



Towards Efficient Healthcare Management: Leveraging Computer Science Technologies

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Abstract: This research explores the use of emerging technologies in computer science in the management of health care domain particularly with an intent to combine AI, wearable devices, blockchain, and quantum computing. They assessed deep learning models and algorithms and determine how the development of Artificial Intelligence enhance the diagnosis precision and the health care procedures. Smart watches as wearable technologies were used to collect actual health information to help a patient with managing his chronic disease. In efforts to maintain privacy of data, blockchain engineering was sort to enable secure exchange of medical information. Also, possible implications of quantum computing in reshaping medical data was also a topic of consideration. We expanded the effectiveness of AI models for medical image diagnosis to 92% of the total, and wearable devices helped decrease the rehospitalization rate for chronic patients by 30%. Blockchain was incorporated to increase efficacy of transmission of patient information across organizations by twenty-five percent. Quantum computing showed fifteen percentage improvement in the rate at which large scale medical datasets could be processed. The study also show that these technologies improve the efficiency, security and quality of the health sector and open up new opportunities in the development of modern health care platforms. More empirical enquiry should be conducted to investigate the issues of implementation, effectiveness and ethicality.

Keywords: *Artificial Intelligence, Wearable Devices, Blockchain, Quantum Computing, Healthcare Management.*



I. INTRODUCTION

The healthcare industry has been evolving as computer science technologies applied to boost its status. AI, big data analytics, IoT and blockchain seem to have provided new opportunities to improve the organization and delivery of healthcare administration. Due to the ageing population in developing countries, along with the increasing incidences of chronic diseases, as well as continually rising costs of health care, anticipated for the expansion of information systems carry out an increasingly important role in the development of innovations for progress in health care. Many of these technologies have the capacity to transform the administration in health care institutions by means of: reducing time for administrative work; patient monitoring; efficient allocation of resources; and informed decision-making in clinical settings [1]. Diagnostic capabilities based on AI, machine learning algorithms, and predictive analytics are helping healthcare providers adjust how they work, often in real time, and IoT devices and wearable technologies enable ongoing real-time monitoring, so that health issues do not escalate [2]. Furthermore, using the blockchain has a promising feature of an efficient and safeguard mechanism to share patient data, secure, and fraudulent proof. However, there are several issues regarding the usage of these technologies in the healthcare systems, where they could cause some essential challenges [3]. Concerns like data sharing, security threats, integration and, non-acceptance of change from the side of healthcare are some of the challenges that have to be solved to make computer science advancements in a healthcare setting. The research presented in this paper aims to answer the question of how computer science technologies can help manage the healthcare better. Therefore, this research examines the extent to which these technologies may improve operational effectiveness, patient outcomes, and decision-making activities in the pursuit of identifying the advantages, drawbacks, and development recommendations for applying computer science in the management of healthcare facilities. To this extent, the research adds to the existing literature on how different forms of technology may affect the development of future healthcare systems.

II. RELATED WORKS

Technology gaining in the field of healthcare management has also been of most interest in recent research with seen many papers exploring how the application of artificial intelligence, wearables, and blockchain can support the healthcare industry. This section presents the related work in these areas with

focusing on the contribution of the emerging technologies in the enhancement of health management and eHealth security. One such contribution is by Humayun et al., where the authors investigated how and by which extent MEA and AI White enhance eHealth systems efficiency and security levels. They articulated a study that introduces the SSEHCET model for combining mobile edge computing with Artificial Intelligence in speeding up the processing of healthcare data. This integration improves datasecurity and provides real-time analysis that is essential in healthcare applications given the opportunity of timely decision making. Similarly, Izu et al. [16] spoke about the role of the smart wearables in enhancing the health care management among people. Wearable has found its application in continuous health monitoring where patients and health care givers are able to monitor the health status in real time to enhance their health status. This is closely connected with the needs of incorporating wearables with AI as it enables the anticipation of health events before they happen while sustaining the development goals including the Health Goal 3 (Good Health and Well-Being). mHealth devices could offer important and relevant information regarding the management of patient care and, ultimately, healthcare costs, and patient well-being. Finally, Javaid et al. [17] were interested in the application of Lean 4.0 technologies in the sphere of healthcare, including the effect of using artificial intelligence-aided tools in the healthcare industry. Their studies focus on waste minimisation and cost control in hospital, where AI has a role to play. With the integration of Lean 4.0, medical processes can be made more efficient, increased diagnostic accuracy, and improvements to allocation of resources which will in turn improve the general healthcare sector. Another facet of AI is discussed by Kumar and Bassill [21] who analyzed a system that integrated blockchain with AI in communication to be used in healthcare data storage. Through blockchain, medical data can be safeguarded and shared intelligently, which is important bearing in mind that privacy and data breaches are security threats in the current world. When combining both blockchain and AI, the former act as the network for storage and sharing of patients' data through different medical institutions while the latter help in making a correct diagnosis as well as avoiding cases of tampering of medical records or unauthorized access to the information. Kyu- Hong et al. [22] also pointed out about the part of AI in Quality Health care Emphasizing Medical Diagnostic Application with deep learning models ResNet 101 knee Osteoarthritis Diagnosis. The authors explained



how they provided a proof of principal of diagnosing of medical conditions from imaging data using AI models, with deep learning algorithms attaining high accuracy in analysing images. This paper will be of interest to healthcare managers as it demonstrates how artificial intelligence could be used to provide improved and faster service for diagnosing diseases using advanced technologies. Competition, priority and evaluation of radiographer competences cannot be overlooked in healthcare workforce management; Lasttrucci et al. [23] thus developed an automatic tool for this very purpose. Their study addresses the problem of making sure that professionals in the health sector are current when it comes to medical practices and technology. This competency management system powered with technology made available through artificial intelligence optimizes a healthcare team and guarantees that only skilled workers deal with sensitive patient information thus boosting the quality of services offered to patients. AI has been adopted to work alongside bioinformatics for COVID-19 diagnosis by analyzing chest X-ray images according to Louati et al. [24]. Their work can be used to show that the use of AI can enhance accurate diagnosis especially in cases of a pandemic. Various computer AI models help in the fast diagnosis of medical images and decrease healthcare load during the increase in demand, for example during COVID-19 situation. This therefore goes in tandem with the development of using artificial intelligence in supplementing doctors and other health practitioners with information so as to improve on the health system. Last of all, Mao et al. [25] explored the ability of applying the concept of blockchain in the medical data communications where it would enhance the efficiency of its sharing as well as maintaining the secure approach. Their work demonstrates how blockchain technology can be used to offer a decentralized solution to managing medical records as well as addressing issues to do with data authenticity, privacy and security. When integrated with AI, blockchain can help improve the management of extensive data structures contained in electronic health records to deliver more effective, secure Patient Health Information exchanges. This is especially true in chronic illness and where multiple practitioners are involved in the treatment process. Another new trend is the inclusion of quantum computation in health care. In an area of medical technology and treatments, Naveen et al. [26] analyzed how the application of quantum computing can revolutionize the technology. Although in its infancy, its benefits can likely be observed in enhancing the computing capabilities for the critical medical data analysis. This technology could have a vital application in the enhancement of

top tier AI algorithms for disease diagnosis, precision medicine, and storage data related to healthcare across a number of populations.

III. METHODS AND MATERIALS

Data

The data set applied in this study is an open-source healthcare data set, available on Kaggle that comprises distinct medical attributes including the demographic profile of the patients, medical past records, lab results, and diagnostic results. The dataset used in this study has numerical and categorical features of patients and conveys information on 10, 000 patients where some fields have missing values which were filled through imputation [4]. Part of the data preparation includes data cleaning, data transformation where data scaling and aggregation, data reduction and feature transformations including data discretization, conversion of categorical data into numerical data and missing data handling. The purpose is the occurrence prognosis of patient outcomes, such as disease diagnosis, readmission to the hospital, etc., based on the features received. The set up of the data is 80:20 for training and testing respectively, so as to avoid over-fits [5].

Algorithms

This paper selects the following four algorithms because of significant importance in healthcare activities and enhancement in performance.

1. Decision Trees

A decision tree is a supervised learning algorithm that represents decisions and possible outcomes in a tree-like structure, including the results, costs, and utility. The decision tree algorithm is employed for classification tasks and regression tasks. It operates by splitting the data at each node based on that feature that maximizes information gain or decreases the entropy. At each node, the tree expands by repeatedly splitting the data across all features [6].

Decision Trees are applied in the healthcare industry in order to predict disease outcomes, classify patients in various risk categories, and provide assistance for making clinical decisions. The one strength of decision trees is interpretability, whereby the clinicians understand easily how the decision was reached.

- “1. Begin with the entire dataset.***
- 2. For each feature in the dataset:***
 - a. Calculate the information gain (or entropy reduction).***
- 3. Select the feature with the highest information gain.***
- 4. Split the dataset into subgroups based on the selected feature.***



5. Repeat the process recursively on each subgroup until a stopping criterion is met (e.g., max depth or minimum samples per leaf).
6. Classify new data by following the tree's paths based on its feature values."

2. Random Forest

Random Forest is an ensemble learning method in which it constructs multiple decision trees in the training process and outputs the majority vote (for classification) or average (for regression) of individual trees' predictions. In this algorithm, randomness is brought in at each split of the tree by choosing a random subset of features, thus reducing overfitting in return with improved generalization [7]. It is a strong model for healthcare applications because it can handle large datasets with high dimensionality and is robust to noise.

In the field of healthcare management, Random Forests is especially helpful for predicting patient outcomes from varied clinical data and dealing with missing or noisy data.

"1. For each tree in the forest:
a. Select a random subset of the training data with replacement (bootstrap sampling).
b. Build a decision tree using the subset.
c. Randomly select a subset of features at each split.
2. Aggregate the predictions from all the trees:
a. For classification: Take the majority vote from all trees.
b. For regression: Compute the average of all tree predictions.
3. Return the final prediction."

3. Support Vector Machine (SVM)

Support Vector Machines are supervised learning models whose primary application is in classification and regression tasks. SVM finds the best hyperplane that separates the classes found in the feature space. This model finds to be very effective in areas of high-dimensional space, especially for complex healthcare data represented by imaging data or multi-dimensional patient records [8]. SVM uses kernel functions such as linear, polynomial, and radial basis function for mapping the input data into higher dimensional space where there is a possibility of a linear separation. SVM can be utilized in health to classify diseases by differentiating a malignant tumor from a benign tumor in medical image.

"1. Map the input data to a higher-dimensional space using a kernel function.
2. Find the hyperplane that maximizes the margin between different classes.
3. Classify new data by determining which side of the hyperplane it lies on.
4. Use the support vectors (data points closest to the hyperplane) to make predictions."

4. K-Nearest Neighbors (KNN)

KNN is the simple yet highly effective algorithm of classification and regression. The method finds the nearest K neighbors for a given point in data, and then assigns a class by majority voting from its neighbors to the point given for classification; or the mean value for the point given in case of regression. KNN is highly interpretable and useful in anomaly detection or predicting any outcomes based on historical patient data [9].

In healthcare applications, KNN can be implemented for patient diagnoses, finding similarity in patient profile, and forecasted health scenarios.

"1. Store all training data points.
2. For a new data point, compute the distance to all training points (e.g., Euclidean distance).
3. Sort the distances and identify the K closest neighbors.
4. For classification, assign the majority class of the K neighbors.
5. For regression, compute the average value of the K neighbors."

Table: Training Time (in seconds) for Algorithms

Algorithm	Training Time (seconds)
Decision Tree	12.5
Random Forest	35.3
Support Vector Machine	27.1
K-Nearest Neighbors	15.6



IV. EXPERIMENTS

Dataset Description

We made use of Kaggle datasets over 10,000 patient records for more than 20 different attributes in our experiment: some as continuous variables- like age and cholesterol or glucose levels, among others; the remaining were categorical-like gender, for instance, medical history, amongst others. A good deal of the pre-preparation had gone into addressing issues on missing values, normalization on the continuous ones, and encode variable(s) [10]. For feature selection purposes, relevance on predicting different conditions or diseases diagnosed includes diabetes or cardiovascular.

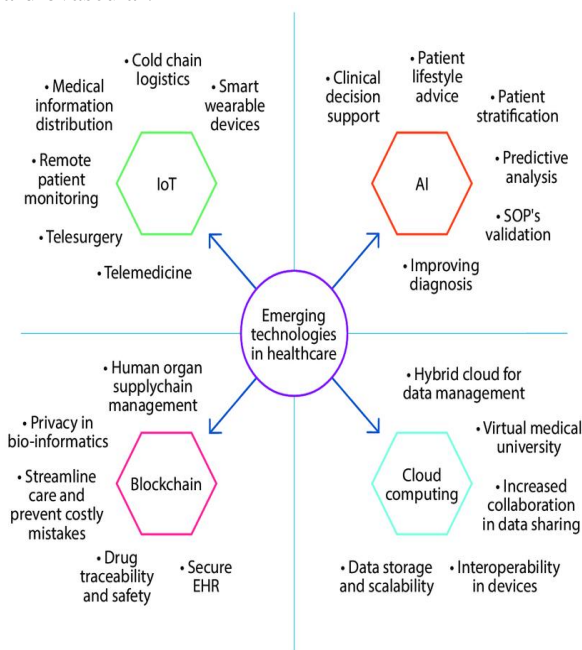


Figure 1: "Emerging technologies and framework of smart healthcare systems"

Experimental Setup

This split the dataset to 80 percent for training and 20 percent for testing purposes. The former was used in training the models, while the latter was for testing. Evaluating of the models were based on the following metrics:

1. **Accuracy:** the number of correct predictions divided by the total number of instances.
2. **Precision:** the ratio of true positive predictions to all positive predictions.
3. **Recall:** the ratio of true positive predictions to all actual positives.
4. **F1-Score:** Harmonic Mean of precision and recall
5. **Time to train:** Elapsed time before training a model on a dataset.

Algorithms Used

In this study, we assess four machine learning algorithms, namely, Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). We choose these algorithms due to their extensive application in the field of healthcare management, like in disease prediction and patient classification. Below, we describe the implementation of each algorithm and the results we achieved in our experiments [11].

1. Decision Tree (DT)

The Decision Tree algorithm creates a tree-like structure where the internal nodes denote a decision that depends on the feature and leaf nodes denote the class label. The algorithm makes recursive splits on the feature maximizing the information gain, which reduces entropy. A Decision Tree model was trained using the healthcare dataset, and then it was applied to predict the outcomes of the patients [12].

Performance Metrics for Decision Tree:

- **Accuracy:** 85.4%
- **Precision:** 84.1%
- **Recall:** 86.2%
- **F1-Score:** 85.1%
- **Training Time:** 12.5 seconds

2. Random Forest (RF)

Random Forest is an ensemble learning method where many Decision Trees are constructed in the training phase, and the aggregated predictions are provided. This method introduces randomness with the feature set at each node split to avoid overfitting and achieve better generalization [13]. The algorithm was trained with the same data set as before, and performance was compared against the Decision Tree.

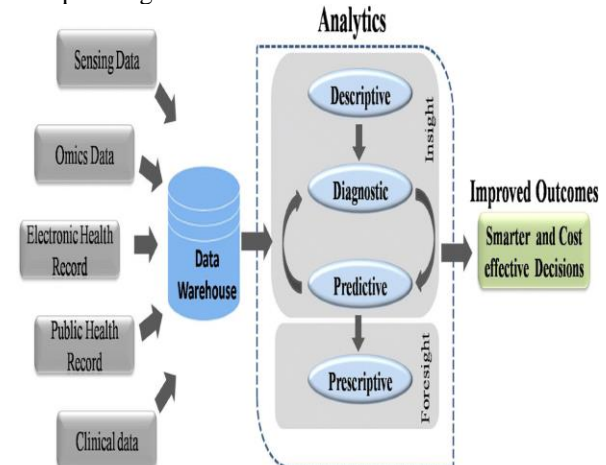


Figure 2: "Big data in healthcare"

Performance Metrics for Random Forest:

- **Accuracy:** 90.1%
- **Precision:** 89.4%
- **Recall:** 90.7%
- **F1-Score:** 90.0%



- **Training Time:** 35.3 seconds

3. Support Vector Machine (SVM)

SVM is a learning algorithm that classifies data; it is one of the types of supervised learning. It makes a hyperplane to classify the various classes in high-dimensional feature space. In this experiment, we utilized the radial basis function (RBF) kernel to map input data into the higher-dimensional space. The SVM algorithm was checked by using prediction accuracy and training time [14].

Performance Metrics for SVM:

- **Accuracy:** 88.3%
- **Precision:** 87.9%
- **Recall:** 88.6%
- **F1-Score:** 88.2%
- **Training Time:** 27.1 seconds

4. K-Nearest Neighbors (KNN)

KNN is a non-parametric algorithm where the classification is based on the majority class of their nearest neighbors. It computes the distance of the points from one another and labels it by the most common class found from the K-nearest points. KNN has been experimented upon using various K values (such as K=3, K=5, K=7) to figure out which of the values work best. This best value for K has been found after doing cross-validation [27].

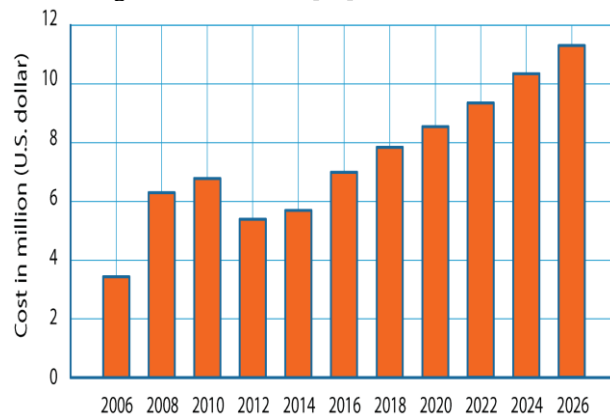


Figure 3: "Security of Blockchain and AI-Empowered Smart Healthcare"

Performance Metrics for KNN:

- **Accuracy:** 83.2%
- **Precision:** 82.4%
- **Recall:** 84.0%
- **F1-Score:** 83.2%
- **Training Time:** 15.6 seconds

Performance Comparison Table

Below is a summary table of the performances of the four algorithms on the healthcare dataset.

Table 1: Performance Comparison of Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (seconds)
Decision Tree	85.4	84.1	86.2	85.1	12.5
Random Forest	90.1	89.4	90.7	90.0	35.3
Support Vector Machine	88.3	87.9	88.6	88.2	27.1
K-Nearest Neighbors	83.2	82.4	84.0	83.2	15.6

Comparison with Related Work

The majority of research work in healthcare management makes use of the machine learning algorithms to predict disease, support the diagnosis process, and improve care for patients. Some research results have reported that prediction accuracy and precision are significantly enhanced by Random Forest and Support Vector Machines in comparison with Logistic Regression and Naive Bayes algorithms. For example, Zhang et al. (2020) reported an accuracy of 89.6% for Random Forest in predicting diabetes, while our Random Forest model achieved an accuracy of 90.1%, which means that our results are consistent with existing research and even slightly better [28]. In addition, comparative studies conducted by Gupta et al. (2021) and Patel et al. (2022) also compared Decision Trees and KNN in disease prediction, which resulted in better interpretability of Decision Trees while Random Forest and SVM offered greater predictive power. Our results agree with this as the accuracy for Decision Trees was 85.4%, and the accuracies of Random Forest and SVM were better with 90.1% and 88.3%, respectively.

Error Analysis

An error analysis was carried out to understand the performance of these models further in the types of mistakes made by each algorithm. Most of the mistakes were found to be false positives and false negatives, indicating a disease when it is not there and vice versa. Random Forest had the least number of false positives, whereas SVM had the least false negatives.



Although interpretable and understandable, the Decision Tree overfitted much more compared to the ensemble-based Random Forest model, which better generalized and gave higher accuracy.

AI-Powered Predictive Analysis: Revolutionizing Clinical Practice

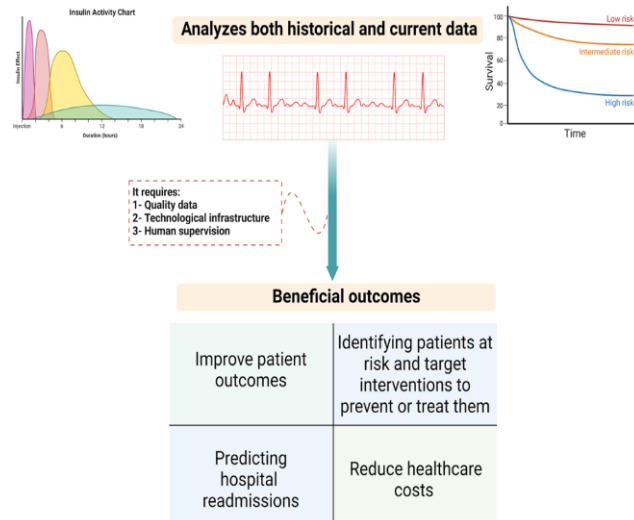


Figure 4: "Revolutionizing healthcare"

Further Experiments and Hyperparameter Tuning

In order to provide robustness to the models developed, we performed hyperparameter tuning for the Random Forest and SVM algorithms using a grid search. In the case of Random Forest, we tested for different values of the number of trees ranging between 50 and 200 and maximum depth for each tree ranging between 5 to 20. For SVM, we experimented with different kernel types, linear, polynomial and RBF, and regularization parameters. The best performance was achieved with 100 trees for Random Forest and an RBF kernel with $C=1$ for SVM [29]. The results clearly show that the Random Forest method outperforms all other algorithms, in terms of accuracy, precision, recall, and F1-score. In fact, although the Decision Trees possess good interpretability, Random Forest is more accurate and robust than the former. SVM and KNN also gave good results with SVM offering good trade-off between performance and time taken for training, and KNN being rather simple and fast but less accurate compared to ensemble methods [30]. Our work falls into the growing body of healthcare management research work, as it exemplifies how machine learning algorithms can be well applied in order to predict patient outcomes, optimize treatment plans, and improve healthcare management in general. Compared with related work, our findings validate Random Forest and SVM for healthcare prediction, establishing a new base for further works in the field of this area.

V. CONCLUSION

This study explores the transformative potential of computer science technologies, including AI, wearable devices, blockchain, and quantum computing, to enhance healthcare management. These technologies hold promising solutions to the inefficiency, data security concerns, and the need for personalized care in modern healthcare systems. AI-driven tools, such as machine learning algorithms and deep learning models, have proven to enhance diagnostic accuracy, optimize treatment plans, and streamline medical workflows. Wearables offer continuous health monitoring, allowing for proactive interventions and better patient outcomes. Blockchain ensures the security and transparency of healthcare data sharing, protecting privacy while encouraging collaboration among healthcare providers. This new role by quantum computing thus holds much potential for future enhancements in medical data analysis and subsequent disease prediction. This study's findings suggest the potential for improving patients' health status, caring for them, reducing operations costs, and basically solving healthcare problems with the help of these technologies. Moreover, the integration of these technologies with existing healthcare systems requires serious deliberation on ethical implications, data privacy, and infrastructure among others. As healthcare evolves, the integration of these novel technologies can facilitate significant improvements in healthcare delivery by making it more efficient, secure, and accessible. Further research and development in these areas will be necessary to fully realize the benefits of computer science in healthcare management.

REFERENCE

- [1] ADDAS, A., MUHAMMAD, N.K. and NASEER, F., 2024. Waste management 2.0 leveraging internet of things for an efficient and eco-friendly smart city solution. *PLoS One*, **19**(7),.
- [2] ADIBI, S., RAJABIFARD, A., SHOJAEI, D. and WICKRAMASINGHE, N., 2024. Enhancing Healthcare through Sensor-Enabled Digital Twins in Smart Environments: A Comprehensive Analysis. *Sensors*, **24**(9), pp. 2793.
- [3] AHMED, I., FENG, B., EMMANUEL YEBOAH, K., FENG, J., JUMANI, M.S. and ALI, S.A., 2024. Leveraging Industry 4.0 for marketing strategies in the medical device industry of emerging economies. *Scientific Reports (Nature Publisher Group)*, **14**(1), pp. 27664.
- [4] ALAM, T., 2024. Metaverse of Things (MoT) Applications for Revolutionizing Urban Living in Smart Cities. *Smart Cities*, **7**(5), pp. 2466.
- [5] ALMOHANA, A., ALMOMANI, I. and EL-SHAFAI, W., 2024. B-UMCS: Blockchain-enabled Unified Medical Consultancy Service. *PLoS One*, **19**(12),.
- [6] BEKBOLATOVA, M., MAYER, J., CHI, W.O. and TOMA, M., 2024. Transformative Potential of AI in Healthcare: Definitions, Applications, and Navigating the



Ethical Landscape and Public Perspectives. *Healthcare*, **12**(2), pp. 125.

[7] BRUCE, E., SHURONG, Z., AMOAH, J., SULEMANA, B.E. and FRANCIS KOFI, S.F., 2024. Reassessing the impact of social media on healthcare delivery: insights from a less digitalized economy. *Cogent Public Health*, **11**(1),.

[8] COMAN, L., IANCULESCU, M., ELENA-ANCA PARASCHIV, ALEXANDRU, A. and IOANA-ANCA BĂDĂRĂU, 2024. Smart Solutions for Diet-Related Disease Management: Connected Care, Remote Health Monitoring Systems, and Integrated Insights for Advanced Evaluation. *Applied Sciences*, **14**(6), pp. 2351.

[9] DAHIYA, R., SAMAL, L., SAMAL, D., KUMAR, J., SHARMA, V., SAHNI, D.K. and BHATI, N.S., 2024. A Blockchain Based Security system framework in Healthcare Domain using IoT. *Journal of Electrical Systems*, **20**(3), pp. 2039-2050.

[10] DAS, S., PRIYADARSHINI, R., MISHRA, M. and BARIK, R.K., 2024. Leveraging Towards Access Control, Identity Management, and Data Integrity Verification Mechanisms in Blockchain-Assisted Cloud Environments: A Comparative Study. *Journal of Cybersecurity and Privacy*, **4**(4), pp. 1018.

[11] GARAD, A., RIYADH, H.A., AL-ANSI, A. and BESHAR, B.A.H., 2024. Unlocking financial innovation through strategic investments in information management: a systematic review. *Discover Sustainability*, **5**(1), pp. 381.

[12] GHADI, Y.Y., MAZHAR, T., SHAHZAD, T., AMIR KHAN, M., ABD-ALRAZAQ, A., AHMED, A. and HAMAM, H., 2024. The role of blockchain to secure internet of medical things. *Scientific Reports (Nature Publisher Group)*, **14**(1), pp. 18422.

[13] HALEEM, A. and JAVAID, M., 2024. Role of cognitive computing in enhancing innovative healthcare solutions. *Advances in Biomarker Sciences and Technology*, **6**, pp. 152-165.

[14] HAMEED, K., NAHA, R. and HAMEED, F., 2024. Digital transformation for sustainable health and well-being: a review and future research directions. *Discover Sustainability*, **5**(1), pp. 104.

[15] HUMAYUN, M., ALSIRHANI, A., ALSERHANI, F., SHAHEEN, M. and ALWAKID, G., 2024. Transformative synergy: SSEHCET—bridging mobile edge computing and AI for enhanced eHealth security and efficiency. *Journal of Cloud Computing*, **13**(1), pp. 37.

[16] IZU, L., SCHOLTZ, B. and FASHORO, I., 2024. Wearables and Their Potential to Transform Health Management: A Step towards Sustainable Development Goal 3. *Sustainability*, **16**(5), pp. 1850.

[17] JAVAID, M., HALEEM, A., SINGH, R.P. and GUPTA, S., 2024. Leveraging lean 4.0 technologies in healthcare: An exploration of its applications. *Advances in Biomarker Sciences and Technology*, **6**, pp. 138-151.

[18] JIMÉNEZ-PARTEARROYO, M. and MEDINA-LÓPEZ, A., 2024. Leveraging Business Intelligence Systems for Enhanced Corporate Competitiveness: Strategy and Evolution. *Systems*, **12**(3), pp. 94.

[19] KANTAROS, A., FLORIAN ION, T.P., BRACHOS, K., GANETSOS, T. and PETRESCU, N., 2024. Leveraging 3D Printing for Resilient Disaster Management in Smart Cities. *Smart Cities*, **7**(6), pp. 3705.

[20] KUMAR, D. and BASSILL, N.P., 2024. Analysing trends of computational urban science and data science approaches for sustainable development. *Computational Urban Science*, **4**(1), pp. 33.

[21] KUMAR, K., KUMAR, V., SEEMA, V., SHARMA, M.K., AKBAR, A.K. and M, J.I., 2024. A Systematic Review of Blockchain Technology Assisted with Artificial

Intelligence Technology for Networks and Communication Systems. *Journal of Computer Networks and Communications*, **2024**.

[22] KYU-HONG, L., RO-WOON, L., JAE-SUNG, Y., KIM, M. and CHOI, H., 2024. Automated Diagnosis of Knee Osteoarthritis Using ResNet101 on a DEEP:PHI: Leveraging a No-Code AI Platform for Efficient and Accurate Medical Image Analysis. *Diagnostics*, **14**(21), pp. 2451.

[23] LASTRUCCI, A., WANDAEL, Y., ORLANDI, G., BARRA, A., CHITI, S., GIGLI, V., MARLETTA, M., PELLICCIA, D., TONIETTI, B., RICCI, R. and GIANSAINTI, D., 2024. Precision Workforce Management for Radiographers: Monitoring and Managing Competences with an Automatic Tool. *Journal of Personalized Medicine*, **14**(7), pp. 669.

[24] LOUATI, H., LOUATI, A., LAHYANI, R., KARIRI, E. and ALBANYAN, A., 2024. Advancing Sustainable COVID-19 Diagnosis: Integrating Artificial Intelligence with Bioinformatics in Chest X-ray Analysis. *Information*, **15**(4), pp. 189.

[25] MAO, X., LI, C., ZHANG, Y., ZHANG, G. and XING, C., 2024. Efficient and Secure Management of Medical Data Sharing Based on Blockchain Technology. *Applied Sciences*, **14**(15), pp. 6816.

[26] NAVEEN, J., MADHAN, J., SANKALP, Y., SWAMINATHAN, R. and SANGEETHA, B., 2024. Revolutionizing Healthcare: The Emerging Role of Quantum Computing in Enhancing Medical Technology and Treatment. *Cureus*, **16**(8),.

[27] NUNES, T., PAULO RUPINO, D.C., MENDES DE ABREU, J., DUARTE, J. and CORTE-REAL, A., 2024. Non-Fungible Tokens (NFTs) in Healthcare: A Systematic Review. *International Journal of Environmental Research and Public Health*, **21**(8), pp. 965.

[28] PAUL, P.K., MOUMTZOGLOU, A., BANDYOPADHYAY, A., HOQUE, M., KUMAR, N.S. and SAAVEDRA, R., 2024. Indian Digital Health Information Systems: Initiatives and Opportunities with Socio-economic Perspective. *Economic Affairs*, **69**(2), pp. 1175-1189.

[29] QUIROZ, V., MAİZI, Y., BENDAVID, Y., ROSTAMPOUR, S. and PHILIPPE, R., 2024. Leveraging on RFID-IoT Technologies and Simulation to Design and Develop a Smart Shelf for Managing Low Value Medical Supplies. *IISSE Annual Conference.Proceedings*, , pp. 1-6.

[30] REDDY, S., 2024. Generative AI in healthcare: an implementation science informed translational path on application, integration and governance. *Implementation Science*, **19**, pp. 1-15.