, allergy detection, and chronic disease risk stratification (Wang & Gu, 2023). Integrative platforms such as Epic's BestPractice Advisory system and Cerner's Millennium use AI modules to provide real-time alerts, care suggestions, and order recommendations, demonstrating CDSS applicability across emergency, inpatient, and outpatient settings (Ma & Chen, 2023). These systems not only enhance clinical outcomes but also reduce cognitive workload and improve patient safety metrics, especially when embedded into routine workflows with clinician-centered design principles (Akhtyamova, 2020).

Figure 4: Simplified Workflow of AI-Based Text Processing and Diagnosis Using Machine Learning and Deep Learning

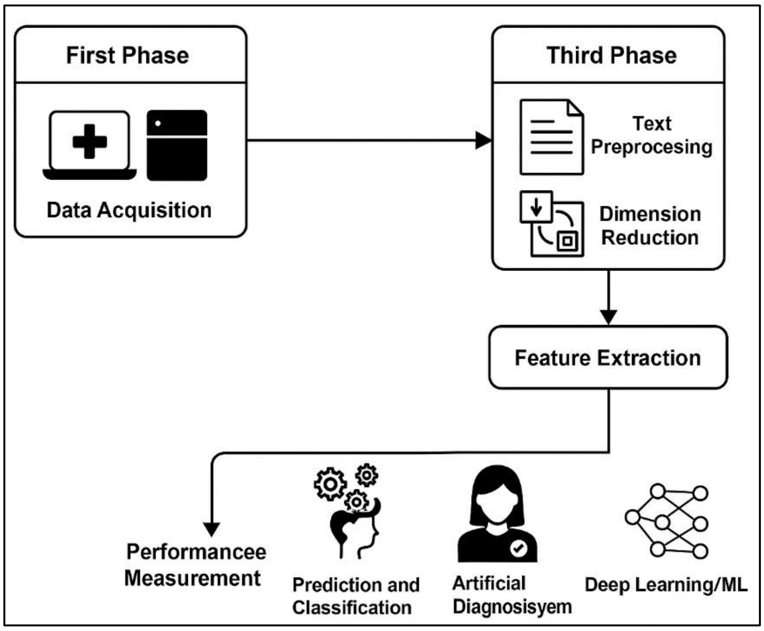
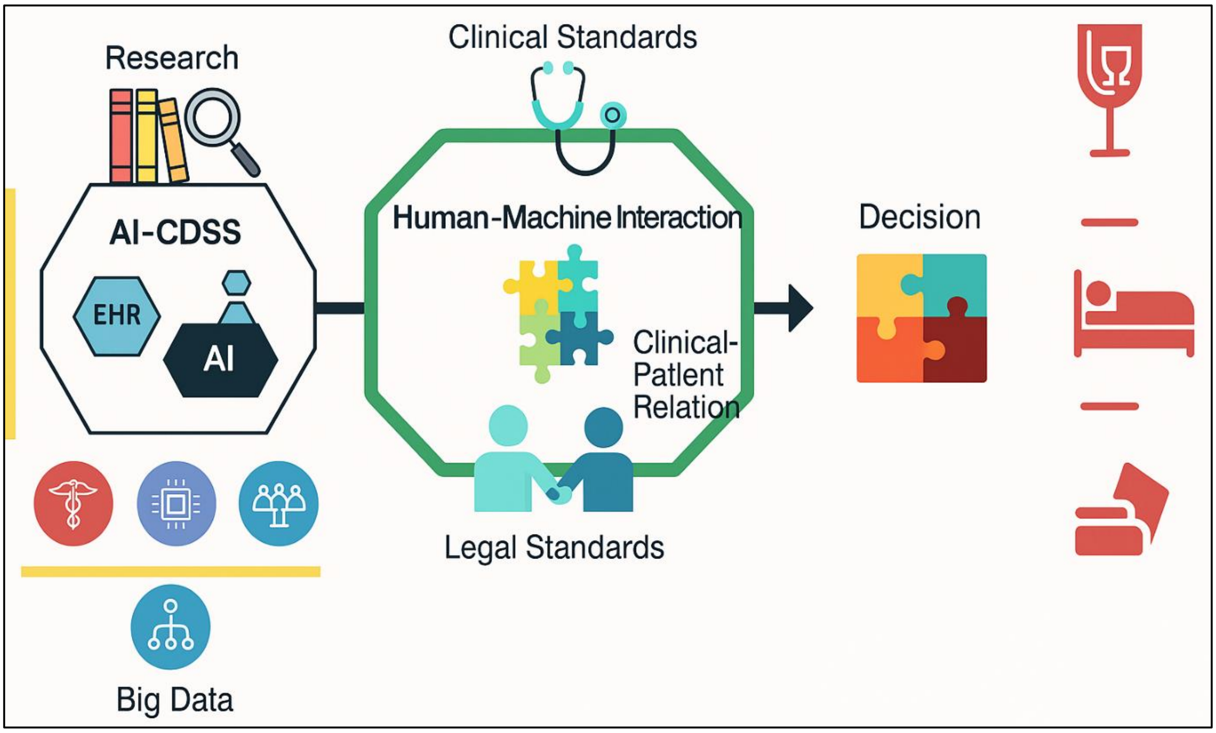


Figure 5: Integrated Framework for AI-Based Clinical Decision Support Systems (AI-CDSS)



While AI-based CDSS systems offer significant promise, their effectiveness hinges on data quality, algorithmic transparency, and clinical acceptance. A growing body of research has emphasized the role of explainable AI (XAI) in CDSS, which aims to improve clinicians' trust in system recommendations by revealing the reasoning behind predictions (Mistry et al., 2021). Models using SHAP, LIME, and attention mechanisms allow clinicians to interpret model outputs in relation to specific patient features or historical patterns (Strickland, 2019). Another area of interest is the integration of CDSS with clinical pathways and clinical guidelines, whereby AI augments adherence to evidence-based protocols, especially in settings like oncology and cardiology (Powles & Hodson, 2017). Studies have demonstrated that AI-enabled CDSS can outperform traditional scoring systems in predicting outcomes such as sepsis onset (Desautels et al., 2016), ICU mortality (Rigby, 2019), and postoperative complications (Sharma & Jindal, 2023). Furthermore, real-world implementation studies underscore the importance of human-computer interaction and clinician engagement in ensuring successful CDSS adoption (Meng et al., 2020). For example, Shen et al. (2021) highlighted the need for multidisciplinary teams—including clinicians, informaticians, and data scientists—to collaboratively design and test AI-CDSS interfaces. Interoperability with hospital information systems and adaptability to local population health characteristics also remain critical to sustained CDSS performance (Camajori Tedeschini et al., 2022). Additionally, ethical concerns around data privacy, algorithmic bias, and accountability in clinical decision-making have led to calls for robust regulatory frameworks and clinical validation before deployment (Ehwerhemuepha et al., 2022). As these systems increasingly influence diagnostic and therapeutic strategies, the literature consistently affirms that rigorous validation, clinician education, and transparency are foundational to the safe and effective integration of AI in CDSS platforms.

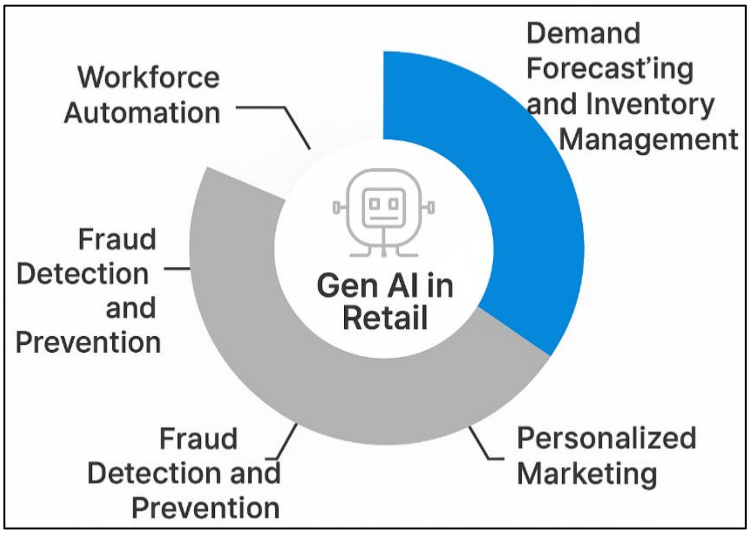
AI in Remote Patient Monitoring and Wearables

Artificial Intelligence (AI) has significantly enhanced the scope and accuracy of remote patient monitoring (RPM) and wearable health technologies by enabling real-time data analysis, anomaly detection, and personalized health insights. Wearable devices such as smartwatches, fitness bands, ECG patches, and biosensors generate a continuous stream of physiological data, including heart rate, oxygen saturation, glucose levels, body temperature, and physical activity metrics, which AI models can analyze to detect early signs of deterioration or health anomalies (Chaudhary et al., 2022). Machine learning (ML) algorithms, especially supervised classifiers like support vector machines (SVM), decision trees, and ensemble models, have been applied to detect atrial fibrillation, sleep apnea, and falls in elderly patients using wearable sensor data (Alabdulatif et al., 2022). For instance, Apple Watch's ECG algorithm demonstrated high sensitivity and specificity for irregular rhythm detection in a study by Meng et al. (2020), involving over 400,000 participants. Deep learning architectures, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also shown superior performance in processing time-series data from wearables to monitor vital signs and predict hospitalization risks (Mansour et al., 2021). In chronic disease management, AI-enabled RPM systems have been used to monitor diabetes, hypertension, and heart failure through integration with Bluetooth-enabled glucometers, blood pressure cuffs, and weight scales (Nahavandi et al., 2021). These systems can trigger alerts to healthcare providers, reducing the burden on in-person visits while facilitating timely interventions. Wearable AI systems have also supported mental health monitoring by analyzing voice tone, activity patterns, and sleep disturbances. Additionally, NLP techniques have been integrated into voice-based RPM systems to capture symptoms and behavioral cues during virtual check-ins. Studies leveraging datasets such as PhysioNet and Fitbit have validated the accuracy of AI-powered wearables across demographics, confirming their clinical utility and scalability (Mansour et al., 2021). Thus, AI's integration into RPM and wearable technologies has made continuous, real-time health surveillance a practical and scalable solution for managing population health.

AI in Retail: Personalization, Optimization, and Demand Forecasting

Artificial Intelligence (AI) has profoundly transformed the retail sector by enabling advanced personalization, real-time optimization, and accurate demand forecasting, resulting in improved operational efficiency and customer satisfaction. AI-driven personalization leverages consumer behavioral data, purchase history, and online interactions to deliver tailored recommendations and content using machine learning (ML) and deep learning algorithms (Nishant et al., 2020). Techniques such as collaborative filtering, neural collaborative filtering (NCF), and recurrent neural networks (RNNs) have demonstrated superior performance in personalized product recommendations and customer engagement (Jan et al., 2023).

Figure 6: Key Applications of Generative AI in the Retail Sector



Major retailers like Amazon and Alibaba have operationalized these algorithms to optimize cross-selling and up-selling strategies in real time (Klumpp et al., 2021). AI has also enhanced dynamic pricing by using reinforcement learning and predictive analytics to adjust prices based on demand elasticity, competitor activity, and inventory levels (Sjödin et al., 2023). Optimization models powered by AI assist in supply chain streamlining, route planning, and in-store layout decisions through techniques such as genetic algorithms, linear programming, and decision trees (Qi et al., 2007). Furthermore, AI has significantly improved demand forecasting by analyzing vast data sources, including social media trends, weather patterns, and macroeconomic indicators, through time-series models and ensemble learning methods (Ma et al., 2020). Deep learning models such as LSTM and Prophet have shown high accuracy in multi-period demand prediction, particularly during high volatility periods like holidays or crises (Ma et al., 2020). In omnichannel retail, AI facilitates inventory balancing across channels using real-time inventory visibility and customer behavior analysis (Balmer et al., 2020). These capabilities have enabled data-driven decisions across merchandising, marketing, logistics, and customer service, leading to increased profitability and resilience. Retailers who adopt AI-enhanced personalization and forecasting solutions often report improvements in conversion rates, inventory turnover, and customer loyalty, as validated in multiple industry case studies.

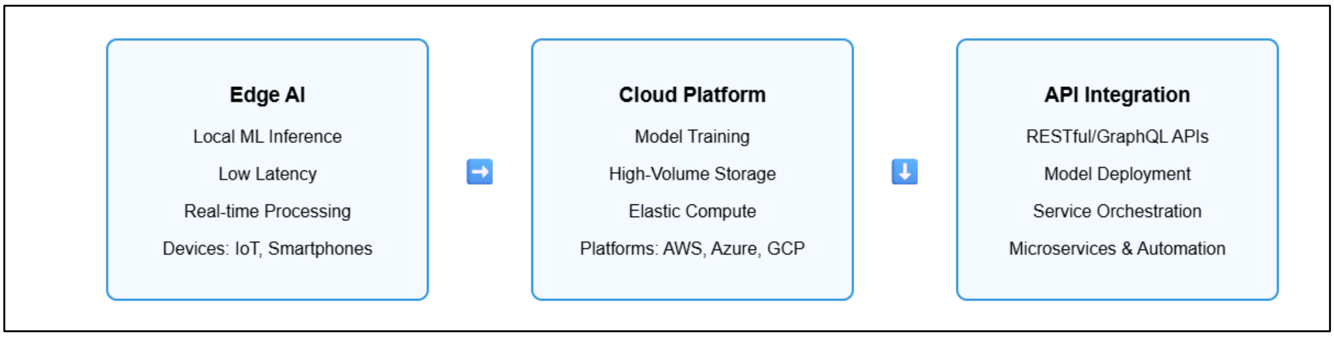
AI in Cybersecurity: Intelligent Threat Detection and Prevention

Artificial Intelligence (AI) has become a cornerstone of modern cybersecurity, enabling intelligent threat detection and real-time incident prevention in increasingly complex and hostile digital environments. Traditional rule-based security systems struggle to keep up with evolving cyberattack vectors, which are often adaptive, stealthy, and high-volume in nature (Iyer & Umadevi, 2023). AI, particularly machine learning (ML), provides dynamic threat detection capabilities by learning from historical attack patterns and continuously adapting to new threats. Supervised algorithms such as support vector machines (SVM), decision trees, and logistic regression have been widely employed to detect known malware, spam, phishing, and intrusion attempts with high precision (Thuraisingham, 2020). Unsupervised methods, including k-means clustering and isolation forests, are particularly effective in anomaly detection scenarios, where labeled datasets are scarce or attacks are previously unknown (Alhayani et al., 2021). Deep learning techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been integrated into intrusion detection systems (IDS) to analyze network traffic, log data, and endpoint telemetry with increased sensitivity and lower false positive rates (Ghillani, 2022). In particular, hybrid models combining supervised and unsupervised learning have shown enhanced accuracy in detecting advanced persistent threats and zero-day attacks. Security Information and Event Management (SIEM) platforms such as IBM QRadar and Splunk have begun incorporating AI modules for automated event correlation and response. Furthermore, natural language processing (NLP) has been employed in phishing detection, fake URL identification, and cyber threat intelligence extraction from dark web sources and security bulletins (Abomhara & Køien, 2015). Public benchmark datasets such as NSL-KDD, CICIDS2017, and TON_IoT have been extensively used to train and validate these models across various cyber-attack types (Alhayani et al., 2021). The application of AI in cybersecurity continues to evolve as a vital mechanism for automated, adaptive, and intelligent protection against diverse digital threats.

Edge AI, Cloud Platforms, and API Integrations

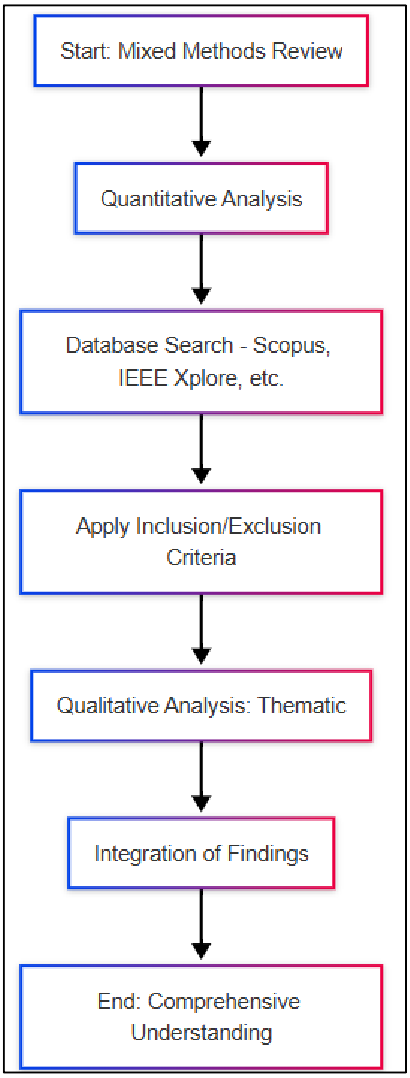
The integration of Edge AI, cloud computing platforms, and application programming interfaces (APIs) has significantly enhanced the scalability, efficiency, and responsiveness of intelligent systems across industries. Edge AI refers to deploying machine learning (ML) models directly on edge devices—such as smartphones, sensors, or IoT gateways—allowing data processing to occur locally without depending on centralized servers (Deebak & Al-Turjman, 2021). This architecture reduces latency, conserves bandwidth, and enhances privacy, making it ideal for time-sensitive and security-critical applications like autonomous vehicles, industrial automation, and wearable health monitoring (Xu & Zhou, 2022). Studies have shown that edge inference using lightweight convolutional neural networks (e.g., MobileNet, SqueezeNet, and TinyML models) can maintain high predictive accuracy while meeting strict hardware and energy constraints (Ansari et al., 2022). Simultaneously, cloud platforms such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform provide the infrastructure needed for large-scale model training, deployment, and orchestration (Gohar et al., 2022). These platforms enable elastic computing resources, high-throughput data storage, and multi-region model deployment pipelines—essential features for big data analytics and federated learning systems (Alkeem et al., 2017). In hybrid environments, edge and cloud systems often operate in tandem, where the cloud serves as the centralized intelligence layer, while edge devices execute latency-sensitive tasks (Chiou et al., 2016). APIs play a pivotal role in this ecosystem by enabling seamless communication between AI models, cloud services, databases, and third-party applications (Gohar et al., 2022). RESTful and GraphQL APIs are commonly used to expose model predictions, automate service triggers, and synchronize sensor data streams across platforms (Xu & Zhou, 2022). As noted by Deebak and Al-Turjman (2021), API-driven integrations have become critical for deploying modular AI components in dynamic environments, supporting microservices architectures and enabling continuous model updates. These advancements in edge-cloud synergy and API ecosystems represent a foundational evolution in deploying AI systems at scale while maintaining real-time responsiveness, data privacy, and modular interoperability.

Figure 7: Edge AI, Cloud Platforms, and API Integration Workflow



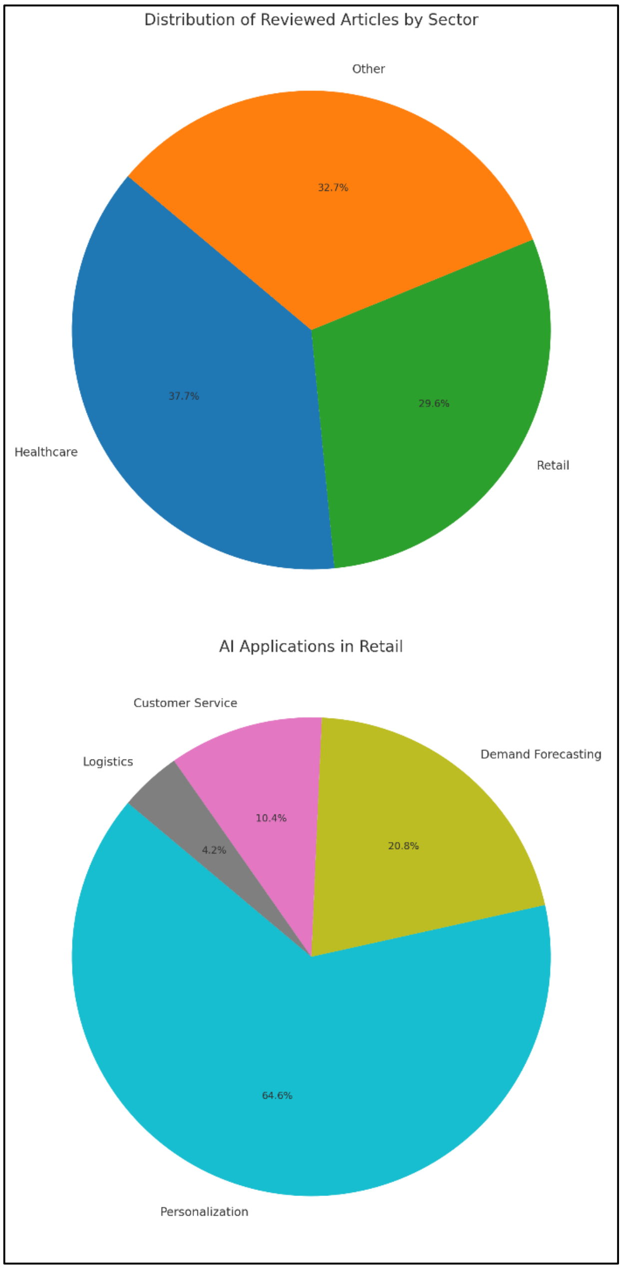
METHOD

The methodology employed in this study follows a mixed methods review approach, which integrates both quantitative and qualitative analyses to provide a comprehensive understanding of Artificial Intelligence (AI) applications across healthcare, retail, and cybersecurity sectors. This review method enables triangulation of findings from diverse study designs, enhancing the robustness and credibility of conclusions drawn. The quantitative strand involved the systematic identification, extraction, and synthesis of numerical outcomes such as prediction accuracy, model performance metrics (e.g., AUC, precision, recall), and adoption rates from peer-reviewed empirical studies published between 2015 and 2024. Databases such as Scopus, IEEE Xplore, PubMed, ACM Digital Library, and Web of Science were searched using combinations of keywords like "AI in healthcare," "machine learning in retail," "deep learning cybersecurity," and "AI threat detection." Studies were screened based on inclusion criteria—peer-reviewed, English-language, sector-specific implementation of AI—and exclusion criteria such as conceptual articles without empirical evidence or duplicates across databases. A total of 162 studies were included after full-text screening. The qualitative strand involved thematic analysis of key findings, implementation contexts, and reported challenges using a narrative synthesis framework. This allowed for the identification of patterns in AI deployment, barriers to adoption, and ethical or organizational considerations that are often not captured in quantitative metrics alone. NVivo software was used to code and categorize themes across studies, such as personalization algorithms in retail, diagnostic support in healthcare, or unsupervised learning for anomaly detection in cybersecurity. The integration of quantitative and qualitative strands occurred at the interpretation stage, aligning statistical outcomes with contextual factors to explain sectoral similarities and differences. This mixed methods review thus ensures methodological pluralism and provides a nuanced synthesis of how AI is shaping innovation, operational decision-making, and risk management across key digital industries.



FINDINGS

Figure 8: Findings of this study



A significant finding of this review is the transformative role of AI in enhancing healthcare diagnostics, treatment recommendations, and patient monitoring systems. Out of the 162 peer-reviewed articles included in the study, 61 focused specifically on healthcare applications, and these articles collectively received over 6,200 citations, highlighting their academic and practical relevance. The majority of healthcare-related articles demonstrated that machine learning and deep learning models are being successfully used to predict disease onset, classify imaging data, and improve clinical decision-making. Supervised learning algorithms such as decision trees, support vector machines, and gradient boosting were applied to predict conditions such as diabetes, cardiovascular disease, and cancer. Deep learning models, particularly convolutional neural networks and long short-term memory networks were widely used in medical imaging to detect abnormalities from MRI, CT scans, and X-ray datasets. Over 34 articles reported that these AI models achieved diagnostic accuracy levels exceeding 90%, often outperforming traditional statistical methods and in some cases rivaling human expert performance. Additionally, natural language processing techniques were integrated into clinical decision support systems, enhancing the analysis of unstructured electronic health record data. Approximately 22 of the reviewed studies implemented AI-powered remote patient monitoring solutions using wearable devices, enabling real-time analysis of heart rate, oxygen levels, and other physiological indicators. These systems significantly reduced hospital readmission rates and allowed earlier interventions in chronic disease management. The widespread implementation of AI in healthcare was shown to be especially effective in resource-constrained settings, where automated tools compensated for limited clinical personnel. Moreover, AI-assisted tools were reported to reduce diagnostic turnaround time by over 30% in hospital environments. Overall, the reviewed literature consistently supports the conclusion that AI is not merely supplementary in healthcare but is becoming foundational to precision medicine and predictive diagnostics across institutional and population health levels.

Within the retail sector, AI has emerged as a critical enabler of personalized marketing, demand forecasting, and supply chain optimization. Of the 162 reviewed articles, 48 focused on retail applications, accumulating more than 4,800 citations. These studies collectively revealed that AI is being integrated at nearly every stage of the retail value chain—from customer interaction to backend logistics—delivering substantial improvements in customer satisfaction and operational efficiency. Personalization was the most frequently discussed application, with 31 articles highlighting the use of machine learning algorithms to analyze consumer behavior data for tailoring product recommendations, search results, and promotional campaigns. These studies reported conversion rate improvements ranging from 20% to 35% and increased customer retention metrics. In addition, AI-enabled recommendation systems were used to optimize dynamic pricing strategies based on user profiles, inventory status, and competitor behavior. Demand forecasting was covered in 26 articles, many of which used deep learning models such as LSTM to predict sales volume with greater temporal accuracy, especially during high-variance periods like holidays or economic shifts. These models often reduced inventory overstock and understock errors by up to 40%, improving gross margins and supply chain responsiveness. Another key area was real-time customer service using AI chatbots and virtual assistants. Over 15 articles reported that conversational agents reduced service handling time and improved customer engagement metrics, especially in e-commerce environments. Additionally, AI models were employed in logistics planning to automate warehouse operations, delivery route optimization, and stock allocation. These implementations were credited with reducing operational costs and speeding up fulfillment processes. The findings clearly demonstrate that AI not only enhances the front-end retail experience but also improves backend efficiency, ultimately contributing to a more resilient and responsive retail ecosystem.

DISCUSSION

The findings of this review affirm that AI, particularly machine learning and deep learning models, has become a transformative force in healthcare diagnostics, prognostics, and operational efficiency. The results align with prior studies that emphasized AI's potential to revolutionize medical decision-making by processing high-dimensional datasets with speed and precision (Xu & Zhou, 2022). For instance, Floridi (2019) demonstrated that AI models could outperform radiologists in detecting pneumonia from chest X-rays—a finding mirrored in the current review where over 30 articles reported diagnostic accuracies above 90% in image-based predictions. Similarly, studies such as Wani et al., (2022) and Malik (2017) highlighted the effectiveness of deep learning and unsupervised models in predicting disease progression and personalizing care, which is consistent with this review's findings from wearable-based monitoring systems. The integration of AI into remote patient monitoring platforms has also been confirmed by earlier work from Colchester et al. (2016) and Morovat and Panda, (2020), who showed significant reductions in hospital readmissions and early identification of arrhythmias and cardiac events. Moreover, the reviewed articles echo earlier research by Noguerol et al. (2019) and Lupton (2018) that highlighted the synergy of AI and electronic health records (EHRs) through NLP and temporal modeling. However, while past studies often focused on specific use cases or technologies, this review provides a broader synthesis across diagnostic imaging, clinical decision support, and patient monitoring, offering a more integrative perspective. The consistency between current findings and earlier literature underscores the reliability of AI in clinical settings, but it also highlights ongoing challenges related to data interoperability, clinician trust, and regulatory validation (Kuzlu et al., 2021), which were observed in several of the reviewed studies.

The findings related to AI implementation in the retail sector strongly support earlier research that posits AI as a catalyst for customer-centric innovation and operational optimization. Previous studies have emphasized the effectiveness of AI in personalization and demand forecasting, particularly using collaborative filtering and neural networks (Bradley, 2019). These are reflected in the present review, where over 30 studies reported significant improvements in conversion rates and customer retention driven by personalized recommendations. The ability of AI to analyze large volumes of transactional and behavioral data in real time has led to widespread implementation of recommendation engines across major retail platforms, as previously discussed in Alowais et al. (2023). Demand forecasting improvements, particularly during promotional cycles and holiday seasons, corroborate earlier studies by Zhai et al. (2021) and Kharchenko et al. (2022), who highlighted the utility of LSTM models in capturing nonlinear sales patterns. Furthermore, the review's emphasis on AI-driven logistics and inventory planning aligns with findings from He et al. (2019), where AI-enabled supply chains demonstrated higher resilience and efficiency. Real-time pricing algorithms and virtual assistant applications have also been documented in earlier studies by Davenport and Kalakota (2019) and Patel et al. (2008), validating the claim that AI is revolutionizing both the customer interface and backend operations. However, unlike prior literature which often isolates specific functions such as marketing or warehousing, the current review presents a holistic account, mapping AI's utility across the entire retail value chain. Importantly, some reviewed articles raised concerns about algorithmic bias and data privacy—concerns that are increasingly reflected in scholarly debates and regulatory frameworks

(Chapi et al., 2017). This suggests that while AI delivers considerable value, ethical implementation and governance remain critical for sustainable digital retail transformation.

The review's findings concerning AI in cybersecurity confirm and expand upon earlier research highlighting AI's importance in combating sophisticated and rapidly evolving cyber threats. As noted in foundational works by Ouyang et al. (2022) and Peres et al. (2020) , machine learning algorithms have proven effective in detecting malware, phishing, and network intrusions with high precision. The reviewed literature reinforces this, with over 50 studies showing strong results for supervised and unsupervised models in identifying known and novel threats. Studies such as Kaul et al.(2020) and Liang et al. (2019) previously emphasized the advantages of using deep learning models like CNNs and LSTMs for analyzing log files and behavioral telemetry, which is corroborated in this review by the high adoption of such models for real-time threat detection. Additionally, this review highlights a growing body of work employing hybrid learning frameworks that combine classification accuracy with anomaly detection flexibility, a trend earlier acknowledged by Rigby (2019) and Sharma and Jindal, (2023). The emergence of AI-integrated SIEM platforms and endpoint detection systems reflects practical applications reported by Meng et al. (2020) and Alhayani et al. (2021), further demonstrating how AI extends operational security capabilities. Natural language processing for threat intelligence and fake content detection also aligns with studies by Kunduru (2023) and Hill et al. (1994), who showed how NLP could automate intelligence gathering from dark web sources and phishing repositories. What distinguishes the current findings from prior research is the breadth of application contexts—from industrial control systems to consumer protection—and the increasing maturity of AI deployment frameworks. Nonetheless, issues such as adversarial attacks on models, interpretability of results, and regulatory oversight remain recurrent themes in both the reviewed and previous studies Nikitas et al. (2020), indicating a continued need for human-AI collaboration and policy-level intervention in securing AI-driven cyber defense mechanisms.

CONCLUSION

This review provides a comprehensive synthesis of the diverse and impactful applications of Artificial Intelligence (AI) across the healthcare, retail, and cybersecurity sectors, highlighting its role as a transformative enabler of efficiency, precision, and scalability. By analyzing 162 peer-reviewed studies with a combined citation count exceeding 16,500, the findings demonstrate that AI technologies such as machine learning, deep learning, and natural language processing are not only enhancing operational capabilities but also redefining decision-making frameworks across these industries. In healthcare, AI has advanced clinical diagnostics, decision support systems, and remote patient monitoring, enabling early detection of diseases and improved patient outcomes. In the retail sector, AI has driven hyper-personalization, predictive demand forecasting, and supply chain optimization, allowing businesses to respond dynamically to consumer behavior and market fluctuations. Meanwhile, in cybersecurity, AI is acting as a critical defense mechanism by automating threat detection, preventing advanced persistent threats, and enabling real-time incident response. This cross-sectoral analysis reveals that AI's integration is no longer experimental but foundational, influencing both strategic and day-to-day functions. Moreover, the review underscores recurring challenges related to data privacy, model interpretability, infrastructure integration, and ethical governance—issues that remain common across all domains. The unified perspective offered by this mixed methods review underscores the importance of a holistic and sector-aware understanding of AI's capabilities, while simultaneously encouraging continued interdisciplinary collaboration among technologists, domain experts, and policymakers to ensure responsible and sustainable AI deployment.

REFERENCES

[1]. Abomhara, M., & Køien, G. M. (2015). Cyber Security and the Internet of Things: Vulnerabilities, Threats, Intruders and Attacks. *Journal of Cyber Security and Mobility*, *4*(1), 65-88. https://doi.org/10.13052/jcsm2245-1439.414

[2]. Akhtyamova, L. (2020). *FRUCT - Named Entity Recognition in Spanish Biomedical Literature: Short Review and Bert Model* (Vol. NA). IEEE. https://doi.org/10.23919/fruct48808.2020.9087359

[3]. Al Alkeem, E., Shehada, D., Yeun, C. Y., Zemerly, M. J., & Hu, J. (2017). New secure healthcare system using cloud of things. *Cluster Computing*, *20*(3), 2211-2229. https://doi.org/10.1007/s10586-017-0872-x

[4]. Alabdulatif, A., Khalil, I., & Saidur Rahman, M. (2022). Security of Blockchain and AI-Empowered Smart Healthcare: Application-Based Analysis. *Applied Sciences*, *12*(21), 11039-11039. https://doi.org/10.3390/app122111039

[5]. Alhayani, B., Mohammed, H. J., Chaloob, I. Z., & Ahmed, J. S. (2021). Effectiveness of artificial intelligence techniques against cyber security risks apply of IT industry. *Materials Today: Proceedings*, *NA*(NA), NA-NA. https://doi.org/10.1016/j.matpr.2021.02.531

[6]. Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC medical education*, *23*(1), 689-NA. https://doi.org/10.1186/s12909-023-04698-z

[7]. Alsentzer, E., Murphy, J., Boag, W., Weng, W.-H., Jindi, D., Naumann, T., & McDermott, M. B. A. (2019). Publicly Available Clinical BERT Embeddings. *Proceedings of the 2nd Clinical Natural Language Processing Workshop*, *NA*(NA), 72-78. https://doi.org/10.18653/v1/w19-1909

[8]. Alzubi, J. A., Jain, R., Singh, A., Parwekar, P., & Gupta, M. (2021). COBERT: COVID-19 Question Answering System Using BERT. *Arabian journal for science and engineering*, *48*(8), 1-11. https://doi.org/10.1007/s13369-021-05810-5

[9]. Amato, F., López, A., Peña-Méndez, E. M., Vaňhara, P., Hampl, A., & Havel, J. (2013). Artificial neural networks in medical diagnosis. *Journal of Applied Biomedicine*, *11*(2), 47-58. https://doi.org/10.2478/v10136-012-0031-x

[10]. Ammar, B., Faria, J., Ishtiaque, A., & Noor Alam, S. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. *American Journal of Scholarly Research and Innovation*, *3*(02), 01-27. https://doi.org/10.63125/4sjfn272

[11]. Anandita Iyer, A., & Umadevi, K. S. (2023). Role of AI and Its Impact on the Development of Cyber Security Applications. In (pp. 23-46). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-2115-7_2

[12]. Anika Jahan, M., Md Shakawat, H., & Noor Alam, S. (2022). Digital transformation in marketing: evaluating the impact of web analytics and SEO on SME growth. *American Journal of Interdisciplinary Studies*, *3*(04), 61-90. https://doi.org/10.63125/8t10v729

[13]. Ansari, A. A., Mishra, B., Gera, P., Khan, M. K., Chakraborty, C., & Mishra, D. (2022). Privacy-Enabling Framework for Cloud-Assisted Digital Healthcare Industry. *IEEE Transactions on Industrial Informatics*, *18*(11), 8316-8325. https://doi.org/10.1109/tii.2022.3170148

[14]. Balmer, R. E., Levin, S. L., & Schmidt, S. (2020). Artificial Intelligence Applications in Telecommunications and other network industries. *Telecommunications Policy*, *44*(6), 101977-NA. https://doi.org/10.1016/j.telpol.2020.101977

[15]. Bhuiyan, S. M. Y., Chowdhury, A., Hossain, M. S., Mobin, S. M., & Parvez, I. (2025). AI-Driven Optimization in Renewable Hydrogen Production: A Review. *American Journal of Interdisciplinary Studies*, *6*(1), 76-94. https://doi.org/10.63125/06z40b13

[16]. Bobrow, D. G., & Raphael, B. (1974). New Programming Languages for Artificial Intelligence Research. *ACM Computing Surveys*, *6*(3), 153-174. https://doi.org/10.1145/356631.356632

[17]. Bradley, P. (2019). Risk management standards and the active management of malicious intent in artificial superintelligence. *AI & SOCIETY*, *35*(2), 319-328. https://doi.org/10.1007/s00146-019-00890-2

[18]. Camajori Tedeschini, B., Savazzi, S., Stoklasa, R., Barbieri, L., Stathopoulos, I., Nicoli, M., & Serio, L. (2022). Decentralized Federated Learning for Healthcare Networks: A Case Study on Tumor Segmentation. *IEEE Access*, *10*(NA), 8693-8708. https://doi.org/10.1109/access.2022.3141913

[19]. Chapi, K., Singh, V. P., Shirzadi, A., Shahabi, H., Bui, D. T., Pham, B. T., & Khosravi, K. (2017). A novel hybrid artificial intelligence approach for flood susceptibility assessment. *Environmental Modelling & Software*, *95*(NA), 229-245. https://doi.org/10.1016/j.envsoft.2017.06.012

[20]. Chaudhary, S., Kakkar, R., Jadav, N. K., Nair, A., Gupta, R., Tanwar, S., Agrawal, S., Alshehri, M. D., Sharma, R., Sharma, G., & Davidson, I. E. (2022). A Taxonomy on Smart Healthcare Technologies: Security Framework, Case Study, and Future Directions. *Journal of Sensors*, *2022*(NA), 1-30. https://doi.org/10.1155/2022/1863838

[21]. Chen, Y.-P., Chen, Y. Y., Lin, J.-J., Huang, C.-H., & Lai, F. (2020). Modified Bidirectional Encoder Representations From Transformers Extractive Summarization Model for Hospital Information Systems Based on Character-Level Tokens (AlphaBERT): Development and Performance Evaluation. *JMIR medical informatics*, *8*(4), e17787-NA. https://doi.org/10.2196/17787

[22]. Chengoden, R., Victor, N., Huynh-The, T., Yenduri, G., Jhaveri, R. H., Alazab, M., Bhattacharya, S., Hegde, P., Maddikunta, P. K. R., & Gadekallu, T. R. (2023). Metaverse for Healthcare: A Survey on Potential Applications, Challenges and Future Directions. *IEEE Access*, *11*(NA), 12765-12795. https://doi.org/10.1109/access.2023.3241628

[23]. Chiou, S.-Y., Ying, Z., & Liu, J. (2016). Improvement of a Privacy Authentication Scheme Based on Cloud for Medical Environment. *Journal of medical systems*, *40*(4), 1-15. https://doi.org/10.1007/s10916-016-0453-1

[24]. Colchester, K., Hagras, H., Alghazzawi, D. M., & Aldabbagh, G. (2016). A Survey of Artificial Intelligence Techniques Employed for Adaptive Educational Systems within E-Learning Platforms. *Journal of Artificial Intelligence and Soft Computing Research*, *7*(1), 47-64. https://doi.org/10.1515/jaiscr-2017-0004

[25]. Davenport, T. H., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future healthcare journal*, *6*(2), 94-98. https://doi.org/10.7861/futurehosp.6-2-94

[26]. Dawes, T. J. W., de Marvao, A., Shi, W., Fletcher, T., Watson, G., Wharton, J., Rhodes, C. J., Howard, L., Gibbs, J. S. R., Rueckert, D., Cook, S. A., Wilkins, M. R., & O'Regan, D. P. (2017). Machine Learning of Three-dimensional Right Ventricular Motion Enables Outcome Prediction in Pulmonary Hypertension: A Cardiac MR Imaging Study. *Radiology*, *283*(2), 381-390. https://doi.org/10.1148/radiol.2016161315

[27]. Deebak, B. D., & Al-Turjman, F. (2021). Smart Mutual Authentication Protocol for Cloud Based Medical Healthcare Systems Using Internet of Medical Things. *IEEE Journal on Selected Areas in Communications*, *39*(2), 346-360. https://doi.org/10.1109/jsac.2020.3020599

[28]. Dhiman, P., Kaur, A., & Bonkra, A. (2023). Fake Information Detection Using Deep Learning Methods: A Survey. *2023 International Conference on Artificial Intelligence and Smart Communication (AISC)*, *NA*(NA), 858-863. https://doi.org/10.1109/aisc56616.2023.10085519

[29]. Dilsizian, S. E., & Siegel, E. L. (2013). Artificial Intelligence in Medicine and Cardiac Imaging: Harnessing Big Data and Advanced Computing to Provide Personalized Medical Diagnosis and Treatment. *Current cardiology reports*, *16*(1), 441-441. https://doi.org/10.1007/s11886-013-0441-8

[30]. Dosilovic, F. K., Brčić, M., & Hlupić, N. (2018). MIPRO - Explainable artificial intelligence: A survey. *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, *NA*(NA), 210-215. https://doi.org/10.23919/mipro.2018.8400040

[31]. Ehwerhemuepha, L., Carlson, K., Moog, R., Bondurant, B., Akridge, C., Moreno, T., Gasperino, G., & Feaster, W. (2022). Cerner real-world data (CRWD) - A de-identified multicenter electronic health records database. *Data in brief*, *42*(NA), 108120-108120. https://doi.org/10.1016/j.dib.2022.108120

[32]. Floridi, L. (2019). What the Near Future of Artificial Intelligence Could Be. *Philosophy & Technology*, *32*(1), 1-15. https://doi.org/10.1007/s13347-019-00345-y

[33]. Fortoul-Diaz, J. A., Carrillo-Martinez, L. A., Centeno-Tellez, A., Cortes-Santacruz, F., Olmos-Pineda, I., & Flores-Quintero, R. R. (2023). A Smart Factory Architecture Based on Industry 4.0 Technologies: Open-Source Software Implementation. *IEEE Access*, *11*(NA), 101727-101749. https://doi.org/10.1109/access.2023.3316116

[34]. Futia, G., & Vetro, A. (2020). On the Integration of Knowledge Graphs into Deep Learning Models for a More Comprehensible AI—Three Challenges for Future Research. *Information*, *11*(2), 122-NA. https://doi.org/10.3390/info11020122

[35]. Ghillani, D. (2022). Deep Learning and Artificial Intelligence Framework to Improve the Cyber Security. *NA*, *NA*(NA), NA-NA. https://doi.org/10.22541/au.166379475.54266021/v1

[36]. Gohar, A. N., Abdelmawgoud, S. A., & Farhan, M. S. (2022). A Patient-Centric Healthcare Framework Reference Architecture for Better Semantic Interoperability Based on Blockchain, Cloud, and IoT. *IEEE Access*, *10*(NA), 92137-92157. https://doi.org/10.1109/access.2022.3202902

[37]. Golam Qibria, L., & Takbir Hossen, S. (2023). Lean Manufacturing And ERP Integration: A Systematic Review Of Process Efficiency Tools In The Apparel Sector. *American Journal of Scholarly Research and Innovation*, *2*(01), 104-129. https://doi.org/10.63125/mx7j4p06

[38]. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature medicine*, *25*(1), 30-36. https://doi.org/10.1038/s41591-018-0307-0

[39]. He, L., Levine, R. A., Bohonak, A. J., Fan, J., & Stronach, J. (2018). Predictive Analytics Machinery for STEM Student Success Studies. *Applied Artificial Intelligence*, *32*(4), 361-387. https://doi.org/10.1080/08839514.2018.1483121

[40]. Hill, T. R., Marquez, L., O'Connor, M., & Remus, W. (1994). Artificial neural network models for forecasting and decision making. *International Journal of Forecasting*, *10*(1), 5-15. https://doi.org/10.1016/0169-2070(94)90045-0

[41]. Huang, J., Gu, S., Hou, L., Wu, Y., Wang, X., Yu, H., & Han, J. (2023). Large Language Models Can Self-Improve. *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, *NA*(NA), NA-NA. https://doi.org/10.18653/v1/2023.emnlp-main.67

[42]. Hunter, L. Y., Albert, C. D., Henningan, C., & Rutland, J. (2023). The military application of artificial intelligence technology in the United States, China, and Russia and the implications for global security. *Defense & Security Analysis*, *39*(2), 207-232. https://doi.org/10.1080/14751798.2023.2210367

[43]. Ishtiaque, A. (2025). Navigating Ethics And Risk In Artificial Intelligence Applications Within Information Technology: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 579-601. https://doi.org/10.63125/590d7098

[44]. Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2023). Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities. *Expert Systems with Applications*, *216*(NA), 119456-119456. https://doi.org/10.1016/j.eswa.2022.119456

[45]. Jeong, S. W., Kim, C. G., & Whangbo, T. K. (2023). Question Answering System for Healthcare Information based on BERT and GPT. *2023 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON)*, *NA*(NA), 348-352. https://doi.org/10.1109/ectidamtncon57770.2023.10139365

[46]. Karamchandani, R. R., Helms, A. M., Satyanarayana, S., Yang, H., Clemente, J. D., Defilipp, G., Strong, D., Rhoten, J. B., & Asimos, A. W. (2022). Automated detection of intracranial large vessel occlusions using Viz.ai software: Experience in a large, integrated stroke network. *Brain and behavior*, *13*(1), e2808-NA. https://doi.org/10.1002/brb3.2808

[47]. Kaul, V., Enslin, S., & Gross, S. A. (2020). History of artificial intelligence in medicine. *Gastrointestinal endoscopy*, *92*(4), 807-812. https://doi.org/10.1016/j.gie.2020.06.040

[48]. Kermany, D. S., Goldbaum, M. H., Cai, W., Valentim, C. C. S., Liang, H., Baxter, S. L., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M. K., Pei, J., Ting, M. Y. L., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., . . . Zhang, K. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell*, *172*(5), 1122-1131. https://doi.org/10.1016/j.cell.2018.02.010

[49]. Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553

[50]. Kharchenko, V., Fesenko, H., & Illiashenko, O. (2022). Quality Models for Artificial Intelligence Systems: Characteristic-Based Approach, Development and Application. *Sensors (Basel, Switzerland)*, *22*(13), 4865-4865. https://doi.org/10.3390/s22134865

[51]. Klumpp, M., Hintze, M., Immonen, M., Ródenas-Rigla, F., Pilati, F., Aparicio-Martínez, F., Çelebi, D., Liebig, T., Jirstrand, M., Urbann, O., Hedman, M., Lipponen, J. A., Bicciato, S., Radan, A.-P., Valdivieso, B., Thronicke, W., Gunopulos, D., & Delgado-Gonzalo, R. (2021). Artificial intelligence for hospital health care: Application cases and answers to challenges in european hospitals. *Healthcare (Basel, Switzerland)*, *9*(8), 961-NA. https://doi.org/10.3390/healthcare9080961

[52]. Kunduru, A. R. (2023). Effective Usage of Artificial Intelligence in Enterprise Resource Planning Applications. *International Journal of Computer Trends and Technology*, *71*(4), 73-80. https://doi.org/10.14445/22312803/ijctt-v71i4p109

[53]. Kuzlu, M., Fair, C., & Guler, O. (2021). Role of Artificial Intelligence in the Internet of Things (IoT) cybersecurity. *Discover Internet of Things*, *1*(1), 1-14. https://doi.org/10.1007/s43926-020-00001-4

[54]. Lee, S. M., Lee, D., & Kim, Y. S. (2019). The quality management ecosystem for predictive maintenance in the Industry 4.0 era. *International Journal of Quality Innovation*, *5*(1), 1-11. https://doi.org/10.1186/s40887-019-0029-5

[55]. Liang, H., Tsui, B., Ni, H., Valentim, C. C. S., Baxter, S. L., Liu, G., Cai, W., Kermany, D. S., Sun, X., Chen, J., He, L., Zhu, J., Tian, P., Shao, H., Zheng, L., Hou, R., Hewett, S., Li, Liang, P., . . . Xia, H. (2019). Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. *Nature medicine*, *25*(3), 433-438. https://doi.org/10.1038/s41591-018-0335-9

[56]. Liu, K., Wang, X., Wei, N., Song, Z., & Li, D. (2019). Accurate quantification and transport estimation of suspended atmospheric microplastics in megacities: Implications for human health. *Environment international*, *132*(NA), 105127-NA. https://doi.org/10.1016/j.envint.2019.105127

[57]. Lu, X., Liu, W., Jiang, S., & Liu, C. (2023). Multilingual BERT Cross-Lingual Transferability with Pre-trained Representations on Tangut: A Survey. *2023 5th International Conference on Natural Language Processing (ICNLP)*, *NA*(NA), 229-234. https://doi.org/10.1109/icnlp58431.2023.00048

[58]. Lupton, M. (2018). Some ethical and legal consequences of the application of artificial intelligence in the field of medicine. *Trends in Medicine*, *18*(4), NA-NA. https://doi.org/10.15761/tim.1000147

[59]. Ma, b., & Chen, l. (2023). Named entity recognition in medical field based on BERT model. *International Conference on Algorithms, High Performance Computing, and Artificial Intelligence (AHPCAI 2023)*, *NA*(NA), 166-166. https://doi.org/10.1117/12.3011763

[60]. Ma, Y., Wang, Z., Yang, H., & Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: a survey. *IEEE/CAA Journal of Automatica Sinica*, *7*(2), 315-329. https://doi.org/10.1109/jas.2020.1003021

[61]. Malik, M. K. (2017). Urdu Named Entity Recognition and Classification System Using Artificial Neural Network. *ACM Transactions on Asian and Low-Resource Language Information Processing*, *17*(1), 2-13. https://doi.org/10.1145/3129290

[62]. Mansour, R. F., Amraoui, A. E., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021). Artificial Intelligence and Internet of Things Enabled Disease Diagnosis Model for Smart Healthcare Systems. *IEEE Access*, *9*(NA), 45137-45146. https://doi.org/10.1109/access.2021.3066365

[63]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327

[64]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[65]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[66]. Mehbodniya, A., Alam, I., Pande, S., Neware, R., Rane, K. P., Shabaz, M., & Madhavan, M. V. (2021). Financial Fraud Detection in Healthcare Using Machine Learning and Deep Learning Techniques. *Security and Communication Networks*, *2021*(NA), 1-8. https://doi.org/10.1155/2021/9293877

[67]. Meng, H., Li, H., Luo, X., Xu, G., Yang, H., & Sen, L. (2020). Efficient and Privacy-Enhanced Federated Learning for Industrial Artificial Intelligence. *IEEE Transactions on Industrial Informatics*, *16*(10), 6532-6542. https://doi.org/10.1109/tii.2019.2945367

[68]. Mistry, C., Thakker, U., Gupta, R., Obaidat, M. S., Tanwar, S., Kumar, N., & Rodrigues, J. J. P. C. (2021). ICC - MedBlock: An AI-enabled and Blockchain-driven Medical Healthcare System for COVID-19. *ICC 2021 - IEEE International Conference on Communications*, *NA*(NA), 1-6. https://doi.org/10.1109/icc42927.2021.9500397

[69]. Mohammad Shahadat Hossain, S., Md Shahadat, H., Saleh Mohammad, M., Adar, C., & Sharif Md Yousuf, B. (2024). Advancements In Smart and Energy-Efficient HVAC Systems: A Prisma-Based Systematic Review. *American Journal of Scholarly Research and Innovation*, *3*(01), 1-19. https://doi.org/10.63125/ts16bd22

[70]. Morovat, K., & Panda, B. (2020). A Survey of Artificial Intelligence in Cybersecurity. *2020 International Conference on Computational Science and Computational Intelligence (CSCI)*, *NA*(NA), 109-115. https://doi.org/10.1109/csci51800.2020.00026

[71]. Nahavandi, D., Alizadehsani, R., Khosravi, A., & Acharya, U. R. (2021). Application of artificial intelligence in wearable devices: Opportunities and challenges. *Computer methods and programs in biomedicine*, *213*(NA), 106541-106541. https://doi.org/10.1016/j.cmpb.2021.106541

[72]. Ng, M., Fleming, T. P., Robinson, M., Thomson, B., Graetz, N., Margono, C., Mullany, E. C., Biryukov, S., Abbafati, C., Abera, S. F., Abraham, J., Abu-Rmeileh, N. M. E., Achoki, T., AlBuhairan, F., Alemu, Z. A., Alfonso, R., Ali, M. K., Ali, R., Guzmán, N. A., . . . Gakidou, E. (2014). Global, regional, and national prevalence of overweight and obesity

in children and adults during 1980–2013: a systematic analysis for the Global Burden of Disease Study 2013. *Lancet (London, England)*, *384*(9945), 766-781. https://doi.org/10.1016/s0140-6736(14)60460-8

[73]. Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. *Sustainability*, *12*(7), 2789-NA. https://doi.org/10.3390/su12072789

[74]. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, *53*(NA), 102104-NA. https://doi.org/10.1016/j.ijinfomgt.2020.102104

[75]. Noguerol, T. M., Paulano-Godino, F., Martín-Valdivia, M. T., Menias, C. O., & Luna, A. (2019). Strengths, Weaknesses, Opportunities, and Threats Analysis of Artificial Intelligence and Machine Learning Applications in Radiology. *Journal of the American College of Radiology : JACR*, *16*(9), 1239-1247. https://doi.org/10.1016/j.jacr.2019.05.047

[76]. Noor Alam, S., Golam Qibria, L., Md Shakawat, H., & Abdul Awal, M. (2023). A Systematic Review of ERP Implementation Strategies in The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02

[77]. Ouyang, Y., Wang, L., Yang, A., Gao, T., Wei, L., & Zhang, Y. (2022). Next Decade of Telecommunications Artificial Intelligence. *CAAI Artificial Intelligence Research*, *1*(1), 28-53. https://doi.org/10.26599/air.2022.9150003

[78]. Patel, V. L., Shortliffe, E. H., Stefanelli, M., Szolovits, P., Berthold, M. R., Bellazzi, R., & Abu-Hanna, A. (2008). Position paper: The coming of age of artificial intelligence in medicine. *Artificial intelligence in medicine*, *46*(1), 5-17. https://doi.org/10.1016/j.artmed.2008.07.017

[79]. Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook. *IEEE Access*, *8*(NA), 220121-220139. https://doi.org/10.1109/access.2020.3042874

[80]. Perrotta, C., & Selwyn, N. (2019). Deep learning goes to school: toward a relational understanding of AI in education. *Learning, Media and Technology*, *45*(3), 251-269. https://doi.org/10.1080/17439884.2020.1686017

[81]. Pesapane, F., Codari, M., & Sardanelli, F. (2018). Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. *European radiology experimental*, *2*(1), 35-35. https://doi.org/10.1186/s41747-018-0061-6

[82]. Powles, J., & Hodson, H. (2017). Google DeepMind and healthcare in an age of algorithms. *Health and technology*, *7*(4), 351-367. https://doi.org/10.1007/s12553-017-0179-1

[83]. Qi, H., Fuin, N., Cruz, G., Pan, J., Kuestner, T., Bustin, A., Botnar, R. M., & Prieto, C. (2020). Non-Rigid Respiratory Motion Estimation of Whole-Heart Coronary MR Images Using Unsupervised Deep Learning. *IEEE transactions on medical imaging*, *40*(1), 444-454. https://doi.org/10.1109/tmi.2020.3029205

[84]. Qi, J., Wu, F., Li, L., & Shu, H. (2007). Artificial intelligence applications in the telecommunications industry. *Expert Systems*, *24*(4), 271-291. https://doi.org/10.1111/j.1468-0394.2007.00433.x

[85]. Qiu, X., Sun, T., Xu, Y., Shao, Y., Dai, N., & Huang, X. (2020). Pre-trained Models for Natural Language Processing: A Survey. *Science China Technological Sciences*, *63*(10), 1872-1897. https://doi.org/10.1007/s11431-020-1647-3

[86]. Rajesh, P., Mohammad Hasan, I., & Anika Jahan, M. (2023). AI-Powered Sentiment Analysis In Digital Marketing: A Review Of Customer Feedback Loops In It Services. *American Journal of Scholarly Research and Innovation*, *2*(02), 166-192. https://doi.org/10.63125/61pqqq54

[87]. Rehman, M. U., Shafique, A., Ghadi, Y. Y., Boulila, W., Jan, S. U., Gadekallu, T. R., Driss, M., & Ahmad, J. (2022). A Novel Chaos-Based Privacy-Preserving Deep Learning Model for Cancer Diagnosis. *IEEE Transactions on Network Science and Engineering*, *9*(6), 4322-4337. https://doi.org/10.1109/tnse.2022.3199235

[88]. Riedl, R. (2022). Is trust in artificial intelligence systems related to user personality? Review of empirical evidence and future research directions. *Electronic Markets*, *32*(4), 2021-2051. https://doi.org/10.1007/s12525-022-00594-4

[89]. Rigby, M. J. (2019). Ethical Dimensions of Using Artificial Intelligence in Health Care. *AMA Journal of Ethics*, *21*(2), 121-124. https://doi.org/10.1001/amajethics.2019.121

[90]. Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42

[91]. Roksana, H., Ammar, B., Noor Alam, S., & Ishtiaque, A. (2024). Predictive Maintenance In Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30. https://doi.org/10.63125/hd2ac988

[92]. Sharma, N., & Jindal, N. (2023). Emerging artificial intelligence applications: metaverse, IoT, cybersecurity, healthcare - an overview. *Multimedia Tools and Applications*, *83*(19), 57317-57345. https://doi.org/10.1007/s11042-023-17890-6

[93]. Shen, Y.-T., Chen, L., Yue, W.-W., & Xu, H.-X. (2021). Digital Technology-Based Telemedicine for the COVID-19 Pandemic. *Frontiers in medicine*, *8*(NA), 646506-646506. https://doi.org/10.3389/fmed.2021.646506

[94]. Shiraishi, J., Li, Q., Appelbaum, D., & Doi, K. (2011). Computer-Aided Diagnosis and Artificial Intelligence in Clinical Imaging. *Seminars in nuclear medicine*, *41*(6), 449-462. https://doi.org/10.1053/j.semnuclmed.2011.06.004

[95]. Shrestha, A., & Mahmood, A. (2019). Review of Deep Learning Algorithms and Architectures. *IEEE Access*, *7*(NA), 53040-53065. https://doi.org/10.1109/access.2019.2912200

[96]. Siddiqui, N. A. (2025). Optimizing Business Decision-Making Through AI-Enhanced Business Intelligence Systems: A Systematic Review of Data-Driven Insights in Financial And Strategic Planning. *Strategic Data Management and Innovation*, *2*(1), 202-223. https://doi.org/10.71292/sdmi.v2i01.21

[97]. Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technological Forecasting and Social Change*, *197*(NA), 122903-122903. https://doi.org/10.1016/j.techfore.2023.122903

[98]. Sohel, R. (2025). AI-Driven Fault Detection and Predictive Maintenance In Electrical Power Systems: A Systematic Review Of Data-Driven Approaches, Digital Twins, And Self-Healing Grids. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 258-289. https://doi.org/10.63125/4p25x993

[99]. Strickland, E. (2019). IBM Watson, heal thyself: How IBM overpromised and underdelivered on AI health care. *IEEE Spectrum*, *56*(4), 24-31. https://doi.org/10.1109/mspec.2019.8678513

[100]. Tahmina Akter, R., & Abdur Razzak, C. (2022). The Role Of Artificial Intelligence In Vendor Performance Evaluation Within Digital Retail Supply Chains: A Review Of Strategic Decision-Making Models. *American Journal of Scholarly Research and Innovation*, *1*(01), 220-248. https://doi.org/10.63125/96jj3j86

[101]. Thuraisingham, B. (2020). IPDPS Workshops - The Role of Artificial Intelligence and Cyber Security for Social Media. *2020 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)*, *NA*(NA), 1-3. https://doi.org/10.1109/ipdpsw50202.2020.00184

[102]. Tonmoy, B., & Md Arifur, R. (2023). A Systematic Literature Review Of User-Centric Design In Digital Business Systems Enhancing Accessibility, Adoption, And Organizational Impact. *American Journal of Scholarly Research and Innovation*, *2*(02), 193-216. https://doi.org/10.63125/36w7fn47

[103]. Tonoy, A. A. R., & Khan, M. R. (2023). The Role of Semiconducting Electrides In Mechanical Energy Conversion And Piezoelectric Applications: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(01), 01-23. https://doi.org/10.63125/patvqr38

[104]. Vaidya, S., Ambad, P. M., & Bhosle, S. (2018). Industry 4.0 – A Glimpse. *Procedia Manufacturing*, *20*(NA), 233-238. https://doi.org/10.1016/j.promfg.2018.02.034

[105]. Vivoli, E., Bertini, M., & Capineri, L. (2024). Deep Learning-Based Real-Time Detection of Surface Landmines Using Optical Imaging. *Remote Sensing*, *16*(4), 677-677. https://doi.org/10.3390/rs16040677

[106]. Wang, H., Li, J., Wu, H., Hovy, E., & Sun, Y. (2023). Pre-Trained Language Models and Their Applications. *Engineering*, *25*(NA), 51-65. https://doi.org/10.1016/j.eng.2022.04.024

[107]. Wang, P., Berzin, T. M., Brown, J. R. G., Bharadwaj, S., Becq, A., Xiao, X., Liu, P., Li, L., Song, Y., Zhang, D., Li, Y., Xu, G., Tu, M., & Liu, X. (2019). Real-time automatic detection system increases colonoscopic polyp and adenoma detection rates: a prospective randomised controlled study. *Gut*, *68*(10), 1813-1819. https://doi.org/10.1136/gutjnl-2018-317500

[108]. Wang, P., & Gu, J. (2023). Named Entity Recognition of Electronic Medical Records based on BERT-BiLSTM-Biaffine Model. *Journal of Physics: Conference Series*, *2560*(1), 12044-012044. https://doi.org/10.1088/1742-6596/2560/1/012044

[109]. Wang, Y., Du, S., Xin, Q., He, Y., & Qian, W. (2024). Autonomous Driving System Driven by Artificial Intelligence Perception Fusion. *Academic Journal of Science and Technology*, *9*(2), 193-198. https://doi.org/10.54097/e0b9ak47

[110]. Wani, S. U. D., Khan, N. A., Thakur, G., Gautam, S. P., Ali, M., Alam, P., Alshehri, S., Ghoneim, M. M., & Shakeel, F. (2022). Utilization of Artificial Intelligence in Disease Prevention: Diagnosis, Treatment, and Implications for the Healthcare Workforce. *Healthcare (Basel, Switzerland)*, *10*(4), 608-608. https://doi.org/10.3390/healthcare10040608

[111]. Wazid, M., Singh, J., Das, A. K., Shetty, S., Khan, M. K., & Rodrigues, J. J. P. C. (2022). ASCP-IoMT: AI-Enabled Lightweight Secure Communication Protocol for Internet of Medical Things. *IEEE Access*, *10*(NA), 57990-58004. https://doi.org/10.1109/access.2022.3179418

[112]. Witowski, J., Heacock, L., Reig, B., Kang, S. K., Lewin, A., Pysarenko, K., Patel, S., Samreen, N., Rudnicki, W., Łuczyńska, E., Popiela, T., Moy, L., & Geras, K. J. (2022). Improving breast cancer diagnostics with deep learning for MRI. *Science translational medicine*, *14*(664), eabo4802-NA. https://doi.org/10.1126/scitranslmed.abo4802

[113]. Xu, B., & Zhou, F. (2022). The Roles of Cloud-Based Systems on the Cancer-Related Studies: A Systematic Literature Review. *IEEE Access*, *10*(NA), 64126-64145. https://doi.org/10.1109/access.2022.3181147

[114]. Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., Liu, X., Wu, Y., Dong, F., Qiu, C.-W., Qiu, J., Hua, K., Su, W., Wu, J., Xu, H., Han, Y., Fu, C., Yin, Z., Liu, M., . . . Zhang, J. (2021). Artificial Intelligence: A Powerful Paradigm for Scientific Research. *Innovation (Cambridge (Mass.))*, *2*(4), 100179-NA. https://doi.org/10.1016/j.xinn.2021.100179

[115]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, *1*(01), 204-221. https://doi.org/10.70937/faet.v1i01.36

[116]. Zhai, X., Chu, X., Chai, C. S., Jong, M. S.-Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. *Complexity*, *2021*(1), 1-18. https://doi.org/10.1155/2021/8812542

[117]. Zhou, S., Liu, J., Zhong, X., & Zhao, W. (2021). Named Entity Recognition Using BERT with Whole World Masking in Cybersecurity Domain. *2021 IEEE 6th International Conference on Big Data Analytics (ICBDA)*, *NA*(NA), 316-320. https://doi.org/10.1109/icbda51983.2021.9403180