# Applications of AI in Cloud Computing: Transforming Industries and Future Opportunities

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# Applications of AI in Cloud Computing: Transforming Industries and Future Opportunities

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## ARTICLE INFO

## ABSTRACT

The convergence of Artificial Intelligence (AI) and cloud computing has emerged as a transformative paradigm, driving innovation and operational efficiency across industries. AI-as-a-Service (AIaaS) platforms, such as AWS, Microsoft Azure, and Google Cloud AI, have democratized access to advanced analytics, enabling businesses of all sizes to leverage powerful machine learning algorithms. This paper explores the multifaceted applications of AI in cloud computing, emphasizing its role in big data analytics, real-time decision-making, and predictive modeling. Key use cases across healthcare, finance, retail, and smart cities are discussed, showcasing the layered integration of AI across smart devices, network infrastructure, and cloud platforms. Additionally, the paper highlights emerging trends, including quantum-enhanced cloud AI, while addressing challenges such as data privacy, algorithmic bias, and sustainability. By presenting a comprehensive review of technological frameworks and real-world implementations, this study underscores the potential of AI-cloud integration in reshaping industries and fostering global innovation.

**Index Terms :** Artificial Intelligence in Cloud Computing, AI-as-a-Service, Big Data Analytics, Real-Time Decision-Making, Predictive Modeling, Smart Cities, Quantum Computing, Sustainability in AI.

## Introduction

The rapid advancement of technology has positioned Artificial Intelligence (AI) and cloud computing as two pivotal forces driving digital transformation across industries. The integration of these technologies, often facilitated through platforms offering AI-as-a-Service (AIaaS) such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud AI, has revolutionized how organizations manage, analyze, and derive value from their data. These platforms not only democratize access to powerful AI tools but also enable businesses to scale their operations with unparalleled efficiency [1], [2].

AI-cloud integration has emerged as a cornerstone for accelerating innovation across sectors including healthcare, finance, retail, manufacturing, and smart cities. By leveraging the vast computational resources of the cloud, AI algorithms can process large datasets in real time, delivering actionable insights and

enabling predictive capabilities. This symbiotic relationship has made it possible to tackle complex challenges such as personalized medicine, fraud detection, and supply chain optimization, fundamentally reshaping traditional business models [3], [4].

The objectives of this paper are threefold: first, to explore the transformative applications of AI in cloud computing across various industries; second, to analyze the technological frameworks and methodologies that enable these applications; and third, to discuss the societal implications and future opportunities associated with this integration. By examining real-world case studies and emerging trends, this review aims to provide a comprehensive understanding of how AI-cloud integration is redefining the technological landscape. The proliferation of AI-cloud solutions has not only enhanced operational efficiency but has also democratized advanced analytics for small businesses and developing economies. However, challenges such as ethical concerns, data privacy, and environmental sustainability remain significant. Addressing these challenges while harnessing the potential of AI-cloud integration will be crucial for shaping a future that is both innovative and inclusive.

## AI Applications in Data Analytics and Decision-Making

The integration of AI with cloud computing has revolutionized data analytics and decision-making by enabling scalable, efficient, and real-time solutions across industries. This section explores the transformative role of AI in analyzing large datasets, providing actionable insights, and improving industry-specific decision-making. Key components of the AI based cloud data analytics is shown in Figure 1.
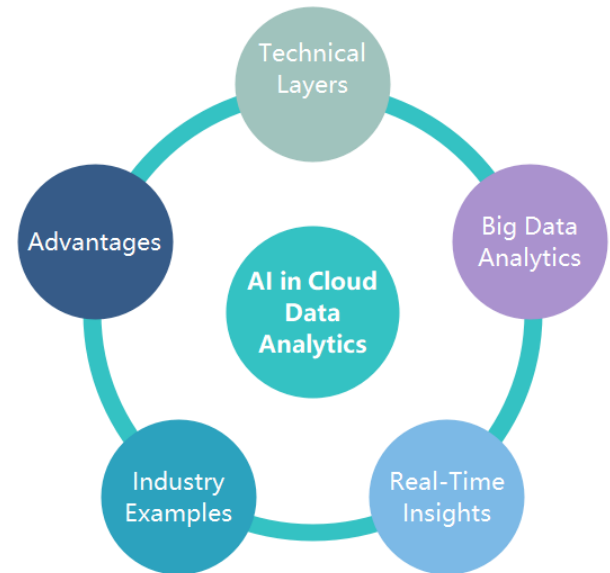


Figure 1 Key components of AI applications in cloud data analytics

### Big Data Analytics Across Layers

AI-powered cloud platforms have revolutionized the way massive datasets are processed and analyzed, offering unprecedented capabilities for industries such as retail, healthcare, manufacturing, and finance. These platforms utilize advanced machine learning algorithms to extract meaningful patterns and insights from structured and unstructured data. For instance, tools like Snowflake and Databricks enable businesses to analyze customer behavior, optimize inventory management, and enhance supply chain efficiency. Google BigQuery further extends these capabilities by allowing real-time data querying and predictive modeling at scale.

In the healthcare sector, AI-powered analytics provide crucial insights by processing vast amounts of electronic health records (EHRs), genomic data, and diagnostic images. Machine learning algorithms can identify anomalies, predict patient outcomes, and recommend treatments more accurately and efficiently than traditional methods. Retail industries leverage AI for customer segmentation, dynamic pricing, and trend forecasting, tailoring their strategies to meet the ever-evolving consumer demands. Finance, on the other hand, uses AI-driven cloud platforms to detect fraud,

assess credit risks, and ensure compliance with regulatory requirements. The layered architecture of AI applications enables efficient data processing at multiple stages. At the smart device layer, data is gathered and preprocessed using image recognition algorithms or heuristic methods, ensuring accuracy at the source. The network layer facilitates seamless transmission of this data across connected systems using cognitive models like Bayesian networks, enhancing communication efficiency. Finally, the cloud layer employs robust machine learning frameworks to perform centralized analytics, integrating data from multiple sources and enabling high-level decision-making. This layered approach ensures that AI applications are not only scalable and reliable but also tailored to address industry-specific challenges effectively.
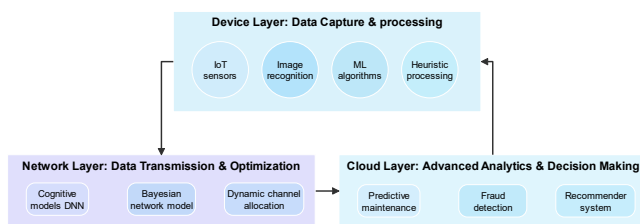


Figure 2 architecture of an AI-powered real-time analytics ecosystem.

## Real-Time Insights and Predictive Analytics

The ability of AI to process real-time data streams and generate actionable insights is transforming industries. Predictive analytics, powered by machine learning and statistical models, enables organizations to anticipate future outcomes and respond proactively. AI models deployed on the cloud can analyze massive, continuous data streams to detect patterns, forecast trends, and automate decision-making processes. This capability is particularly critical in time-sensitive applications such as fraud detection in finance, personalized recommendations in e-commerce, and predictive maintenance in manufacturing. Financial institutions rely heavily on real-time AI analytics to monitor transactional data for suspicious activities. AI algorithms trained on historical data can detect anomalies indicative of fraudulent behavior within milliseconds, minimizing potential losses and safeguarding customers. Similarly, in e-commerce, recommendation engines powered by AI analyze browsing patterns and purchase histories in real-time to personalize user experiences, enhancing customer satisfaction and driving sales. In manufacturing, predictive maintenance uses AI to monitor equipment performance, identify potential failures, and schedule timely repairs, reducing downtime and operational costs.

The network layer plays a pivotal role in enabling real-time analytics by ensuring efficient data transmission. Techniques such as dynamic channel allocation and coalition game models maximize network performance, reducing latency and ensuring that AI systems can process and respond to data instantaneously. Furthermore, the scalability of the cloud layer allows organizations to deploy AI models that adapt to varying workloads and data volumes without compromising performance. The ability to integrate real-time insights with predictive analytics across these layers ensures that businesses can remain agile, efficient, and competitive in a data-driven world.

## Implementation Across Industries

AI applications in cloud data analytics operate across multiple layers, each contributing uniquely to the overall system's functionality. The smart device layer involves localized processing, where data is captured and preprocessed using AI-driven technologies. For example, image recognition algorithms improve the accuracy of systems in automated sorting or defect detection processes, while genetic algorithms enhance robotic path planning by optimizing routes and minimizing collisions. These localized systems provide the foundation for efficient data collection and preliminary analysis. The network layer ensures seamless data transmission between devices, leveraging AI techniques to maximize connectivity and reduce resource contention. Generative deep neural networks, for instance, enable cognitive wireless networks to

perform complex tasks like spectrum allocation and interference management, optimizing communication efficiency. Similarly, Bayesian networks improve the awareness and responsiveness of wireless sensor networks, facilitating better integration of IoT devices in applications such as smart cities and industrial automation.

At the cloud layer, more complex data processing and decision-making occur. Reinforcement learning algorithms enable autonomous resource allocation, ensuring optimal utilization of cloud resources. Methods like clustering and support vector machines reduce the complexity of high-dimensional datasets, allowing for more precise and actionable insights. Applications such as predictive maintenance benefit significantly from this layered architecture, as the smart device layer collects real-time equipment data, the network layer transmits this data seamlessly, and the cloud layer processes it to predict potential failures. The multi-layered implementation of AI applications ensures that organizations can achieve scalability, efficiency, and real-time responsiveness. These layers work cohesively to address diverse challenges across industries, providing robust solutions tailored to specific needs. As shown in Table 1, these layers and their respective methods offer numerous advantages, from enhanced accuracy to resource optimization, underscoring the transformative potential of AI-driven analytics.

Table 1 Summary of AI methodologies and their applications across smart device, network, and cloud layers, highlighting the employed techniques, associated advantages, and industry-specific improvements.

| Layer | Application Objects | Methods | Advantages/Improvements | References |
|---|---|---|---|---|
| Smart Devi | Shaft parts measure | Image processing | Improved system accuracy and robustness | [5] |
| ce Layer | ment system | algorithm | | |
| | Automatic workpiece sorting system | Image judgment and recognition | High-precision classification of workpieces | [6] |
| | Multi-robot system path planning | Improved heuristic search method | Solved the problem of path adaptability and conflicts of time and space | [7] |
| | Mobile robot system path planning | Genetic algorithm and gene rearrangement | Shortened path length and ensured that robots do not intersect with obstacles | [8] |
| Network Layer | Cognitive industrial wireless network | Generative deep neural network | Implemented different network tasks | [9] |
| | Cognitive wireless sensor network | Bayesian network model | Maximized network awareness and improved network performance | [10] |
| | Wireless sensor network | Variable-width channel allocation strategy | Improved resource utilization and transmission efficiency | [11] |
| | Uncertain wireless sensor network | Dynamic Bayesian coalition game | Improved data transmission performance | [12] |

| | | | | |
|---|---|---|---|---|
| | Distributed industrial system | MapReduce and machine learning | Faster data extraction | [5] |
| | Parallel data processing system | Rough set theory | Handles large-scale incomplete data | [13] |
| | High complexity and dimensional data | Clustering and Support Vector Machines | Reduced complexity and dimensionality of manufacturing data | [14] |
| Cloud Layer | Cloud resource allocation system | Reinforcement learning | Realization of cloud autonomous decision resource distribution | [8] |
| | Multi-task load balancing method | Active Markov decision | Cloud host load balancing and resource optimization scheduling | [15] |
| | Equipment status monitoring method | Deep learning | Predicted remaining life of the equipment and improved accuracy up to 99.51% | [6] |

## AI-Driven IoT and Edge Applications

The integration of AI with IoT and edge computing has unlocked transformative applications across industries. By processing data locally and leveraging cloud AI, IoT systems have achieved lower latency, enhanced scalability, and better efficiency. This section explores the impact of AI on IoT ecosystems, edge computing integration, and real-world applications.

## *IoT Ecosystems*

AI has significantly enhanced IoT applications, enabling systems to process and analyze data from interconnected devices. Predictive maintenance, for instance, uses AI algorithms to monitor industrial equipment and predict failures before they occur, minimizing downtime and operational costs. In smart homes, AI personalizes user experiences with energy management systems, voice assistants, and automated security features. Industrial IoT (IIoT) leverages AI to optimize supply chains, improve worker safety, and monitor environmental conditions. Cloud-hosted AI further supports IoT by integrating large datasets from diverse devices, enabling global scalability and adaptability to various domains.

Table 2 Summary of AI Applications in IoT Ecosystems

| Application Area | AI Role in IoT Ecosystems | Benefits | References |
|---|---|---|---|
| Industrial IoT | AI optimizes factory operations and safety systems. | Enhanced worker safety, productivity. | [16] |
| Healthcare IoT | Remote monitoring with AI-enabled devices. | Improved patient outcomes. | [17], [18] |
| Smart Farming | AI analyzes soil and crop health data. | Higher yields, optimized resources. | [19] |
| Real-Time Surveillance | AI processes video and sensor feeds in IoT devices. | Improved security and faster response times. | [20] |

## Edge Computing Integration

Edge computing serves as a vital extension of cloud computing, enabling data to be processed closer to its source and minimizing latency. This paradigm enhances real-time decision-making capabilities, preserves privacy, and alleviates the network congestion associated with centralized data processing. It finds extensive applications in areas such as autonomous systems, healthcare, smart cities, and industrial automation.

### 1) Autonomous Systems and Real-Time Decisions

One of the most impactful applications of edge computing is in autonomous vehicles. Self-driving cars generate massive volumes of sensor data from LiDAR, cameras, and radar systems. These systems rely on edge computing for real-time decision-making, such as obstacle detection, navigation, and collision avoidance. By processing data locally on edge devices, these vehicles achieve rapid response times that are critical for passenger safety. In addition, drones and robots used in logistics or surveillance also benefit from edge computing. These systems analyze live video feeds and telemetry data at the edge to optimize flight paths, track objects, or identify anomalies. The localized processing reduces reliance on cloud connectivity, ensuring uninterrupted operations even in areas with limited network coverage.
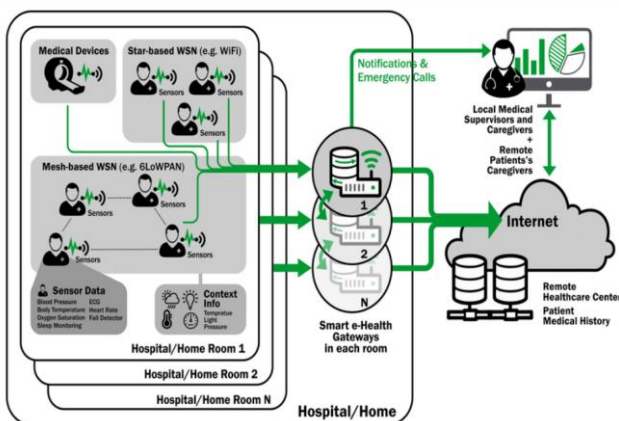


Figure 3 edge nodes sensors IoT based system for healthcare [18]

### 2) Enhancing Healthcare with Edge Devices

Edge computing is revolutionizing healthcare by enabling remote monitoring and diagnosis through AI-powered edge devices. Wearable health monitors and IoT-enabled medical equipment collect data such as heart rate, blood pressure, and oxygen saturation levels. These devices analyze data locally and provide immediate alerts for irregularities, empowering timely interventions. Hospitals and clinics deploy AI-enabled edge systems for imaging diagnostics, such as identifying anomalies in X-rays or MRIs. These systems reduce the workload on centralized servers while delivering faster results. Edge computing also supports telemedicine platforms, where edge devices handle initial consultations or monitor chronic conditions, ensuring low-latency responses and secure patient data handling.

### 3) Smart Cities: Optimizing Urban Systems

Smart cities are at the forefront of edge computing adoption. AI-driven edge devices installed at intersections monitor and manage traffic flow, reducing congestion and travel times. These systems analyze data from cameras, sensors, and connected vehicles in real-time, optimizing signal timings and rerouting traffic dynamically.

Edge computing is also instrumental in energy management for smart grids. Sensors deployed in residential and commercial buildings analyze electricity usage locally, enabling demand-response programs that optimize power distribution. Air quality monitoring stations equipped with AI algorithms evaluate pollution levels and suggest mitigation strategies, contributing to healthier urban environments. In industrial settings, edge computing supports predictive maintenance and operational efficiency. Machines equipped with edge-enabled IoT sensors continuously monitor performance parameters such as vibration, temperature, and energy consumption. AI models running on edge devices identify patterns indicative of wear or failure, scheduling maintenance proactively to avoid

downtime. Manufacturing plants integrate edge computing with robotics for real-time quality control. Cameras on assembly lines detect defects immediately, allowing for corrective actions without halting production. This capability is particularly crucial in high-speed operations, where centralized processing would introduce unacceptable delays.
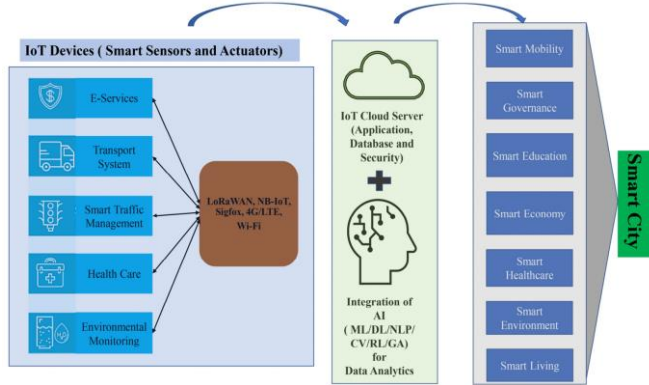


Figure 4 An overview of the methodology for introducing applications in a smart city through [21]

### 4) Addressing Privacy and Security Concerns

Edge computing inherently enhances data privacy by limiting the amount of sensitive information transmitted to the cloud. For example, in smart homes, edge devices process data locally, ensuring that personal information, such as user behavior or security footage, remains secure. Similarly, healthcare edge systems analyze patient data without transferring it offsite, mitigating the risks associated with centralized storage.

AI models deployed on edge devices are also trained for cybersecurity applications, such as detecting network intrusions or unauthorized access attempts. By decentralizing the analysis, these systems minimize the potential impact of a single point of failure, offering a more robust defense mechanism. By processing data locally, edge computing significantly reduces the volume of information sent to cloud servers. This advantage is particularly evident in applications generating continuous data streams, such as video surveillance or environmental monitoring. The reduced reliance on network bandwidth not only lowers operational costs but also ensures that critical applications remain functional during connectivity disruptions. The integration of edge and cloud computing creates a hybrid architecture that balances localized processing with the scalability of centralized systems. While edge devices handle real-time analytics, the cloud provides long-term data storage and advanced AI model training. For instance, an autonomous vehicle may rely on edge computing for immediate navigation but upload its data to the cloud for refining algorithms and enhancing performance over time.

### Case Studies

Real-world examples of AI-driven IoT and edge computing demonstrate the transformative impact of these technologies. Smart cities, for instance, employ AI-enabled IoT devices to reduce traffic congestion, improve energy efficiency, and monitor air quality. Healthcare applications use AI to analyze patient data in real-time, ensuring better diagnoses and timely interventions. Agriculture leverages AI to optimize irrigation and pest control, enhancing yields while conserving resources. These applications showcase the potential of AI to address challenges across diverse industries.

Table 3 Case Studies of AI Integration in Key Industries

| Industry | Impact of AI Integration | Examples | References |
|---|---|---|---|
| Smart Cities | AI improves urban resource management. | Traffic optimization, environmental monitoring. | [19] |
| Healthcare | Remote monitoring improves patient care. | Early diagnoses, timely alerts. | [22] |
| Agriculture | AI optimizes farming practices. | Precision irrigation, pest management. | [23] |

## Emerging Applications of AI in Cloud Computing

Artificial Intelligence (AI), coupled with cloud computing, has profoundly impacted various industries by enabling smarter systems, improving operational efficiency, and providing scalable solutions. This section examines how AI-driven cloud computing innovations are reshaping the healthcare, retail, and finance sectors, as well as their potential in cross-domain applications like climate modeling, disaster recovery, and precision agriculture.

### *Industry-Specific Innovations*

Healthcare

The integration of AI into cloud-enabled healthcare systems has revolutionized patient care and diagnostics. AI algorithms are used for predictive analytics, enabling early disease detection and tailored treatment plans. For example, applications in cardiovascular monitoring rely on cloud-connected sensors and deep learning models to analyze vast amounts of real-time patient data. AI in healthcare cloud platforms supports decision-making, reduces errors, and optimizes workflows, as evidenced by platforms like Amazon's AWS and IBM Watson [24]. AI-driven tools in healthcare have also enhanced operational efficiency. For instance, neural networks combined with fuzzy logic models have been deployed in hospital financial management to automate repetitive tasks, achieving over 97% accuracy in cost analysis [25]. Furthermore, edge AI in medical IoT applications reduces latency in data processing, enabling near-instantaneous responses in critical care scenarios [26].

Retail

In retail, AI-driven cloud platforms have revolutionized inventory management, dynamic pricing, and customer behavior analysis. AI models predict demand patterns and optimize stock levels, reducing waste and ensuring availability. Companies like Amazon leverage AI for their cashier-less stores, integrating computer vision, deep learning, and cloud computing to provide seamless shopping experiences [1]. Retailers also employ machine learning for

personalized marketing. By analyzing customer preferences and transaction history, AI recommends products and adjusts pricing strategies to maximize engagement. Cloud platforms enhance scalability, allowing these algorithms to handle vast datasets efficiently. Predictive analytics further assist in identifying emerging trends and tailoring products to customer needs, thus increasing overall sales performance [27].

Finance

AI and cloud computing in the financial sector have enhanced fraud detection, credit risk analysis, and algorithmic trading. Machine learning algorithms analyze transactional data to identify fraudulent activities in real-time, minimizing financial losses. Reinforcement learning and predictive modeling are employed in trading systems to forecast market trends and optimize portfolio management [3]. Moreover, AI facilitates automated customer interactions through chatbots, which are increasingly integrated into cloud platforms for improved scalability and 24/7 availability. Financial institutions also use natural language processing (NLP) for sentiment analysis, enabling better risk assessment and investment strategies. The adaptability of cloud platforms supports these innovations by allowing rapid deployment and scaling of AI-driven solutions.

Table 4 AI-Driven Innovations Across Multiple Sectors

| Sector | Key Applications | AI Techniques Used | References |
|---|---|---|---|
| **Healthcare** | Predictive diagnostics, medical imaging analysis, personalized treatment, hospital operations management | Deep Learning (CNNs, LSTMs), Fuzzy Logic, IoT Integration | [2], [28]–[30] |
| **Retail** | Smart inventory management, | Predictive Analytics, | [1] |

| | dynamic pricing models, personalized recommendations, cashier-less stores | Computer Vision, Reinforcement Learning | |
|---|---|---|---|
| **Finance** | Fraud detection, credit scoring, risk management, algorithmic trading | Natural Language Processing (NLP), Reinforcement Learning, Predictive Modeling | [31] |
| **Climate Modeling** | Weather pattern prediction, environmental impact assessment, renewable energy forecasting | Machine Learning (SVMs, Random Forests), Big Data Analytics | [32], [33] |
| **Disaster Recovery** | Impact assessment, real-time rescue coordination, recovery planning | Computer Vision, AI-Driven Satellite Analysis, IoT-Enhanced Decision Systems | [34] |
| **Agriculture** | Precision farming, irrigation optimization, pest prediction, crop yield forecasting | IoT Sensors, Deep Learning Models, Reinforcement Learning | [35] |

## Conclusion and Future Directions

Transformative Potential of AI-Cloud Integration
The integration of Artificial Intelligence (AI) with cloud computing has proven transformative across diverse industries, enabling smarter decision-making, enhanced operational efficiency, and scalability. By leveraging AI-as-a-Service (AIaaS) platforms such as AWS, Azure, and Google Cloud AI, organizations have unlocked advanced capabilities in data analytics, predictive modeling, and real-time decision-making. The hierarchical integration of AI across the smart device, network, and cloud layers has reshaped sectors including healthcare, retail, finance, agriculture, and smart cities. These advancements underscore the immense potential of AI-cloud solutions to optimize workflows, reduce costs, and address pressing societal challenges.

Democratizing AI for Small Businesses and Developing Economies
Despite its transformative impact, the adoption of AI-cloud technologies remains uneven, with small businesses and developing economies often facing barriers related to cost, accessibility, and expertise. Democratizing AI requires reducing the entry threshold for these entities by providing cost-effective, scalable solutions tailored to their needs. Initiatives like low-code/no-code AI platforms, modular AI services, and cloud credits for startups can help level the playing field. Furthermore, governments and international organizations should foster partnerships to enhance digital infrastructure and training programs, empowering underserved communities to harness AI for local economic growth and innovation.

Future Trends: Quantum-Enhanced Cloud AI
Quantum computing represents the next frontier in AI-cloud integration. Quantum-enhanced AI has the potential to solve complex optimization, modeling, and simulation problems that are intractable for classical systems. Applications such as drug discovery, climate modeling, and supply chain optimization stand to benefit significantly from the unparalleled computational power of quantum systems. Leading cloud providers are already exploring quantum-classical hybrid systems, where quantum processors work alongside traditional AI models to deliver superior performance. However, further research and

development are needed to make quantum AI commercially viable and accessible to broader industries.

Addressing Ethical Concerns

As AI-cloud systems continue to evolve, ethical concerns such as bias, accountability, and sustainability must be addressed proactively. The risk of algorithmic bias, often stemming from unrepresentative training data, requires rigorous validation processes and transparent reporting mechanisms. Accountability frameworks, including explainable AI (XAI) techniques, should ensure that decision-making processes remain interpretable and fair. Sustainability is another pressing concern, as the energy consumption associated with AI training and cloud infrastructure continues to grow. Research into energy-efficient algorithms and renewable-powered data centers is critical to reducing the environmental footprint of AI-cloud systems. Moreover, regulatory frameworks must evolve to safeguard data privacy, security, and equitable access to AI technologies.

## References

[1]. Y. Zhao, "Research on the application of artificial intelligence and Cloud Computing in new retail models -take Amazon as example," Advances in Economics, Management and Political Sciences, vol. 29, no. 1, pp. 98–105, Nov. 2023.

[2]. S. Shukla, "Utilizing cloud services for advanced E-health applications, enhancing diagnostics and treatment through vertex AI and vision API," in 2023 International Workshop on Biomedical Applications, Technologies and Sensors (BATS), Catanzaro, Italy, 2023.

[3]. J. L. C. Sanz and Y. Zhu, "Toward Scalable Artificial Intelligence in Finance," in 2021 IEEE International Conference on Services Computing (SCC), Chicago, IL, USA, 2021.

[4]. A. Neustein, P. N. Mahalle, P. Joshi, and G. R. Shinde, Eds., AI, IoT, big data and cloud computing for industry 4.0, 1st ed. Cham, Switzerland: Springer International Publishing, 2023.

[5]. "Big data analysis using BigQuery on cloud computing platform," Australian Journal of Engineering and Innovative Technology, pp. 1–9, Jan. 2021.

[6]. F. Jiang and C. Leung, "A data analytic algorithm for managing, querying, and processing uncertain big data in cloud environments," Algorithms, vol. 8, no. 4, pp. 1175–1194, Dec. 2015.

[7]. W. Wu, L. He, W. Lin, and R. Mao, "Accelerating federated learning over reliability-agnostic clients in mobile edge computing systems," IEEE Trans. Parallel Distrib. Syst., pp. 1–1, 2020.

[8]. AI Based Performance Benchmarking & Analysis of Big Data and Cloud Powered Applications: An in Depth View. .

[9]. Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda," Int. J. Inf. Manage., vol. 48, pp. 63–71, Oct. 2019.

[10]. Z. Chang, S. Liu, X. Xiong, Z. Cai, and G. Tu, "A survey of recent advances in edge-computing-powered artificial intelligence of things," IEEE Internet Things J., vol. 8, no. 18, pp. 13849–13875, Sep. 2021.

[11]. Y.-T. Zhuang, F. Wu, C. Chen, and Y.-H. Pan, "Challenges and opportunities: from big data to knowledge in AI 2.0," Front. Inf. Technol. Electron. Eng., vol. 18, no. 1, pp. 3–14, Jan. 2017.

[12]. M. Muniswamaiah, T. Agerwala, and C. Tappert, "Challenges of big data applications in cloud computing," in 9th International Conference on Computer Science, Engineering and Applications (CCSEA 2019), 2019.

[13]. D. Ardagna et al., "Predicting the performance of big data applications on the cloud," J.

Supercomput., vol. 77, no. 2, pp. 1321–1353, Feb. 2021.

[14]. J. Ding et al., "Instance-optimized data layouts for cloud analytics workloads," in Proceedings of the 2021 International Conference on Management of Data, Virtual Event China, 2021.

[15]. B. Dageville et al., "The snowflake elastic data warehouse," in Proceedings of the 2016 International Conference on Management of Data, San Francisco California USA, 2016.

[16]. Y. Hao, Y. Miao, L. Hu, M. S. Hossain, G. Muhammad, and S. U. Amin, "Smart-edge-CoCaCo: AI-enabled smart edge with joint computation, caching, and communication in heterogeneous IoT," IEEE Netw., vol. 33, no. 2, pp. 58–64, Mar. 2019.

[17]. F. Al-Doghman, N. Moustafa, I. Khalil, N. Sohrabi, Z. Tari, and A. Y. Zomaya, "AI-enabled secure microservices in edge computing: Opportunities and challenges," IEEE Trans. Serv. Comput., vol. 16, no. 2, pp. 1485–1504, Mar. 2023.

[18]. Enhancing Healthcare Efficacy Through IoT-Edge Fusion: A Novel Approach for Smart Health Monitoring and Diagnosis. .

[19]. S. Lakrouni, M. Sebgui, and S. Bah, "Using AI and IoT at the edge of the network," in 2022 8th International Conference on Optimization and Applications (ICOA), Genoa, Italy, 2022.

[20]. C. Gong, F. Lin, X. Gong, and Y. Lu, "Intelligent cooperative edge computing in internet of things," IEEE Internet Things J., vol. 7, no. 10, pp. 9372–9382, Oct. 2020.

[21]. M. E. E. Alahi et al., "Integration of IoT-enabled technologies and Artificial Intelligence (AI) for smart city scenario: Recent advancements and future trends," Sensors (Basel), vol. 23, no. 11, p. 5206, May 2023.

[22]. Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing,"

Proc. IEEE Inst. Electr. Electron. Eng., vol. 107, no. 8, pp. 1738–1762, Aug. 2019.

[23]. I. A. Ridhawi, S. Otoum, M. Aloqaily, and A. Boukerche, "Generalizing AI: Challenges and opportunities for plug and play AI solutions," IEEE Netw., vol. 35, no. 1, pp. 372–379, Jan. 2021.

[24]. Cloud-Based Internet of Things in Healthcare Applications: A Systematic Literature Review. .

[25]. V. Janga, D. A. Wako, A. S. Genale, B. B. Sundaram, A. Pandey, and P. Karthika, "Artificial intelligence in cloud technology and wireless network technology using health care system," in 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2022.

[26]. S. Iftikhar, M. Golec, D. Chowdhury, S. S. Gill, and S. Uhlig, "FogDLearner: A deep learning-based cardiac health diagnosis framework using fog computing," in Australasian Computer Science Week 2022, Brisbane Australia, 2022.

[27]. Driven by Artificial Intelligence (AI) - Improving Operational Efficiency and Competitiveness in Business. .

[28]. A. H. Sodhro and N. Zahid, "AI-enabled framework for fog computing driven E-healthcare applications," Sensors (Basel), vol. 21, no. 23, p. 8039, Dec. 2021.

[29]. E. Kyrimi, S. McLachlan, K. Dube, M. R. Neves, A. Fahmi, and N. Fenton, "A comprehensive scoping review of Bayesian networks in healthcare: Past, present and future," Artif. Intell. Med., vol. 117, no. 102108, p. 102108, Jul. 2021.

[30]. A. İ. Tekkeşin, "Artificial intelligence in healthcare: Past, present and future," Anatol. J. Cardiol., vol. 22, no. Suppl 2, pp. 8–9, Oct. 2019.

[31]. A. Khadidos, A. V. V. S. Subbalakshmi, A. Khadidos, A. Alsobhi, S. M. Yaseen, and O. M. Mirza, "Wireless communication based cloud network architecture using AI assisted with IoT

for FinTech application," Optik (Stuttg.), vol. 269, no. 169872, p. 169872, Nov. 2022.

[32]. S. Fox, "An evaluation of radiative transfer simulations of cloudy scenes from a numerical weather prediction model at sub-millimetre frequencies using airborne observations," Remote Sens. (Basel), vol. 12, no. 17, p. 2758, Aug. 2020.

[33]. R. Singh, C. M. Kishtawal, and P. K. Pal, "Use of Atmospheric Infrared Sounder clear-sky and cloud-cleared radiances in the Weather Research and Forecasting 3DVAR assimilation system for mesoscale weather predictions over the Indian region," J. Geophys. Res., vol. 116, no. D22, Nov. 2011.

[34]. R. A. Atmoko, D. Yang, and R. Y. Adhitya, "Cloud robotics architecture and challenges on disaster management," in HIGH-ENERGY PROCESSES IN CONDENSED MATTER (HEPCM 2020): Proceedings of the XXVII Conference on High-Energy Processes in Condensed Matter, dedicated to the 90th anniversary of the birth of RI Soloukhin, Novosibirsk, Russia, 2020.

[35]. A. Aiswarya, R. Anantapalli, R. Singh, and S. Nandhini, "Detection and regulation of soil moisture and nutrients using cloud computing and Internet of Things in agriculture," J. Comput. Theor. Nanosci., vol. 16, no. 8, pp. 3183–3186, Aug. 2019.