Revolutionizing Patient Care with AI and Cloud Computing: A Framework for Scalable and Predictive Healthcare Solutions

Hara Krishna Reddy Koppolu[1], Mahesh Recharla[2], Chaitran Chakilam[3]

[1]Data Engineering Lead
Email: *harakrishnareddyk[at]gmail.com*
ORCID ID: 0009-0004-9130-1470

[2]Sr. Oracle EBS Developer
Email: *recharlamaheshh[at]gmail.com*
ORCID ID: 0009-0008-3636-4320

[3]Validation Engineer
Email: *chaitrann.chakilam[at]gmail.com*
ORCID ID: 0009-0008-3625-4754

Abstract: ***The demand for smart healthcare systems is dramatically increasing due to the growing variety of high-tech and intelligent devices supporting health monitoring and data gathering. Wearable devices such as Fitbits, smartwatches, and blood pressure monitors are examples of the current wearable technology. Furthermore, the term smart home refers to homes equipped with smart devices capable of automatically collecting and forwarding patient data to hospitals. Examples of smart home devices include blood oxygen monitors, body temperature sensors, and glucose meters. The emergence of smart healthcare systems aids elderly people in living independently while 24/7 monitoring their health status as well as detection of critical events in smart homes. Moreover, the COVID-19 pandemic highlighted the necessity, potential, and importance of smart healthcare services and systems. Most medical devices and tools appeared several decades ago and are expensive. There is an increasing demand for affordable and effective smart healthcare services for all patients. Three main obstacles exist in utilizing intelligent healthcare services. First, current connected devices and sensors have limited ability for real-time analytics, detecting critical events, and performing quick actions, because their edge devices cannot be smart enough. Second, wearable devices and smart homes generate an enormous volume of continuous data that exceeds the storage and processing capability of cloud servers. Besides, moving all data to the cloud consumes a lot of energy and time and exhausts network bandwidth. Third, captured data in a smart environment must be stored and processed for a long time to have value, while health data is usually sensitive and must be stored and processed privately . On the other hand, patient safety and in-time treatment are paramount in smart healthcare systems and for the related infrastructures, less time consumption in decision making is also critical. There should be intelligent methods to convert the raw data into intent, derive rules from them, and warn patients as soon as an abnormal behavior is detected.***

Keywords: AI in Patient Care, Cloud-Based Healthcare, Predictive Analytics, Scalable Health Solutions, Digital Health Innovation, Healthcare Cloud Infrastructure, Real-Time Health Insights, Clinical Decision Support Systems (CDSS), Remote Health Monitoring, AI-Powered Diagnostics, Health Data Interoperability, Virtual Care Platforms, Patient Outcome Optimization, Intelligent Health Systems, Healthcare Automation

1. Introduction

Artificial intelligence (AI) and machine learning have the potential to transform healthcare. The complex nature of patient care and care organization favors the use of natural language processing (NLP) in large volumes of free text data that are generated daily by healthcare institutions. AI methods have demonstrated their ability to optimize different aspects of cardiology over time. The coexistence of a high volume of structured and unstructured clinical data suggests that a multi-faceted approach can be employed involving different AI techniques.

While complex methods such as deep neural networks deliver impressive performances, this should not remain the only class of techniques used. AI has the potential to optimize different facets of patient care. This review aims to summarize current insights regarding the potential use of AI for clinical use in clinics and how these systems can be implemented in practice. Clinical data science is a discipline that covers most of the aforementioned fields, and it often combines different methods into one end-user application. This review will thus focus on the impact of AI methods on healthcare and the clinician's workflow. Initial focus will be on how the different clinical domains in the care pathway of patients with cardiovascular diseases lend themselves to different AI methods and analysis techniques and what potential return on investment they promise. Next, a review of current insights into the implementation of a data science product into clinical practice will delineate the requirements to maximize the chance of a successful implementation. Finally, the opportunities for enabling optimized patient care through collaboration and resource pooling will be outlined.

The technological evolution and change in healthcare data strategies have ushered in a variety of techniques to build intelligent algorithms that transform these data into actionable insights during diagnosis, treatment, and follow-up. After the introduction of troop reports in the 1990s, multiple reports have demonstrated the potential of application of AI methods to various aspects of cardiology. These include optimizing cardiac imaging, screening for patients who would benefit from secondary cardiovascular prevention, predicting adverse events after complicated cardiac procedures, and most recently automatic detection of aberrant health behaviors through the use of natural language processing.

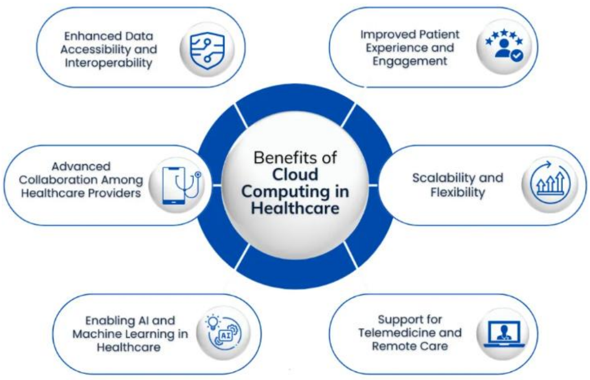

Figure 1: Cloud Computing in Healthcare: Enhancing Patient Care & Data Management.

1.1 Background and Significance

"Improvements in the delivery of healthcare provide a remarkable variety of opportunities and challenges associated with the application of technology. Inevitable advances in computing available to patients and the use of the internet to organize and disseminate patient data on a global scale will revolutionize doctor/patient interaction. The emergence of artificial intelligence (AI) alongside advances in the cloud computing infrastructure will reshape the delivery of health services. Communications technology will allow new distances of interactions between patients, families, communities, and healthcare professionals, as well as between healthcare professionals. In particular, cloud computing is being developed by IT companies to provide the availability and accessibility of data and services at an incredible speed and the capacity for massive scale. Adaptation of cloud computing in healthcare will facilitate instant access to medical knowledge, support better decision making in disease diagnosis, treatment planning, protocol setting, and medical education, as well as efficient communication and collaborations between patients and providers. One of the great advantages of cloud computing is its scalability, which could facilitate better performance by adjusting the size of a resource to match demand."

"AI has been applied across a broad range of industries, and the impact is expected to grow as big data is created on an unprecedented scale. Research on AI techniques such as machine learning, Bayesian networks, and various data mining algorithms has resulted in performance that begins to meet and outstrip human capability. Diagnosis of diseases encompassing blood cell image analysis, early risk stratification of ventricular arrhythmias derived from electrocardiograms, and digital image analysis for cancer detection have been some notable examples. Deep learning of complex networks has produced very timely, startling results in image recognition, object and person detection, text mining, natural language processing, and robotics. AI has also invaded finance, national/urban security, and many other areas".

Equ 1: Predictive Health Risk Score (PHRS).

$$PHRS_i = \sigma(\mathbf{w}^T \mathbf{x}_i + b)$$

- Where:

  $\mathbf{x}_i$ = input vector for patient i (e.g., vitals, lab results)

  $\mathbf{w}$ = model weights

  b = bias term

  σ = sigmoid activation function

2. The Role of AI in Healthcare

Machine learning (ML) is a subset of artificial intelligence (AI) that permits computer systems to increase their performance with respect to task-specific goals by learning from historical data. The term is often used in the context of teaching a computer to perceive and interpret the data it receives. If the data are images, this involves the computer recognizing edges, textures, colors, light, darkness, simplicity, and complexity. ML's neural networks comprise inputs, processing, and outputs, with hidden nodes in between that connect them. Often the hidden nodes operate as mathematical functions of the input and other hidden nodes, transforming the data in intricate ways. These networks are trained with historic data, such that the connections between nodes are adjusted to achieve accuracy of internal predictions and to minimize differences between predicted and actual outputs. The term "deep learning" refers to networks that have many, often hundreds of thousands, of hidden nodes. Contemporary computing capabilities and data abundance make this feasible.

Early models for CAD systems were based upon regression methods. They required strong feature problem knowledge and were adept for small, specialized data sets. Typically, they depended on data requirements that exceeded limitations of previous methods. As data collection accelerated and computing power increased, neural networks were used, permitting a data-driven bottom up approach. Backpropagation algorithms initially used in the late 1980s provided a means for training deep learning networks. An all-at-once approach for the SGD variant of backpropagation was proposed for improved convergence and computational efficiency, as well as reduced overfitting. Techniques for improving labeling of unlabeled images were proposed. Architectures for better productivity, faster training, and improved performance emerged. Notable examples include alexnet and ResNet, which won their respective contests. Variants for performance improvements, like dropout, skip connections, residual learning, and batch normalization emerged.

2.1 AI Algorithms and Their Applications

Artificial intelligence (AI) customarily referred to as machine learning, is a technology that learns like humans but much faster. In a practical scenario, AI receives data; it gets organized and fed to the algorithms. Algorithms then analyze the data through a machine that allows the technology to predict or classify the outcomes. An example of the AI decision-making process is to type "world" into a search

Paper ID: MS2212142204 DOI: https://dx.doi.org/10.21275/MS2212142204

engine, where the virtual assistant collects the data and provides the most relevant information. The same process is applied in the healthcare field. AI systems are provided with health data inputs, algorithms analyze the data inputs through machine learning, and AI outputs the data analysis like five years of health outcomes or a patient's stroke chance prediction. AI can compress and analyze data of hundreds of thousands of hospitals and patients to determine which population is more likely to get a disease. The most classic use of AI in healthcare was a Natural Language Processing (NLP) program that reads a patient's electronic health record and enters every exam and lab examination into its database to identify the possible and differential disease diagnosis.

Cloud computing is the storage of data on the Internet. Cloud-based services provide quicker access to providers and patients for enhanced collaboration and communication. Since cloud computing is a powerful technology that can alter and transform patient care services, it allows rapid access, review, and storage of a large capacity of data. In Nigeria's context, with poor Internet service availability and challenges of electricity and government funding for the purchase of technological tools, the right infrastructure is needed for the software. Such aids will give physicians equitable power in diagnosis review. Additionally, with cloud connectivity, smart machines accessing these data will use AI to analyze treatment predictions and assess anomalies. Trained on wide, varied data harmonization, these applications will enhance but not replace providers' final judgment. Having tablet applications with visual graphic displays of health prediction analysis can educate patients to adopt a healthier lifestyle. For this reason, a national telemedicine policy and standardized fee package structures for patients should be cross-checked by a health provider and patient advocacy group.

2.2 Machine Learning in Medical Diagnostics

Recent developments in AI are increasingly being incorporated in medical systems or infrastructures. These AI systems can assist in making patient care more efficient, easing the burden on physicians, and providing better care for more patients. Despite the technologies influencing unanticipated disciplines in the past 20 years, it is safe to say that the technology has advanced quickly and will shape its course in the medical field over the following few decades. Health experts with computer skills may strive toward the cutting-edge abilities of AI. New technical capabilities may be operated to identify or prevent the warning signs of medical disorders earlier. Even with the improved state of the art, human monitoring is still a necessary course of action. AI requires a proactive human input to prepare the procedures, oversee and adjust the capability, assess the information, and submit the outcomes. Recently, as technology develops, it is increasingly normal to see collaboration between techs and medicine across multiple needs and professions. Yet, it is imperative to understand that frequent daily decisions and behaviors fundamentally account for the majority of medical disorders and events. Won't it be more prosperous if the devices talk to each other and with experts about the patient's needs, and every red flag is already taken care of by the AI before it begins to pose a danger? That is the vision within which the medical AI movement hopes to advance.

In contrast to non-AI systems, instrumentation approaches towards diagnostic AI are fundamentally different. Medical AI is, first and foremost, diagnostic AI. The majority of the current medical AI systems are event driven, not tabular AI systems. With the capability of processing terabytes and petabytes of diagnostics, medical AI mainly depends on diagnostic knowledge acquired from millions of recorded incidents and pareto understanding about patient outcomes. Given personal biosignatures and machine states, the question is reverse-modeling a single psychopathology using data-driven techniques. Scheming from an explanatory hypothesis is altogether more difficult.

Despite advances in medical technology, many behaviors are still politically ambiguous or inadequately clarified. It is challenging to separate general, heterogeneous, and governs conduct from specific, personal, and knowledge-based ones. The systems may be vulnerable to security threats since AI is typically dependent on data networks. Guarding diagnostics with mind-boggling data mix and numerous coding variances on workplace security registers to lessen breach likelihood are conceivable. Drawing per-row hashes of the data and encrypting them with private keys also decreases maintainability and decreases cross-device development. In reality, AI is being applied to commercial automated teleservices. So, in retrospect, using humankind's current knowledge, it may be concluded that AI is indeed beneficial for the healthcare systems to grow better healthily. The advancement of AI in medicine is undeniable; however, there is a persistent fear and a question of whether machine minds will surpass human urgency. In a conventional perspective, seeing the spirit working without supervision makes humans restless. However, once the AI matured, Output inventions would be timeless, as with a more rigorous scrutiny.

3. Cloud Computing in Healthcare

Cloud computing (CC) is an invaluable resource for many sectors, from industry to healthcare. It has led to the emergence of e-health or health information technology. E-health systems provide a widely better health care service by incorporating remote monitoring systems, storing them in the cloud, and enabling health professionals, patient nurses, and caregivers to access them anywhere and any time. The advances in wireless communication, including low-cost medical sensors and advantageous applications for mobile devices, have made the collection and storage of a large amount of health data effortless. Although all these advances and applications offer benefits, they also raise challenges.

Health data should be stored remotely rather than on personal devices/accounts due to privacy issues, in which cloud storage has an important role to play. Indeed, no healthcare data breaches were associated with cloud computing, which should not deter move to the cloud. However, the Health Insurance Portability and Accountability Act (HIPAA) security rule does apply to electronic health record systems and requires certain safeguards, including assessing risk. Other issues include how to choose an appropriate service provider for e-health systems and how to regulate the pricing model, which also can hinder the efforts. Beyond these concerns, this potentially very applicable change to current practices will require real investment in time and resources.

Why hasn't this already happened? For one, doing so would probe the existing and related practices using e-health systems on the cloud. It would also involve uncertainty on the part involving the service provider.

Efforts are now underway to alleviate some of these issues. The e-health system is developed, deployed, and tested on commercial cloud environments. They are attempting to analyse and report the challenges of deploying e-health systems on the cloud in order to help research and introduce a new environment for researchers to build the next generation of e-health systems. Importantly, this experience analysis has not yet been reported in the literature. The potential benefits far exceed the difficulties, and it should be embraced for progress. In addition to service providers' utility, the platform itself can also provide the greatest benefits to health care stakeholders and contribute to healthier individual patients and populations.

3.1 Benefits of Cloud Infrastructure

Cloud computing is crucial to enabling the Internet of Things (IoT) in the healthcare sector. It serves as a basic component of the smart healthcare system. As IoT devices generate massive amounts of data, storage provided by the cloud becomes essential. Cloud computing also facilitates real-time monitoring and analysis of MCU-generated sensor data for trend prediction. For AI-empowered healthcare solutions, the cloud provides an environment for providing device-level features as input for intricate learning algorithms. The cloud is also necessary for processing massive amounts of video footage from smart cameras positioned inside the hospital premises.

Cloud computing delivers seamless accessibility of data over the internet to healthcare staff required for making decisions in emergency situations. Cloud-based databases prevent unauthorized data tampering while allowing data to be shared among relevant stakeholders. Healthcare solutions based on cloud computing help provide timely medical care to patients without them requiring to be present at a healthcare facility. AI-driven smart system solutions are used for intelligent patient profiling of clinical records. In this scenario, the record data must be stored on the cloud to facilitate real-time and instant accessibility of data at the healthcare institutions to provide healthcare solutions. Other cloud-driven applications in the domain of smart healthcare include providing smartwatch alerts, drug-specific patient profiling, sharing trained AI models, and central database access for connected hospitals.

Cheaper care at home for adults with health issues can be enabled through the IoT. Vulnerable patients can be continuously monitored in their home environments using cost-effective sensors and cameras connected through the IoT, transmitting their data wirelessly through nodes to a remote server. Sensors can be used to monitor important parameters such as temperature, heart rate, and blood pressure, and devices can be used to control medicines, doors, and lights, providing care to the patients. A specialized control and monitoring center can receive the sensor data from patients and provide timely health alerts, thereby revolutionizing patient care.

3.2 Security and Compliance in Cloud Solutions

The lack of security in cloud solutions can lead to data breaches, data loss, account theft, and service theft. Challenges such as inadequate x-security, incomplete data loss, slow-detection attacks, trust issues, and low-security performance make it difficult to ensure security in cloud solutions. To address these issues, a security-aware crisp multi-criteria decision-making model is presented, assessing cloud solutions based on security, ease of use, performance, compliance, and reliability. The model developed considers the threats, vulnerabilities, and compliance issues of major cloud service providers and can strengthen user options through a multi-criteria decision-making process. AI improves user experience and provides data security, but the AI algorithm should be accurate for effective decision-making. As cloud computing is a recent development of IT, its users may not fully parse the underlying cloud infrastructure, leading to increasing concerns about data storage security. Cloud computing providers must assure the competence and security of cloud solutions. Thus, the critical factors and criteria of AI-supported cloud solutions are presented. Decision-makers must choose cloud solutions involving many parameters, providers, services, or scoring, adding uncertainty to the process.

Cloud applications for banks were developed to provide customers with data socialization and security outside the organization. Although cloud applications provide socialization for interaction among users, data is vulnerable on the cloud, and security attacks need to be overcome. Designing methods to assure data security on the cloud for institutions is a challenge. Hybrid cloud storage models assure security, redundancy, recovery, and allocation of data on the cloud through access control and layered asymmetric key encryption for attacks. The secure multi-keyword ranked search on encrypted cloud data finds necessary information with cloud data storage on various factors through queries. Storage, security, and privatization of medical data involve a sizable amount of medical research data, including patient history, information, medical history, lab tests, etc. Sending data to the cloud can introduce security vulnerabilities and make the hospitalized patient's data vulnerable in sharing and storage. Data storage on the cloud utilizes IoT to detect extensive information, hence saving servers from junk data. Cloud support and history in health care data transfer the data between the patient and the doctor. Nevertheless, possibilities of data ambiguity must be taken care of, as this can lead in the wrong treatment by physicians.

4. Integrating AI with Cloud Computing

Edge AI models, where AI models run on lightweight hardware (such as wearables or IoT devices), are an efficient way to minimize communication issues. With the evolution of cloud computing, effective AI models requiring more extensive calculations can be run on the cloud rather than client devices. However, cloud-based systems need a stable and continuous connection to the internet. For example, in developing or underdeveloped countries, internet coverage may not be accessible everywhere or during emergencies, posing challenges in patient care delivery. Additionally, slow internet speeds may lead to high latency in decision-making and response times. As such, a hybrid framework, including both models, has been proposed to reap the benefits of both the edge and the cloud for medical image analysis.

Cloud computing has been touted as the next big thing, a game-changer and equalizer. It allows the remarkable processing and storage of archival data and enables any type of data provider to upload huge amounts of information. This massive use of cloud computing also offers a great potential for risk. A robust design and architecture is necessary to mitigate these risks and accurately execute the proposed algorithms for various applications while remaining within an acceptable timeframe. Possible applications in cardiology are monitoring patient compliance, recording changes in vital parameters (high blood pressure, arrhythmias, etc.), and detecting and discovering patterns in relatively small datasets such as Holter ECGs.

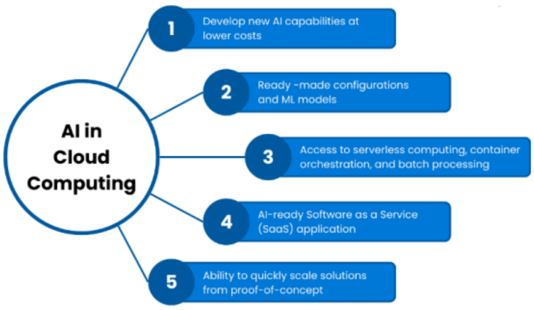

Figure 2: Integrating AI with Cloud Computing

4.1 Framework for Integration

The increased use of AI technologies in health care likely will require substantial changes in approach and implementation strategies. Patient data sharing and integration are prerequisites for AI research and health care systems. As almost all patient data is now stored in EHR by hospitals and health care providers, an approach for EHR compatibility, reduced heterogeneity, and harmonization of patient data could allow research and identification of AI candidate applications across health care systems, as well as improved analytics and export results to centralized AI services. Many cloud and edge-based and hybrid AI architectures, which include multicenter patient data collecting and processing, as well as in-and-out-of-hospital data integration, have been proposed, but few are currently used or fully developed. Simple on-premises EHR-compatible AI components running on a single server are commonly implemented. Nevertheless, as AI deployment within health care systems becomes increasingly frequent, blockchain technology will become an important part of health care infrastructure. One implementation example is MedRec. The MedRec platform leverages blockchain technology to authorize and manage data sharing between healthcare systems in a decentralized approach. While audit logs are maintained in the blockchain, identifiable health care information is not stored in the blockchain and retained in the source EHR systems. MedRec provides an off-chain data storage system and related oracles to facilitate blockchain data input/output for patient health care interactions and smart contracts that permit stricter access control. The MedRec architecture is general and can be deployed in any healthcare sector, notwithstanding required technology, stakeholders, associated rules, legislation, and social acceptability. The proposed framework for AI integration comprises 7 components, each of which involves several functions to clear the path toward rapid AI deployment in health care. The need for a robust framework that is likely to become a globally accepted standard arises from an observed proliferation in the diversity and complexity of healthcare AI applications and related architecture. The framework is needed to minimize fragmentation, promote multi vendor compatibility, and reduce operational complexity. The focus is on areas where clarity and organization are absent. The proposed framework is an initial step toward a holistic and transparent approach that promotes AI in health care. The framework consists of an original combination of mostly existing components, each carrying out important essential roles in AI integration in health care. The thorough definitions entail a more complete understanding. As far as can be ascertained, this framework for AI integration in health care is new, and its proposed application has not been previously described.

4.2 Case Studies of Successful Implementations

In this section, the case studies of the implementation of the Health Guardian platform and the STARR-Wave are introduced. The cases involve both advanced health care technologies developed recently to manage their patients and hackathons organized to encourage the use of the open-access dataset.

1) Health Guardian

The Health Guardian platform has been developed to build an ecosystem of digital health technologies to deliver better health care for the users. In this case, the usage of the full-fledged analytics capability offered by the framework from the inception of technologies is described. Wearable sensors to monitor heart rate, sleep quality, and physical activity and IoT devices to measure blood pressures and diet have been utilized to understand and improve the cardiovascular health conditions of the residents of a nursing home. Daily analytics services were employed to send a daily report to care coordinators to suggest follow-up actions. Weekly analytics services were also employed to summarize the change of 20 digital biomarkers (seasonality, outliers, and trends) over a full week. For further investigation, on-demand analytics services were often requested to conduct targeted individual assessments.

2) SCIRP STARR-Wave Dataset

The STARR-Wave dataset is a highly scalable database for storage and retrieval of waveform signals and clinical data. It was developed at Stanford's Children Hospital with data from bedside patient monitoring devices in the last four years. Recently, the dataset was open-sourced. As part of this endeavor, more than 800,000 hours of de-identified waveforms and signals from 14,000 patient admissions were released. The dataset's deep dive demonstrates the current research opportunities and challenges in this highly innovative research field. To showcase the usage of the database, content selection from various domains of research and application is performed. With the rich signal data produced by new bedside monitoring devices and constant growth of the data, new research questions and solutions will

Paper ID: MS2212142204 DOI: https://dx.doi.org/10.21275/MS2212142204

continue to come up. Data-driven and novel AI-based methods will continuously benefit health care and improve health outcomes.

5. Predictive Analytics in Patient Care

Predictive analytics has the potential to alter patient care by obtaining and analyzing past and present data in order to forecast future occurrences. Predictive models are built using algorithms capable of analyzing huge amounts of data and discovering patterns within the data. Medical data with its diverse and large volume is a perfect landscape for predictive analytics to locate new patterns, evaluate risk factors, and improve treatment protocols. These systems are not static, they continuously learn from new data, adapt to changes, and enhance their performance over time. Predictions are estimates of the likelihood of future events or outcomes based on past and current data. Forecasts about a population are made by constructing a statistical model based on a set of predictors. Illustrations of predictive modeling environments include catastrophe forecasting, sales forecasting, and blood supplies forecasting. While the predictive model is an analytical approach used primarily to design "what will happen" applications in a static environment, the term "decision model" describes methods that synthesize rules for choosing one alternative over another. AI predictive analytics provides a decision support capability comparable to that of a human expert. However, this can involve a vast amount of complex data that exceeds the capacity of existing systems. Also, the required solution may involve analysis methods that would be computationally impractical with current technology. While existing research offers promising approaches which are nevertheless either too nebulous for application in real-world patient care or not generalizable enough to be broadly useful, AI predictive models need to be evaluated in terms of different medical conditions and clinical care situations. The unprecedented influx of patient data from a myriad of sources is a boon to AI predictive analytics. However, much of this data is not normally recorded in database tables and difficulty acquiring data in real time and accuracy poses additional challenges.

5.1 Data Sources for Predictive Modeling

The collection of patient care data across local systems and cloud solutions at scale will be the first step toward better predictive modeling of critical care patients at the facility and enterprise levels for improved patient outcomes and efficient use of resources. Publicly available or shared de-identified data sets from the non-critical care space can enhance existing models and provide insights at wider scales. Cloud considerations, including synchronous live model training against incoming data streams, automatic model selection and retraining, and monitoring performance, development, and implementation costs, will all need to be addressed. AI/ML support for precision care, driven by the widespread deployment of remote patient monitoring devices, point-of-care diagnostic tests, and commercial wearable devices leverage sourced patient intervention. Support for decision-making, workflow automation, alerts, and prescriptions will be meaningful at the care facility and evaluation levels.

AI/ML techniques can automatically generate initial predictive models, although their performance may become less than optimal as environments change with time and patients. Ongoing collection of local administrative data across available operational and clinical data systems will provide the backbone for improved patient care. Interoperability can be improved using cloud-based ML-federated model share/centralized retraining and adaptation solutions. Use of de-identified public or shared data sets can seed some capabilities but only in a limited space and scale. The breadth and depth of data available at the local facility can be leveraged for better predictive modeling of specific care locations, such as the Emergency Room and Operating Room. Like operational data modeling, explainability and bias evaluations will also need to be taken into account in this application space.

Equ 2: Cloud Infrastructure Scalability Index (CSI)

$$CSI = \frac{N_s \cdot R_p}{T_u}$$

- **Where:**

  N_s = number of servers (nodes)

  R_p = requests processed per unit time

  T_u = average resource utilization

5.2. Impact on Patient Outcomes

The nurse's contribution is vital in elevating the role of data-driven decision-making and AI in nursing practice. This includes collaboration with AI engineers to create solutions, ensuring accessibility, availability, and the use of metrics to assess AI effectiveness on patient outcomes, supporting population health. There should be a focus on specific AI functionality in existing products to leverage data science solutions. AI can determine how well a care model meets individual needs, track the impact of patient care processes, and measure nurse performance against desired outcomes.

A more individualized approach to personalizing chronic disease management is evolving in the United States. Meaningful use of health information technology and electronic health records among healthcare providers is increasingly expected by the federal government. One area where electronic health records can be more useful is in the use of real-world data to inform medical decisions from health information technology. The importance of e-health includes visionary and enabled health status. E-health interventions provide opportunities for patients with chronic disease to access health education, clinical services, and self-management tools in a timely, flexible, and user-friendly manner. AI and cloud computing can play a crucial role in improving healthcare services in hospitals and clinics, enhancing patients' digital experiences, revolutionizing chronic disease treatment, and helping patients receive individualized and friendly care.

Healthcare disparities may lead to deteriorating patient outcomes, dissatisfaction, and mistrust in the healthcare community. Understanding the causes of health disparities is an important first step toward addressing their consequences.

AI and cloud computing can predict adverse patient outcomes under similar circumstances and recommend therapeutic interventions for immediate future care. These tools can also track data usage trends and create alerts for care providers to stop problems before they worsen. AI can provide forecast outcomes prediction in demographic areas and offer tailored care for targeting groups.

6. Challenges in Implementing AI and Cloud Solutions

Though the application of cloud computing and AI technologies in healthcare seem promising and potentially revolutionary, challenges need to be surmounted before these technologies can be credibly implemented. Awareness of limitations and potential pitfalls is still limited among healthcare providers and, moreover, awareness is not an established reality among AI characteristically non-expert stakeholders in the healthcare field. It has deeply perturbed the aftermath of healthcare driven out-of-the-ordinary permanently. There is still uncertainty regarding the patient impact of systems that have already been used for years in the clinic. Independent prospective clinical validation of novel AI algorithms in large cohorts, the need for regulatory authorities to adapt to the present era of rapid innovation, and possibly loss of personal patient data privacy could pose moral problems for many healthcare providers. Although excitement for AI is high, there is equal, if not higher, concern regarding the potential harms posed by the rollout of new modeling, technology, or treatment. Given the continual radical emergence of AI models, further evaluations will need to be made to determine the benefit-to-risk ratio of these systems. Basics regarding systems and model interpretability need to be imposed alongside implementation.

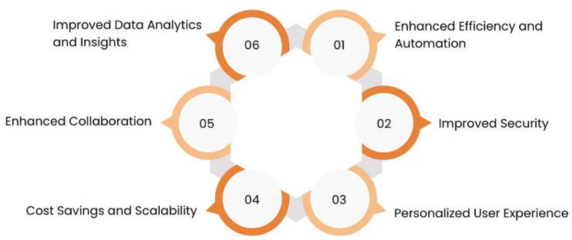

Figure 3: Challenges in Implementing AI and Cloud Solutions

The transformation of patient care with AI and cloud computing depends on collaboration between all stakeholders involved and a transformation of the research culture. Collectively tackling the practical incentivizing issues on the development of the cloud, decentralized, and quality side across wide-use health platforms would lay down a big leap of faith for collaborative AI research. Emerging collaborative frameworks and federated learning methods are to be better scrutinized and developed for healthcare. Leveraging experts' knowledge in the real-world settings at the study conception stage would facilitate trust and increase defendability and wide-use health platform accessibility. Incorporating external, heterogeneous, and real-world healthcare wide-use platforms in AI implementations should carefully consider and harmonize model resource efficiency, compatibility, and parameter-stability. With the tremendous advancement of the above technologies, uplifting the quality of available data, technical resource utilization efficiency, and clinical collaboration would help boost the implementation of AI in real-world settings.

6.1 Technical Barriers

Implementing AI-based digital health technologies into healthcare involves numerous technical barriers. One of them is usability and integration. As presented, usability was both an important facilitator and barrier. It was discussed in terms of eHI implementers customizing the technology to the context and the importance of intuitive design. Customization was also expressed as something that took much time and effort. Integration with related hospital systems was perceived as essential. Lack of interoperability was mentioned as a considerable barrier. A lack of integration with the clinical workflow can block the implementation process. Scalability was mentioned as a consideration by two eHI implementers regarding how relevant AI algorithms could be ported to other departments or hospitals. These considerations included the availability of training data, EHR and coding system being the same, and similar device characteristics, among others. Regarding user accounts and technical barriers, recent works in healthcare AI have shown significant technological advancement in research, yet poor adoption of these capabilities in the clinical setting. Collaboration in model design is often hindered by the organization. For instance, data lake systems, model performance evaluations, and deployment and integration infrastructures have often been built from scratch by every individual clinical team or researcher. This results in fragmented advances in model design and a lack of transparency regarding the evaluation and performance reporting of specific technologies. Even within the same organization, deep learning algorithms developed in one department can be difficult to transfer into models that operate on clinical data from another department.

As such, although there has been considerable technical advancement in healthcare AI recently, there are significant implementation and usability challenges that hinder clinical impacts of such technologies. Building accessible platforms with easy model integration and evaluation capabilities can facilitate collaborative development and reuse of such technologies. Such platforms can accelerate AI development in such a way that multi-center studies become feasible in this regulated and fragmented environment, which may improve model generalizability and robustness, and reduce patient care reproducibility issues seen with individual, localized model development. In addition, these platforms can bring research into the clinical workflow. Cloud infrastructure enables configuration of resource-efficient environments for competitive hardware specifications, with models that scale with each technical component independently.

6.2 Ethical Considerations

This advancement is exciting, but there are also serious challenges that have not yet been resolved. Integrating AI into healthcare with its reliance on patient data raises a question about how to define jurisdiction over that data. Remote collection, storage, and use by entities in different countries makes traditional regulatory frameworks inherently inadequate. AI can remove identify parameters from datasets, but as computation increases in power, it becomes possible to re-identify individuals. It must be ensured that patients can have reasonable control over how their data is used. Also, it must be provided assurance that there are adequate avenues for redress in the event that the data is leaked or misused. Other forms of AI have shown the potential to be repurposed for illegitimate use to harm individuals, and there is a fear that healthcare data could go the same way if not adequately protected. The healthcare industry has long struggled with patient privacy and maintaining confidentiality. A common point of frustration for patients is that data collection is compulsory and is associated with obtaining healthcare, but they know very little about how their data is used after it is collected. With the rise of commercial healthcare AI that use datasets derived from patient data, these concerns are amplified. Patients deserve to know how their data is stored, protected, and used after collection. Also, they need to be able to withdraw their data if they wish to, and they must know how to do this. As the regulation of patient data comes under increased scrutiny, it must be ensured that the values of patient agency and concern embed in new regulation. Operating assumptions for the regulation of healthcare AI include: first, current regulations governing health data privacy do not adequately recognize the power asymmetry and agency of patients. Hence, the agency of patients needs to be embedded in the development of regulations. Second, the regulatory visibility and transparency of the procedures through which data custodians protect data is currently lacking. Third, significant difficulties exist in attempting to anonymize data to the point of ensuring against re-identification. To deal with this it must be ensured that the data custodians adopt best practices for data protection. New regulation can aid in this through the concepts of data custodianship and secondary data.

7. Future Trends in Healthcare Technology

Recent advances in healthcare have seen increased attention given to the role of artificial intelligence (AI), cloud computing, and machine learning (ML) in healthcare. These technologies interact with existing firm-level and healthcare institutional/government factors and have the capability to transform patient care. The focus on the health informatics side facilitates the integral adoption of these digital technologies encompassing intelligent patient care systems. New data acquisition methods and data modes mean that ICT services can combine real-time and continuously collected patient data with long-term trend patient data about comorbidities and social conditions, and treat them all in the cloud for an enhanced prediction of patient treatment outcomes. Cloud computing provides organization flexibility and scalability through shared computing resources independent of location and device. Coupled with AI and ML computation technologies, providers can transform patient care systems to be more highly integrated and personalized. Patient care and disease prediction models can also benefit from cloud-based flexible and robust computing since they constantly need to be trained and updated with larger and evolving data sets. In addition to capabilities to directly impact patient care, cloud computing-based services can also enhance the overall efficiency of continuous patient monitoring systems by improving data dependability through data consolidation, correlation, and noise filtering.

Figure 4: Future Trends in Healthcare Technology

While technology can aid in providing enhanced patient care, it also introduces new compliance challenges for user organizations since they must conform to the regulatory requirements not only for the original use but also for enhanced uses. With the advent of many cloud security compliance models, user organizations will need guidance to choose properly from the multitude. The fast-growing market of AI will offer services that abstract the technical complexity away from users, but it also stirs concerns from a compliance viewpoint and about data privacy. In particular, healthcare providers may not be aware of which data are collected by which services since they may only have access to lightweight APIs. Therefore, interpreting the compliance of patient care services requires understanding details that are invisible from user organizations' perspectives. This creates the challenge of how to verify the compliance of external services properly in a way that assists user organizations to comprehend the compliance stance of data-driven services offering intelligent patient care systems, especially from a regulatory viewpoint.

7.1 Emerging Technologies

Digital Health has emerged as an active interdisciplinary field, driven by the rapid growth of personalized, predictive, and preventative healthcare. The widespread adoption of mobile phones, IoT devices, and wearable sensors for health monitoring has accelerated the growth of Digital Health, together with the affordability of cloud computing services. Traditional healthcare practices can be transformed and improved by incorporating new information technologies into the area of healthcare, such as edge computing, cloud computing, artificial intelligence (AI), etc. Digital biomarkers for health condition monitoring, or patient assessment, are measurements that can be obtained using digital means. Wearable technologies can be used to digitally monitor biodata, including physiological signals, which offer real-time, non-invasive, and objective measurements of the health of an individual. The collected digital biosignals can then be aggregated, preprocessed, encoded, fed into upstream AI and machine learning (ML) models for analysis, and reintegrated back to the wearable devices for action triggering.

The research on AI technologies in Digital Health has already made great strides in various healthcare domains. When AI models are trained with data from a multitude of input sources, a plurality of prediction results from these models, also known as AI ensemble models, would usually yield even better prediction results and performance for the aforementioned Digital Health applications. In the Diabetes Health domain, lifestyle- and health-related sensors, e.g., Advanced wearables for sleep monitoring, Smart home IoT-assisted applications for tracking activity levels, Dietplate, an

AI-powered plate to track the quantity and nutrition of food and beverages, and observational systems connected to multi-modal medical devices for screening diabetic retinopathy and cardiology, can potentially enhance the FBG Forecasting application to generate more accurate predictions of daily insulin needs, with less occurrence for hyperglycemia and hypoglycemia. Data fusion across sensing sources, biological signals, timeslots, and modes is required as many external factors can influence one health prediction task in this domain. This work introduces the Health Guardian (HG) architecture as a system-level design to provide a comprehensive end-to-end solution for the multi-modal assessments of an individual's health.

7.2 The Future of Patient Engagement

The future continues to hold an amazing array of innovations in AI and the cloud that will transform patient engagement. Already, companies have partnered with forward-thinking providers to create cost-efficient telehealth channels that help connect primary care patients to needed specialty care. Expanding telehealth into extended and urgent care allows real-time triage of patients, directing them to the appropriate care location for their needs and insurance status. These approaches better utilize and augment provider capacity, allowing better coverage of expensive fixed costs and increasing cross-revenue between specialties while patients receive more timely care at the lowest effective cost. All parties benefit. Other tools and services foster patient self-care, agenda setting, and improved communications about care transitions, medication adherence, and follow-up appointments to decrease preventable ED visits and readmissions.

As revenue models evolve to reward healthier populations rather than transaction volumes, improvements in patient care, access, health equity, and financial performance will be markedly accelerated. The future of patient engagement is bright for health systems, patients, and their communities alike. AI- and cloud-enabled innovations in telehealth and proactive patient engagement will target the right care at the right time by the right provider. This will improve population health in a manner that is more equitable, cost effective, and satisfying for all. To help prevent disillusionment and moral hazards as AI transforms the interactions between patients and families with their healthcare systems, the trend toward consumerization of care must not only be embraced but championed. These AI-enabled, cloud-delivered products and services will help engage patients in their healthcare journey while supporting, augmenting, and maintaining the primacy of their healthcare systems.

In parallel, the cloud-based augmentation of practice management technology must shift to a more collaborative care platform that allows all types of engagement to be channeled from patient to provider, new-to-practice to onboarding, and enrollment to scheduling and telehealth visits. This connectivity will support coordinated workflows by internal teams as well as partner organizations. Overall, the near-term future looks very promising for the acceleration of the consumption, development, and implementation of AI- and cloud-enabled engagement products and services that link patients, families, and community members more seamlessly to appropriate care within healthcare systems.

8. Scalability of AI Solutions in Healthcare

A methodology for a scalable, collaborative, and resource-efficient platform to facilitate healthcare AI research is presented. Recent advances in artificial intelligence (AI) in healthcare hold the potential to increase patient safety, augment efficiency, and improve patient outcomes. In clinical care itself, AI technologies can aid physicians in diagnosis and treatment selection, risk prediction and stratification, and improving patient and clinician efficiency. In order for healthcare AI research to revolutionize patient care, processes across healthcare data pools should first be harmonized. The barriers to translating data science research to patient care are inadequate data quality, scarce resources, and high patient confidentiality needs. The 2009 Health Information Technology for Economic and Clinical Health Act incentivized hospitals to adopt electronic medical records, which transformed a paper-heavy industry into a well-connected one. These increasingly ubiquitous health information technology (HIT) systems provide an unprecedented rich medical data source. Most electronic health record (EHR) systems store patient data in highly heterogeneous formats, with many institutions also combined with legacy systems. On top of the structured data, there are large amounts of unstructured data such as physician notes, discharge summaries, and reports.

The nature of EHR data also yields a significant degree of missingness, misclassification, and errors. Furthermore, high-dimensional data such as genetic information or fetal cardiotocography would provide valuable clinical insights but require significant storage and processing capacity. Finally, harmonizing these diverse data sources imbued with multiple representations of the same medical events can be a very time-consuming and resource-heavy process. In response to mounting demands for better tools, analysis of healthcare data is an emerging area of research, particularly for AI, ML, and deep learning technique development. Healthcare services and use of health data are now performed on cloud infrastructure as a standard industry practice. This transformation is part of a broader transition from local big data analyses to the cloud, impacting business sectors, worldwide. While the fundamental premise of cloud computing involves cost reduction, there are multiple aspects that can determine the efficiency of cloud operations. The exploratory nature of most ML and AI projects makes it impossible to develop and maintain efficient cloud configurations that could be applied to multiple projects. Cloud computing is becoming commonplace in healthcare services while offering scalable and flexible infrastructure to improve patient care.

8.1 Strategies for Scaling AI Applications

Clinical artificial intelligence (cAI) development strategies are defined by the types of development teams and circumstances surrounding the project. Branding a program a "niche" cAI is a shorthand to highlight the nature of the healthcare topic or setting that defines the scope of algorithm development. This not only conveys the ambitious "scalability", but also implicitly informs of the operational risk of deploying the algorithm across different centers and settings of care. Over the years, many cAI product pipelines have been proposed to solve the development, validation, and deployment challenges. However, there remains no consensus on the exact form that each step of the cAI development pipeline should take. For many well-resourced groups, scaling partners are generally contacted at the very last minute when the algorithm is already fully developed to negotiate deployment, pushing aside the aforementioned concerns. These arrangements often fall flat. While small, agile cAI teams have recommended a "collaborative" model to firmly fix the course of scaling discussions to the very first step of the pipeline, it is unclear whether this is a feasible alternative for large teams.

Despite a restrictive model very much resembling Tinder for EaaS partners helping find the right teammate, there are countless variables in finding the right partner, potentially difficult if not exhausting to account for. Additionally, restricting processing to enormous workloads may minimize overheads and useless dues, but also potentially leads to clumsy processes and unusable outputs that momentarily halt the stepping stones toward banking global user bases. Throughout these worries and uncertainties of cAI product scaling lie the core principles of trust, credibility, and safety. Ultimately, does it cost too much to alert or update hospitals' EHR systems with product development and testing births, successes, failures, and pivotings? Is it worth the risk of losing long-term institutional trust and goodwill as a champion cAST partner before even arriving at this phase? Might it still be better to quite literally "be hated" by a handful of disenchanted centers than "just trusted" by others from a distance?
Unchaining the four interlinked steps upon which the cAI product circle is currently forged into four separate manifestations of processing would allow for parked permutations. It helps a group's exact processes become clearer, whether reentering processing to earlier steps or assisting others new to it in on-boarding at later offerings. Lastly, this untethering allows for subprocesses laid bare of layers to be seen, appreciated, and analyzed on a more atomic level, hopefully accelerating progress across both successes and failures across the field.

8.2 Real-World Examples of Scalable Solutions

The ability to develop scalable solutions is one of the major qualities of the cloud computing concept. Combining the cloud with AI technologies makes the development and adoption of patient care solutions much simpler. Real-world examples of cloud- and AI-based patient care solutions that scale well and have been effectively implemented in national and international healthcare systems include a healthcare data science cloud-based solution. is a cloud-based remote healthcare monitoring architecture developed to solve the challenge of scaling patient care applications from pilot to nationwide deployments. This architecture is a highly scalable solution that combines cloud-based microservices and lightweight IoT-based healthcare wearables. It has been effectively deployed in one of the largest university hospitals in France. The architecture is a critical microservice-based vertical solution that leverages the cloud to seamlessly distribute the computation load across multiple instances of its managing services and their respective cloud-based databases. One of the architecture's innovative concepts is a microservice auto scaling method that adjusts the number of pods of a microservice based on the latency parents of its endpoints. This method takes into account the latency of multiple endpoints as well as the number of microservice pods, which enhances the auto scaling approach from previous works that applied basic scaling methods that monitored the load through CPU and memory usage bases only.

A healthcare data science cloud-based platform has recently been developed to allow institutions to run AI projects on their healthcare data. The open-source platform equips analysts with data pipelines, compute clusters, and a private cloud interface to facilitate data processing, cloud computing, and model implementation. The platform's modular and interoperable design allows institutions, regardless of their data infrastructure, to customize individual modules or integrate the full suite. The platform addresses challenges unique to healthcare AI, such as federated learning, which allows institutions to collaborate training models using raw data distribution while maintaining data privacy and ownership.

9. Interoperability in Healthcare Systems

The heterogeneity of electronic health record (EHR) systems across healthcare entities hampers the provision of interoperable and standardized data for machine learning and predictive analytics. The adoption of "big data" technology would allow the rapid ingestion, processing, and analysis of this data. Data across disparate institutions can be analyzed in aggregate without compromising patient confidentiality. The proposed implementation is built around the application of a global data and model exchange mechanism mediated by user-controlled agents empowered with local learning.

By restricting data access to a global model trained on local data warehouses, decentralized collective-action algorithms enable the application of scalable machine learning methods to extremely large amounts of heterogeneous data while keeping sensitive information secure and private. Use case scenarios of model collaboration involve both data-poor and data-rich settings. There are many models available at various stages of sourcing various data. The design is agnostic to the specifics of the approach or type of model. Healthcare is faced with unique considerations in the design and development of software and hardware. The possible outcomes and risks should be considered. An analysis of the status quo identifies gaps and hurdles that hinder the use and development of general AI. As models of health care evolve, it will be crucial to consider the role of topic experts.

EHR systems store patient data in heterogeneous formats. For example, some systems champion structured data for medications and laboratory data while others fit more with imaging data. In addition, there are large amounts of unstructured data like physician notes, discharge summaries, and reports. Standardizing unstructured data is crucial for the scalability of machine learning applications. Most EHRs are relational databases where the structure of data can be queried using a standardized query language. Frameworks already exist for the transformation and export of relational data to machine learning-ready formats. On the other hand, these data are not infallible and have a significant degree of missingness, misclassification, and errors.

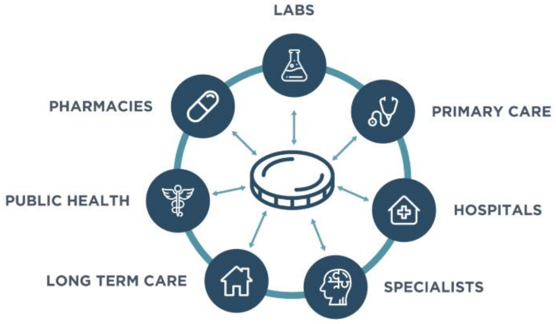

Figure 5: Interoperability in Healthcare Systems

9.1. Importance of Data Sharing

The Fourth Industrial Revolution comes with demand for data and the advanced techniques to prepare and analyze that data. Medical data, perhaps more than most, is a quest, yet sharing that data is logistically difficult. Security and intellectual property are important concerns that have slowed the growth and access, so machine learning and artificial intelligence capabilities have not kept pace compared to other industries. Without shared training data, computer-based model development is narrowly focused by availability and practicality. AI development in medicine has begun, before being prepared for it. There are many examples where the use of AI is being pursued in cancer medicine today, in some cases leading to clinical uptake; these algorithms have transitioned from R&D to clinical use.

The rapid and widespread adoption of these AI approaches in cancer medicine highlights the need to rethink how we manage the key ingredient for their utility–the data. Big oncology data is a double-edged sword. The growing dependence of cancer management on imaging has created a demand for AI-based approaches to improve efficiency, ensure quality and standardization, and reduce costs. Today there exist imaging, clinical, operational, and administrative data silos within healthcare institutions. AI approaches are also transforming cancer research with algorithms that can automatically flag patients for eligibility to open clinical trials, and the development of natural language processing tools.

A growing awareness has emerged around the need to establish purpose-built frameworks for algorithm development, validation, clinical commissioning, and ongoing monitoring, in a clinical setting. To this end, a robust data governance framework will be crucial in supporting and driving AI model management, performance and robust data governance will raise important questions regarding access, curation, and governance of data.

Equ 3: Outcome Improvement Rate (OIR).

$$OIR = \frac{O_{AI} - O_{base}}{O_{base}} \cdot 100$$

- Where:

  O_{AI} = patient outcome metric with AI intervention

  O_{base} = baseline outcome without AI support

9.2. Standards and Protocols for Interoperability

The increasing amount of health data is becoming exponentially big all over the world. This paper summarized some actual integrable and well-deployed systems related to the biocompatible Cloud architecture in the healthcare sector. Additionally, several new technologies have been observed which have interoperability in the actual research, but they have not yet been clinically implemented. This paper aims to show the barriers of interoperability in clinical practice in general, and mainly in the health data processing. Last but not least, a Cloud architecture has been described to process bio-sensor data in a health management system which allows the accessibility of its stimulated processing.

A method was discovered to explore the interoperability of integrating Bio-Sensor Networks and Cloud Computing technology in the healthcare domain. Current research findings and its implemented clinical systems of biocompatibility and Cloud architecture on clinical decision support in the health sector were reviewed by searching scientific databases. Today's clinical systems to integrate bio-sensory data are mainly off-line-based and proprietary systems involving high-cost proprietary devices and software, inhibition of data standardization regarding the pre-processed databases before securing permanently embedded application software, and excess of ecosystem meshes and complexity of designing and deploying operational systems both in research centers and in clinic practice primarily regarding the ongoing network technology.

On the other hand, new technologies like Cloud Computing and data mining, various types of wearable devices, and inference engines have recently been observed in healthcare. Although these technologies can have a dramatic impact on health management systems and their interoperability, in practice; they are expected to be late-adopters in clinical practice.

10. Collaboration between Technology and Healthcare Professionals

Today's healthcare sustainability challenges at society and business level, the expected detrimental effects of an aging population, rising labor costs, resource scarcity, and a persisting pandemic healthcare staffing shortage, necessitate fundamental change at health systems worldwide. Improving sustainability in healthcare is not only vital for the citizen's health and quality of life, but also for ensuring profitable growth for insurance companies, hospitals, teleconsultation platforms, and emerging information and communication technology vendors. There is a significant niche for emerging technologies in healthcare, which is increasingly characterized by The Fourth Industrial Revolution and pharmaceutical processes. New digitally driven end products are expected to emerge, with exponentially accelerating healthcare provision outside of health systems, e.g. via diagnostic wearable sensors and apps for individual health advice on stress management and physician alternative drug prescription.

AI in healthcare is expected to significantly reduce the administrative burden on health administration. The integration of AI in healthcare administration processes is anticipated to streamline administrative processes by 30% in the coming five years. AI in healthcare is expected to also significantly reduce the physician's diagnosis time. In a collaborative and consultative manner, algorithm tools such as symptom checkers and lab data evaluators will assist physicians toward clinical diagnosis against clearly stated guidelines. ChatGPT-like tools will assist physician communication with patients. A significant share of physician time spent on administration and low-value decision-making tasks is expected to be an alternative to high-value tasks in patient care, e.g. complex diagnoses.

In a collaborative and consultative manner, intelligent agent technology such as AI-enabled digital friends and assistive robots is expected to take care of caregiver tasks, e.g. monitoring patient medication adherence and compliance, exercise engagement, and dietary intake. This will be permissible-on-demand for caregivers, governance and security personnel, care demand initiators (e.g. elderly or their family), and medical devices collectively engaging in care provision and personal health management. The monitoring is envisaged by a novel continuous patient engagement mechanism by connecting smart medical devices to social networks.

10.1 Building Effective Teams

What does it mean to build an effective team? Instead of teams becoming more effective over time, they often become less effective. They start out getting along well, but their performance declines as members become bored and dissatisfied. To understand this paradox, social scientists have built models to study how team interactions and performance changes over time. In this model, teams consist of three members that each experience multiple potential interactions in each time step. Based on the success of each interaction, the team's behavior and the interaction options available to team members change over time. The results indicate that when teams become more proficient in their tasks, they also become more vulnerable to the negative effect of boredom. Effective teams become invested in interactions that are already successful at the expense of new approaches, resulting in declining performance over time.

Effective teams possess a broad repertoire of interaction behaviors that they use flexibly as task demands change over time. However, teams can also develop rigid patterns of interaction that constrain their ability to perform effectively in dynamic tasks. These necessary but often vague conditions for team effectiveness have been translated into observable and more concrete phenomena at the behavioral level. These predictors of team effectiveness have proven useful to scholars and practitioners alike in designing, describing, and assessing effective teams.

Human-AI teams built through the teamwork and team training literature are described and the particular design, training, and implementation challenges to be addressed to foster effective human-AI teaming in healthcare are identified. AI systems need to be credited with useful teaming capabilities and appropriately integrated into team networks to be effective teamwork facilitators. Ideal design solutions would not merely replicate existing human-human teamwork structures and practices. Instead, unique AI capabilities would be applied to augment teamwork processes beyond what is currently possible.

10.2 Training Healthcare Professionals

All healthcare professionals should grasp the potential of advanced AI tools and other breakthrough innovations. Such knowledge should blend with robust medical education and a firm grasp of traditional apparatuses that AI cannot replace. Even simple software used in some fields is far from being exploited properly, demonstrating sufficient daylight for AI systems' optimization and win-win scenarios. The goal in this study is to highlight AI's potential applications and limitations in healthcare, used efficiently in two main streams: IT and robots. The first stream allows for improved control of service management systems such as electronic medical records (EMR) and software used to analyze medical images. EMRs give access to all types of patient medical information in any hospital/faculty in a given country, eliminating paperwork and lowering the cost of hired personnel documentation. Image analysis software supports diagnostic interpretation, speeding up image analysis, reducing labor force costs for analysis, decreasing subjective bias, and enabling tele-consultation. The second stream is used in interventional cardiology to perform percutaneous coronary artery (CA) procedures. Robotic navigation has been successfully implemented in anatomy image analysis and device steering in diagnostic CA procedures. Totally robotic navigation systems allow devices to navigate in the body with no supplementary interventionist sign in the catheterization laboratory. An interventional cardiologist can control the device from a separate room, decreasing contagion and civil liability. Long sessions are also safe for the doctor, decreasing the risk of chronic health problems caused by permanent ionizing radiation exposure. The technology itself is safe, with an ongoing need to propagate it to reach all interventional cardiologists. The gap created by the technology itself needs to be integrated with a proper training course, assuring that established rules of good practice are followed to eliminate unnecessary risks. Computerization limitations of the intervention are discussed, with an emphasis on AI's role in training an interventional cardiologist for robotic procedures.

11. Conclusion

Increasingly, artificial intelligence (AI) is revolutionizing the way care is delivered to patients. Hammered by the COVID-19 pandemic, healthcare systems need to leverage demands and resource management more efficiently. Cloud computing (CC) offers enormous resources for data processing, accessibility, and storage when combined with IoT. On such a platform, advanced AI algorithms can run more complex data analysis that could not be realized on local systems before, thus distributing better patient care in a fragmented healthcare ecosystem. There are several applications that detect and manage patient risk based on multiple data sources, needing only a web browser connected to the internet. Users (doctors, care coordinators, care managers and end-users) can easily access the platforms and view automatic or guided analyses without needing data science knowledge.

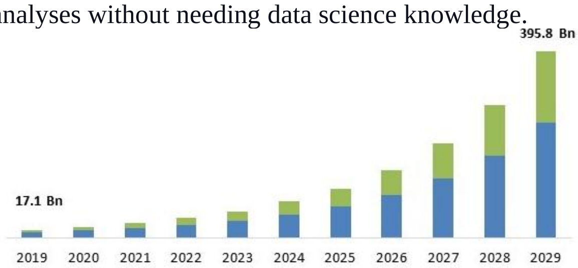

Figure 6: Patient Care with AI and Cloud Computing

Currently, engineers develop machine learning (ML) algorithms that work on a computer laboratory using public datasets. In most cases, they achieve scores below the benchmarks set with models they do not share, making it impossible for the healthcare providers to follow through on the promise of better patient care with predictive analytics. Low-hanging fruits are potential patient risk score dashboard solutions focused on patient admission. Patients admitted by emergency could be deep-dived in real-time with auto-detection engines. The explanation of results could be based on internal rule engines of the ML method. The higher the accuracy of risk prediction, the more explicit auto-checks need to be developed. Off-the-shelf auto-explaining platforms launched on healthcare, however, are only based on publicly available numeric data. As new patient health management institutes have been emerging and more risk models are springing up, healthcare providers desperately seek better and more complex patient risk solutions.

Technology is radically transforming healthcare with market size projections reaching approximately $200 billion by 2030, fueling accelerating advancements in hyper-personalized wearables, robotic surgical systems, and connected health devices. Deep learning based AI, broadly referring to machine learning systems with many hidden layers or parallel data processing capabilities, drives the development of a myriad of next-gen health detection and treatment software. These algorithms have been trained on massive datasets and are delivered via cloud systems, improving patient outcomes and decreasing healthcare costs and delivery inefficiencies. AIoT is now garnering similar attention with burgeoning funding being funneled into edge-enabled health systems. AIoT refers to the internet of things (IoT) systems edge empowered with AI algorithms, continuing the popularization of AI-based health alternatives by providing affordable yet highly accurate edge systems that can be embedded in medical devices or IoT terminals deployed in public spaces.

References

[1] Kommaragiri, V. B., Preethish Nanan, B., Annapareddy, V. N., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Narasareddy and Gadi, Anil Lokesh and Kalisetty, Srinivas.

[2] Pamisetty, V., Dodda, A., Singireddy, J., & Challa, K. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies. Jeevani and Challa, Kishore, Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies (December 10, 2022).

[3] Paleti, S. (2022). The Role of Artificial Intelligence in Strengthening Risk Compliance and Driving Financial Innovation in Banking. International Journal of Science and Research (IJSR), 11(12), 1424–1440. https://doi.org/10.21275/sr22123165037

[4] Komaragiri, V. B. (2022). Expanding Telecom Network Range using Intelligent Routing and Cloud-Enabled Infrastructure. International Journal of Scientific Research and Modern Technology, 120–137. https://doi.org/10.38124/ijsrmt.v1i12.490

[5] Pamisetty, A., Sriram, H. K., Malempati, M., Challa, S. R., & Mashetty, S. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Tax Compliance, and Audit Efficiency in Financial Operations (December 15, 2022).

[6] Mashetty, S. (2022). Innovations In Mortgage-Backed Security Analytics: A Patent-Based Technology Review. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3826

[7] Kurdish Studies. (n.d.). Green Publication. https://doi.org/10.53555/ks.v10i2.3785

[8] Motamary, S. (2022). Enabling Zero-Touch Operations in Telecom: The Convergence of Agentic AI and Advanced DevOps for OSS/BSS Ecosystems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3833

[9] Kannan, S. (2022). AI-Powered Agricultural Equipment: Enhancing Precision Farming Through Big Data and Cloud Computing. Available at SSRN 5244931.

[10] Suura, S. R. (2022). Advancing Reproductive and Organ Health Management through cell-free DNA Testing and Machine Learning. International Journal of Scientific Research and Modern Technology, 43–58. https://doi.org/10.38124/ijsrmt.v1i12.454

[11] Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55-72.

[12] Meda, R. (2022). Integrating IoT and Big Data Analytics for Smart Paint Manufacturing Facilities. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3842

[13] Annapareddy, V. N., Preethish Nanan, B., Kommaragiri, V. B., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Bhardwaj and Gadi, Anil Lokesh and Kalisetty, Srinivas, Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital

Paper ID: MS2212142204 DOI: https://dx.doi.org/10.21275/MS2212142204

Infrastructure, Secure Networks, and Intelligent Manufacturing (December 15, 2022).

[14] Phanish Lakkarasu. (2022). AI-Driven Data Engineering: Automating Data Quality, Lineage, And Transformation In Cloud-Scale Platforms. Migration Letters, 19(S8), 2046–2068. Retrieved from https://migrationletters.com/index.php/ml/article/view/11875

[15] Kaulwar, P. K. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19, 1987-2008.

[16] Malempati, M. (2022). Transforming Payment Ecosystems Through The Synergy Of Artificial Intelligence, Big Data Technologies, And Predictive Financial Modeling. Big Data Technologies, And Predictive Financial Modeling (November 07, 2022).

[17] Recharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.

[18] Lahari Pandiri. (2022). Advanced Umbrella Insurance Risk Aggregation Using Machine Learning. Migration Letters, 19(S8), 2069–2083. Retrieved from https://migrationletters.com/index.php/ml/article/view/11881

[19] Paleti, S., Burugulla, J. K. R., Pandiri, L., Pamisetty, V., & Challa, K. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Regulatory Compliance, And Innovation In Financial Services (June 15, 2022).

[20] Singireddy, J. (2022). Leveraging Artificial Intelligence and Machine Learning for Enhancing Automated Financial Advisory Systems: A Study on AIDriven Personalized Financial Planning and Credit Monitoring. Mathematical Statistician and Engineering Applications, 71 (4), 16711–16728.

[21] Paleti, S., Singireddy, J., Dodda, A., Burugulla, J. K. R., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures (December 27, 2021).

[22] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Available at SSRN 5232395.

[23] Koppolu, H. K. R. (2021). Leveraging 5G Services for Next-Generation Telecom and Media Innovation. International Journal of Scientific Research and Modern Technology, 89–106. https://doi.org/10.38124/ijsrmt.v1i12.472

[24] End-to-End Traceability and Defect Prediction in Automotive Production Using Blockchain and Machine Learning. (2022). International Journal of Engineering and Computer Science, 11(12), 25711-25732. https://doi.org/10.18535/ijecs.v11i12.4746

[25] Chaitran Chakilam. (2022). AI-Driven Insights In Disease Prediction And Prevention: The Role Of Cloud Computing In Scalable Healthcare Delivery. Migration Letters, 19(S8), 2105–2123. Retrieved from https://migrationletters.com/index.php/ml/article/view/11883

[26] Sriram, H. K., ADUSUPALLI, B., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks.

[27] Avinash Pamisetty. (2021). A comparative study of cloud platforms for scalable infrastructure in food distribution supply chains. Journal of International Crisis and Risk Communication Research , 68–86. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2980

[28] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.

[29] Dodda, A. (2022). The Role of Generative AI in Enhancing Customer Experience and Risk Management in Credit Card Services. International Journal of Scientific Research and Modern Technology, 138–154. https://doi.org/10.38124/ijsrmt.v1i12.491

[30] Gadi, A. L. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research, 11-28.

[31] Pamisetty, A. (2022). A Comparative Study of AWS, Azure, and GCP for Scalable Big Data Solutions in Wholesale Product Distribution. International Journal of Scientific Research and Modern Technology, 71–88. https://doi.org/10.38124/ijsrmt.v1i12.466

[32] Adusupalli, B. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research, 45-67.

[33] Dwaraka Nath Kummari. (2022). Iot-Enabled Additive Manufacturing: Improving Prototyping Speed And Customization In The Automotive Sector . Migration Letters, 19(S8), 2084–2104. Retrieved from https://migrationletters.com/index.php/ml/article/view/11882

[34] Data-Driven Strategies for Optimizing Customer Journeys Across Telecom and Healthcare Industries. (2021). International Journal of Engineering and Computer Science, 10(12), 25552-25571. https://doi.org/10.18535/ijecs.v10i12.4662

[35] Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101-122.

[36] AI-Based Financial Advisory Systems: Revolutionizing Personalized Investment Strategies. (2021). International Journal of Engineering and Computer Science, 10(12). https://doi.org/10.18535/ijecs.v10i12.4655

[37] Karthik Chava. (2022). Harnessing Artificial Intelligence and Big Data for Transformative Healthcare Delivery. International Journal on Recent

and Innovation Trends in Computing and Communication, 10(12), 502–520. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11583

[38] Challa, K. (2022). The Future of Cashless Economies Through Big Data Analytics in Payment Systems. International Journal of Scientific Research and Modern Technology, 60–70. https://doi.org/10.38124/ijsrmt.v1i12.467

[39] Pamisetty, V., Pandiri, L., Annapareddy, V. N., & Sriram, H. K. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management (June 15, 2022).

[40] Innovations in Spinal Muscular Atrophy: From Gene Therapy to Disease-Modifying Treatments. (2021). International Journal of Engineering and Computer Science, 10(12), 25531-25551. https://doi.org/10.18535/ijecs.v10i12.4659

[41] Kaulwar, P. K. (2022). Data-Engineered Intelligence: An AI-Driven Framework for Scalable and Compliant Tax Consulting Ecosystems. Kurdish Studies, 10 (2), 774–788.

[42] Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments. (2022). International Journal of Engineering and Computer Science, 11(12), 25691-25710. https://doi.org/10.18535/ijecs.v11i12.4743

[43] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58-75.

[44] Raviteja Meda. (2021). Machine Learning-Based Color Recommendation Engines for Enhanced Customer Personalization. Journal of International Crisis and Risk Communication Research , 124–140. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3018

[45] Rao Suura, S. (2021). Personalized Health Care Decisions Powered By Big Data And Generative Artificial Intelligence In Genomic Diagnostics. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v7i3.3558

[46] Implementing Infrastructure-as-Code for Telecom Networks: Challenges and Best Practices for Scalable Service Orchestration. (2021). International Journal of Engineering and Computer Science, 10(12), 25631-25650. https://doi.org/10.18535/ijecs.v10i12.4671

[47] Vamsee Pamisetty, Lahari Pandiri, Sneha Singireddy, Venkata Narasareddy Annapareddy, Harish Kumar Sriram. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Migration Letters, 19(S5), 1770–1784. Retrieved from https://migrationletters.com/index.php/ml/article/view/11808

[48] Someshwar Mashetty. (2020). Affordable Housing Through Smart Mortgage Financing: Technology, Analytics, And Innovation. International Journal on Recent and Innovation Trends in Computing and Communication, 8(12), 99–110. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11581

[49] Srinivasa Rao Challa,. (2022). Cloud-Powered Financial Intelligence: Integrating AI and Big Data for Smarter Wealth Management Solutions. Mathematical Statistician and Engineering Applications, 71(4), 16842–16862. Retrieved from https://philstat.org/index.php/MSEA/article/view/2977

[50] Paleti, S. (2022). Fusion Bank: Integrating AI-Driven Financial Innovations with Risk-Aware Data Engineering in Modern Banking. Mathematical Statistician and Engineering Applications, 71(4), 16785-16800.

[51] Pamisetty, V. (2022). Transforming Fiscal Impact Analysis with AI, Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance. Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance (November 30, 2022).

[52] Kommaragiri, V. B., Gadi, A. L., Kannan, S., & Preethish Nanan, B. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization.

[53] Annapareddy, V. N. (2022). Integrating AI, Machine Learning, and Cloud Computing to Drive Innovation in Renewable Energy Systems and Education Technology Solutions. Available at SSRN 5240116.

[54] Transforming Renewable Energy and Educational Technologies Through AI, Machine Learning, Big Data Analytics, and Cloud-Based IT Integrations. (2021). International Journal of Engineering and Computer Science, 10(12), 25572-25585. https://doi.org/10.18535/ijecs.v10i12.4665

[55] Venkata Bhardwaj Komaragiri. (2021). Machine Learning Models for Predictive Maintenance and Performance Optimization in Telecom Infrastructure. Journal of International Crisis and Risk Communication Research , 141–167. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3019

[56] Paleti, S. (2021). Cognitive Core Banking: A Data-Engineered, AI-Infused Architecture for Proactive Risk Compliance Management. AI-Infused Architecture for Proactive Risk Compliance Management (December 21, 2021).

[57] Harish Kumar Sriram. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Mathematical Statistician and Engineering Applications, 71(4), 16729–16748. Retrieved from https://philstat.org/index.php/MSEA/article/view/2966

[58] Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29-41.

[59] Data Engineering Architectures for Real-Time Quality Monitoring in Paint Production Lines. (2020). International Journal of Engineering and Computer Science, 9(12), 25289-25303. https://doi.org/10.18535/ijecs.v9i12.4587

[60] Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967
[61] Pandiri, L., & Chitta, S. (2022). Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3760
[62] Kummari, D. N. (2022). AI-Driven Predictive Maintenance for Industrial Robots in Automotive Manufacturing: A Case Study. International Journal of Scientific Research and Modern Technology, 107–119. https://doi.org/10.38124/ijsrmt.v1i12.489
[63] Gadi, A. L. (2022). Cloud-Native Data Governance for Next-Generation Automotive Manufacturing: Securing, Managing, and Optimizing Big Data in AI-Driven Production Systems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3758
[64] Dodda, A. (2022). Secure and Ethical Deployment of AI in Digital Payments: A Framework for the Future of Fintech. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3834
[65] Gadi, A. L. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179-187.
[66] Dodda, A. (2022). Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks. International Journal of Scientific Research and Modern Technology, 1(12), 10-25.
[67] Just-in-Time Inventory Management Using Reinforcement Learning in Automotive Supply Chains. (2021). International Journal of Engineering and Computer Science, 10(12), 25586-25605. https://doi.org/10.18535/ijecs.v10i12.4666
[68] Srinivasa Rao Challa. (2021). From Data to Decisions: Leveraging Machine Learning and Cloud Computing in Modern Wealth Management. Journal of International Crisis and Risk Communication Research , 102–123. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3017
[69] Kommaragiri, V. B. (2021). Enhancing Telecom Security Through Big Data Analytics and Cloud-Based Threat Intelligence. Available at SSRN 5240140.