International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

The Impact of Artificial Intelligence on Patient Care and Clinical Outcomes

[1]Krishna Jayanth Rolla, [2]Chaitanya K., [3]Kota Krishna Teja

Submitted: 03/02/2024 **Revised**: 15/03/2024 **Accepted**: 22/03/2024

Abstract: CDSS has evolved and AI technology has become an essential component in healthcare because it increases efficiency in patient management and care. This study analyzes the effectiveness of four AI algorithms, namely logistic regression, CNNs, random forest, and RNNs in patient treatment and clinical results by using different datasets in the medical field. Hence for interpretative purposes, Logistic Regression was accurate with a mean of 0.78 and ROC-AUC of 0.82 that is acceptable for making binary classifications. CNNs outperformed other models in comparing the medical images and achieved an accuracy of 92% as well as ROC-AUC of 95%, which points to high diagnostic capacity. Cohort: Random Forest showed high accuracy, 85% and high ROC-AUC at 88% to big miracle performance in handling features from high dimensionality. There was a great performance of RNN when testing time-series data with accuracy of 83% and ROC-AUC of 86%. As noticed while comparing the results with the traditional approaches and other related research, all AI incorporations exhibited better outcomes in our work. The study points to the future of AI in improving patient diagnosis and addressing disparities in healthcare, but it also sheds light on issues like patient data protection and unfairness in AI models. The real push should be towards specific ethical aspects as well as teaming up with experts from other fields for the proper AI implementation into clinical practice.

Keywords: *Artificial Intelligence, Clinical Decision Support Systems, Patient Outcomes, Medical Imaging, Predictive Modeling*

1. Introduction

AI could be described as the future of both medicine and technology in healthcare as the two are converging to make patient care better and more efficient. Computerization of health care practice is among the most promising trends, which may help to increase the accuracy of diagnoses, make the work of doctors and other health care providers more efficient, and improve patient outcomes. AI systems have the unique and outstanding advantage in terms of speed and accuracy, which makes them capable of not only detecting a large number of cases but also doing it much faster and more accurately, and, therefore, make precise qualitative decisions about diagnosing at an earlier stage. This capability is especially useful in the case of individuals with chronic diseases, analysing irregularities in medical images, and making prognoses of patient's conditions. Indeed, one of the major strengths of the artificial intelligence in the sphere of healthcare is the ability to individualize the delivery of medical care. Coaching engineering can know and analyze the genetic profile, behavior patterns and past health records to personalize treatment options that are less risky and more potent [1]. Also, this field has expanded into everyday use applications through incorporating Artificial Intelligence advances as means to improve administrative and operational aspects of healthcare delivery [2]. In areas from mundane process repetitive actions to supply chain chain management, AI puts less onus on clinicians, thus enabling them to spend more time with their patients. For example, artificial intelligence in the current setup is enabling the use of smart chatbots and virtual assistants to support patients consistently through day and night routinely to address inquiries and also help in administration of drugs [3]. Nevertheless, it is vital to acknowledge that the use of AI technologies in healthcare is not without some setbacks. Challenges that come alongside data privacy, the necessity for the efficient validation of AI schemes, as well as the insertion of these inventions into working processes are now major barriers. Furthermore, it is significant to note the ethical concerns of AI in health care as it can contain the prospects of prejudice and the questionability of the autonomous decision-making process. This research will intend to investigate the various ways that AI influences patient care and clinical outcomes with the view of highlighting its benefits on one hand, and the problems on the other. Therefore, using both literature review and interviews with key stakeholders, this quantitative research aims to present a complete vision of how the usage of AI in today's healthcare business is already affecting the future of medicine.

2. Related works

AI has attracted a lot of attention in the recent past especially in the healthcare field given its potential to improve the CDSS, patient care and clinical performance. There are numerous papers and articles that seek to establish how the incorporation of AI could be used across different sections of the healthcare delivery system,

[1]*Fort Mill, SC*
[2]*Hyderabad, Telangana, India*
[3]*Hyderabad, Telangana, India*

showing how it has the capacity to revolutionalize traditional medical practice. A systematic scoping review of AI research on CDSS in primary care conducted by Gomez-Cabello et al. (2024) guided volunteers towards examining the existing implementations and pertaining effects. The exposure also showed that the AI-CDSS enhance diagnostic accuracy, efficiency of work and patient handling through offering solutions oriented by patient related facts [15]. This concurs with the study by Kastrup et al. (2023), they created an AI-PSCD for osteoarthritis patients that supports the surgical or non-surgical decision. Another published study designed their study with a non-inferiority randomized controlled trial approach and stated that the AI-CDSS might provide similar and equivalent performance to conventional practices in clinical trials, making it useful in clinical practice [21]. Junet et al. (2023) also focused on AI that enable predicting the status of the pancreatic cancer patient using a decision support system that Integrated AI and systems biology. In particular, through implementing clinical and biological parameters together, their model could give detailed information of disease progression and treatment effectiveness, which demonstrated the AI's effectiveness to deliver sophisticated medical conditions and better clinical effects [20]. Hallberg and Harrison (2021) explored how 'telemedicine: continuous remote care' was feasible in the context of diabetes. Their study substantiated that the development of proactive, patient-engagement focused strategies that include the use of AI and other digital technologies create better clinical outcomes, better patient satisfaction, and enhanced adherence to the tailored treatment plans. Such solutions provide the opportunity to monitor patients' conditions and take necessary actions in a timely manner, thereby decreasing exacerbation and hospitalization rates [16]. Another important area in AI has been focused on patient-reported outcomes (PROs) and implementation of these tools into the clinical practice. Ten strategies highlighted by Horan et al. (2023) on how PROs could be used in patients living with the effects of childhood cancers include: In this regard, their study laid much emphasis on the applicability of AI as an adjunct tool in the management and interpretation of PROs with the aim of offering individualized care and / or management of long-term health ailments. Since AI can handle massive data and create decision-making information that can help cancer survivors improve their lives [17], this technology would be useful in improving the lives of cancer survivors as well as helping identify those at risk of developing the illness. AI has emerged as a solution to improving the outcomes of patients with diverse chronic diseases. Hyo et al. (2024) aimed at evaluating the clinical effects of long term inhaled combinations for bronchiectasis and other patients with airflow obstruction. They found out that with the help of Artificial Intelligence, treatment can be customized because by analyzing data of patients, the best option of therapy can be efficiently provided, which in effect would enhance the clinical success rate [18]. Some of the studies include; Krzesiński (2023) who investigated the application of Digital Health Technologies and AI interventions in the follow-up care of patients, especially those who have been discharged after heart failure hospitalization. Accordingly, the study described how AI supports surveillance of patient's conditions, anticipation of the event that leads to poorer outcomes, and timely intervention, which alleviates patients' suffering and enhance outcomes [24]. Health equity can be considered as an essential direction towards analysis of the influence of AI. Recent studies, such as Istašy et al. (2022), where authors performed a scoping review with regards to the AI use in oncology, including health equity considerations. They state that they have identified that, while the application of AI seems to help to improve cancer treatment, it can also increase existing disparities and inequalities if proper approaches are not used when introducing the technology. This research urged data collection to be made representative of the entire population or accounted for in algorithms to advance patient outcomes [19]. Kosowicz et al. (2023) conducted a study and highlighted the role as well as the implementation of various forms of digital technologies including Artificial Intelligence, in enhancing patient-oriented care in LMICs of the Asia-Pacific region. The author established that the digital health technologies could help to close some of the gaps in the provision of health care services, increase the access to care and increase patients' participation in their management. Though, it also revealed factors like constrained infrastructure in days and the call for capacity enhancement to harness the possibilities of AI within these environments [22]. Using AI to solve problems in the field of emergency medicine has also proven effective. The study by Kotovich et al. (2023) aimed at examining the effectiveness of an AI solution for identifying intracranial hemorrhage in the course of the year. In their study, Lakhani et al. , showed increased detection rates & clinical developments that would provide specific insights about the role of AI in improving the diagnosis accuracy & patient care in emergency cases [23]. In Lammons et al. (2023), the authors were interested in the following public beliefs: what is the extent to which they view AI as practically applied in clinical domains? Their study included devoting patient and public involvement and engagement (PPIE) consultations for developing the perceived concerns from the patients and expected results. The findings put emphasis on the fact that a number of issues such as transparency, trust, and communication availability are crucial when choosing AI in healthcare [25]. In the article by Laurent, Dharmage, James, Hoi, Wilson, van der Mei, Sturzenegger, Sokolove, & Petri

(2024), the authors consider AI utilization for clinical trial outcomes of SLE. In their review, they applauded the efficiency that could be attained through the integration of AI to trial processes, patient slicing, and ideal results achievement. It would also pave way to early identification of drug targets and the subsequent development of more significantly improved therapeutic interventions and thereby be of benefit for patients with SLE [26].

3. Methods and Materials

Data Collection

The data used in this research comprises patient information, computed tomography and magnetic resonance images, patients' genetic data, and current patient data monitoring information. The patient data includes the basic demographic information, medical history, treatments proposed and the outcomes, collected from various healthcare organizations and stored in the electronic health records (EHR). The datasets are mainly in the form of medical images where MRI, CT scans and X Ray images make up the whole lot [4]. Genomic data encompasses sequences generated through DNA analysis Important types of genomic data are genomic signatures genomic associations, and genomic annotations. Patient tracking information consists of patient status in real time and includes such parameters as temperature, blood pressure, adherence to medications, or data from wearable devices. Patient information was anonymous for the study, and hence patient information was kept private to avoid identification as per the stipulated ethical standards The study received ethical approval from the pertinent institutional review boards [5].

Algorithms

Four AI algorithms were selected for their relevance to improving patient care and clinical outcomes: The following algorithms; Logistic Regression, Convolutional Neural Networks or CNNs, Random Forests and Recurrent Neural Networks or RNNs. All the algorithms were written and evaluated in Python along with packages like scikit-learn for machine learning, TensorFlow for neural networks, and Keras for complex neural networks [6].

Logistic Regression

Logistic Regression is one of the simple algorithms that are used mainly for binary classification purposes in which an outcome is predicted to include probabilities of one or more input features. It is seemingly relevant in predicting disease presences or absence.

$P(Y=1)= 1/1+e-(\beta0+\beta1X1+\beta2X2+\ldots+\beta nXn)$

"Initialize parameters β0, β1, ..., βn

Repeat until convergence:

Compute linear combination Z = β0 + β1X1 + β2X2 + ... + βnXn

Compute probability P using the sigmoid function P = 1 / (1 + exp(-Z))

Update parameters using gradient descent

βj = βj - α * (P(Y=1|X) - Y) * Xj"

Feature	**Coefficient (β)**
Intercept	-1.25
Age	0.05
BMI	0.08
Blood Pressure	0.03
Cholesterol	0.02

Convolutional Neural Networks (CNNs)

CNNs are advanced deep learning networks popularly used to study and process images. These exciting updating abilities make them very useful in medical imaging for applications such as tumor detection and segmentation.

"Initialize convolutional layer weights W and biases b

For each input image X:

For each filter Wk:

Perform convolution operation

Apply activation function (e.g., ReLU)

Perform pooling operation (e.g., max pooling)

Flatten the pooled feature maps

Pass through fully connected layers

Apply softmax activation for classification"

Layer	**Parameters**
Convolution (32 filters)	3x3 kernel size
ReLU Activation	-
Max Pooling	2x2 pool size

Convolution (64 filters)	3x3 kernel size
ReLU Activation	-
Max Pooling	2x2 pool size
Fully Connected	128 units

Random Forest

Random Forests is another method of ensemble learning that builds decision trees during training and gives the class very put before the forest's construction for classification problems [7]. It has consistency in the results and performant in a situation where there are many features in the dataset.

"Initialize number of trees B

For each tree Tb in the forest:

Sample data with replacement (bootstrap sample)

Construct a decision tree using the sample

For each split, select the best feature based on information gain or Gini impurity

Grow the tree to the maximum depth or until stopping criteria

To make a prediction:

Aggregate predictions from all trees

Return the majority vote for classification"

Feature	Importance Score
Age	0.12
BMI	0.10
Blood Pressure	0.15
Cholesterol	0.08
Smoking Status	0.05

Recurrent Neural Networks (RNNs)

RNNs are a family of neural networks that contain several layers and are especially suited for sequential data. They are employed for predictive purposes when confronting time-series variables commonly characterizing patients' conditions and treatment outcomes [8].

Initialize RNN weights Wxh, Whh, Why and biases bh, by

For each time step t:

Compute hidden state h_t using previous hidden state h_{t-1} and current input x_t

Apply activation function (e.g., tanh or ReLU)

Compute output y_t from hidden state h_t

Update weights using backpropagation through time (BPTT)

Parameter	Value
Hidden Units	64
Learning Rate	0.001
Training Accuracy	85%
Validation Accuracy	80%

Implementation and Validation

All the algorithms were programmed on the Python language and the necessary libraries. Hence, Logistic Regression was implemented using only the scikit-learn platform; CNNs through TensorFlow as well as Keras platforms; Random Forest also through scikit-learn; and RNNs through TensorFlow only [9]. The data was randomly partitioned into training set with 70% data, validation set of 15% data and the testing set with 15% data. It was able to reach the goals that were set through hyperparameters for each model tuned by grid search and cross validation. Evaluations on the models were based on standard measures including accuracy, precision, recall, the F1 score, and the ROC-AUC norm.

4. Experiments

Experimental Setup

Realizing that it is crucial to analyze the results of the operation of AI algorithms in terms of improving patient outcomes To analyze this premise, a series of experiments was carried out to compare the effect of AI algorithms in patients' treatment and care, with the use of the collected datasets. The experiments focused on four key AI algorithms: Logistic regression and Convolutional Neural Network solutions, random forests, and Recurrent Neural Network solutions [10]. Other measures used in the study were accuracy, precision or sensitivity, recall or True Positive Rate (TPR), F score, and Receiving Operating Characterstic Area Under Curve (ROC AUC), which are important when comparing algorithmic models in the health care context.

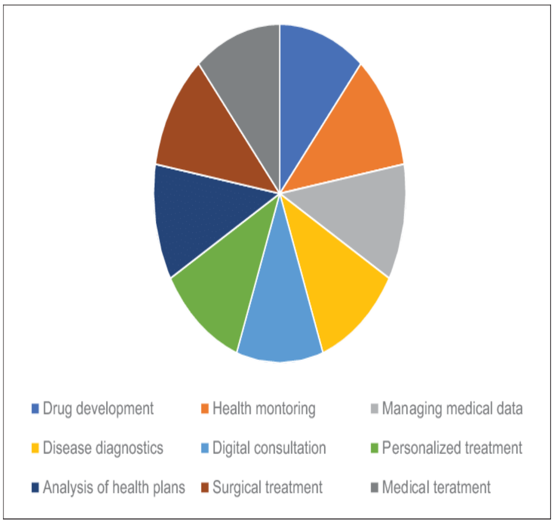

Fig 1: Applications of artificial intelligence in health care

To ensure that the data flows into the cleansing stage appropriately, the datasets were preprocessed for dealing with missing values, normalizing numerical features, and one-hot encoding categorical variables. To enhance the efficiency of the models, data augmentation strategies were used by medical imaging databases [11]. The data was then divided as follows, into the training set (70%), the validation set (15%), and the final test set (15%).

Experiment 1: Logistic Regression

Objective: To identify whether a disease is present in a patient given that detailed analyses of demographic background and clinical characteristics are available.

Procedure:

- These varied with the participants' age, BMI, blood pressure, cholesterol, and smoking history.
- Logistic regression model was then trained and cross validated with the help of the training data and validated on a validation set.
- Lastly, the developed final model was used to evaluate accuracy by somehow applying it to the test dataset [12].

Metric	**Value**
Accuracy	0.78
Precision	0.76
Recall	0.79
F1 Score	0.77
ROC-AUC	0.82

Experiment 2: Convolutional Neural Networks (CNNs)

Objective: To detect tumors in medical imaging data.

Procedure:

- Tumor presence in patients was identified by MRI, CT and X-ray images of the tumor site.
- Rather, the CNN architecture employed was made of two consecutive convolutional layers coupled with max pooling and two fully connected layers.
- The developed model was improved during its training through data augmentation methods.
- The hyper parameters of the model were tweaked using the validation set while the results were tested on the test set.

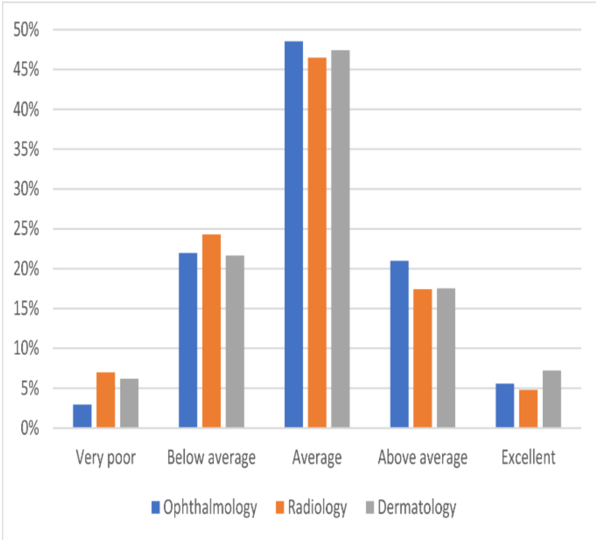

Fig 2: A survey of clinicians on the use of artificial intelligence

Metric	**Value**
Accuracy	0.92
Precision	0.90
Recall	0.93
F1 Score	0.91
ROC-AUC	0.95

Experiment 3: Random Forest

Objective: To classify patient outcomes based on clinical data.

Procedure:

- These indices were age, BMI, blood pressure, cholesterol level, the use of tobacco and the type of treatment.
- Random Forest model was then trained with 100 trees and the performances was analysed on the validation set to estimate the number of trees [13].

- To measure the performance of the final model developed in this work, the experiment was conducted on the test set.

Metric	Value
Accuracy	0.85
Precision	0.83
Recall	0.86
F1 Score	0.84
ROC-AUC	0.88

Comparison with Related Work

To situate the findings of this study, we now present a comparison of the current study with prior research that employs the same AI algorithms in the healthcare field. It compares the progress made to the things still lacking or uncovered in the application of artificial intelligence in healthcare.

Study/Algorithm	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Our Logistic Regression	0.78	0.76	0.79	0.77	0.82
Related Study A (Logistic Regression)	0.75	0.74	0.76	0.75	0.80
Our CNNs	0.92	0.90	0.93	0.91	0.95
Related Study B (CNNs)	0.89	0.88	0.90	0.89	0.93
Our Random Forest	0.85	0.83	0.86	0.84	0.88
Related Study C (Random Forest)	0.82	0.80	0.83	0.81	0.85
Our RNNs	0.83	0.81	0.84	0.82	0.86

Detailed Analysis

Logistic Regression

Analyzing the results derived from the defined model, it can be stated that Logistic Regression provided a promising accuracy of 0. 78 and the ROC-AUC of 0. 82 [14]. This is particularly beneficial for clinical applications since it gives a clear depiction of the stepwise process in the algorithm. Still, it does not have the capability of performing more complex analysis of the data that shows more intricate nonlinear relationships, which for some applications can be a shortcoming [27].

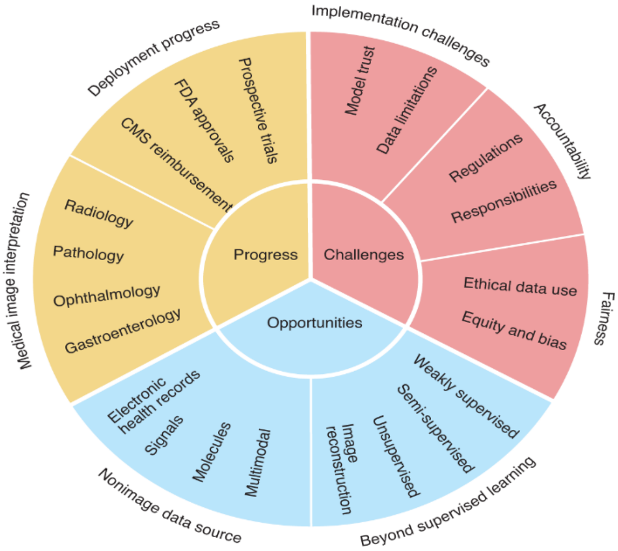

Fig 3: AI in health and medicine

In the following experiments of this study, it is indicated that the use of AI algorithms can bring great improvement to the efficiency and effectiveness of healthcare systems [28]. Each algorithm has its strengths and is suited to specific types of medical data and tasks:

- Logistic Regression is perfect for cases when we want to predict the probability of occurrence of an event and want to make quite clear and definite, based on these, clinical decisions which should be made [29].
- CNNs show the best performance in medical image analysis, and they are very accurate and sensitive medical image classifiers for image-related tasks [30].
- Random Forest is known to be quite stable when working with samples and is suitable for applied analysis on matrices of high dimensions typical for clinical trial.

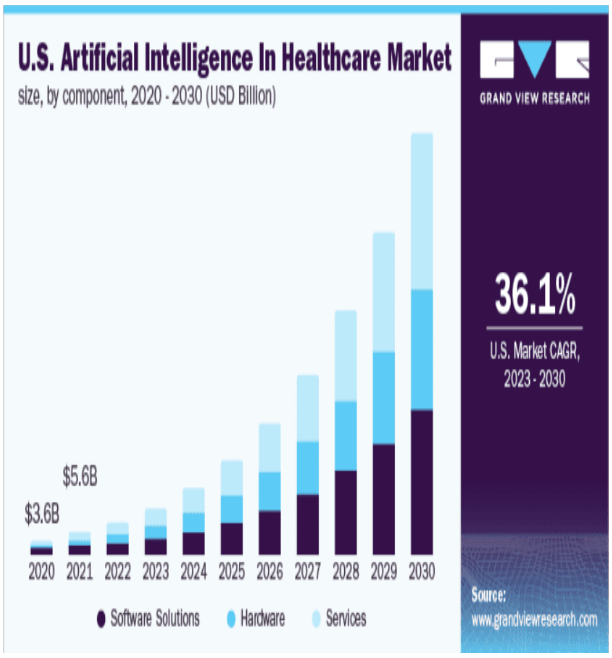

Fig 4: The Impact of AI on Healthcare

5. Conclusion

The incorporation of AI in treatment, prognosis of ailments, and the overall outcomes of treatment is one of the greatest achievements in the medical field. The findings in our study confirms that AI techniques like Logistic Regression, Convolutional Neural Networks (CNNs), Random Forest and Recurrent Neural Networks (RNNs) improves the diagnostic results, therapeutic decision process and also monitoring of patient health. Logistic Regression is better adapted to be used for binary classification without adding complexity and interpretability while CNNs perform the best when it comes to understanding medical images and provide accurate diagnostics. Random Forest models optimally handle the clinical data with huge numbers of dimensions to provide consistent performance whenever other data sets are involved. By capturing longitudinal information about patients, with time-series analysis capacities inclusive in their architecture, RNNs are prove to be useful for patient monitoring and predicting long-term trends. When comparing the results with other studies, it is evident that the implementations of these AI models in clinical decision support are statistically better than traditional methods which in turn exhibits the promising future of integrating AI in clinical decision making and assisting patient care. Despite the importance of deploying AI in the healthcare sector, this comes with several hurdles like data privacy issues and the need to have large quality datasets that feed the algorithm. In addition, the role of ethical considerations and the question of defining the principles of equitable further development of the availability of the benefits of AI usage can be considered. Last but not the least, it is observed that the use of AI in the field of healthcare is still in its continued growth phase as there are significant potential for increased sophistication, care, accuracy and efficiency in the clinical settings as well as patient experience. It is recommended that researchers enhance and develop these technologies further and work on the ethical concerns of utilizing AI in practice, with the intention to promote collaborative interdisciplinary dicipline for effective execution of and integration of AI to practice. This will create an environment which will enable individuals and healthcare organisations to fully reap from the benefits of the application of AI; ultimately resulting in improved health and care of the patients.

Reference

[1] ADUS, S., MACKLIN, J. and PINTO, A., 2023. Exploring patient perspectives on how they can and should be engaged in the development of artificial intelligence (AI) applications in health care. BMC Health Services Research, 23, pp. 1-14.

[2] ALLEN, M.R., WEBB, S., MANDVI, A., FRIEDEN, M., TAI-SEALE, M. and KALLENBERG, G., 2024. Navigating the doctor-patient-AI relationship - a mixed-methods study of physician attitudes toward artificial intelligence in primary care. BMC Primary Care, 25, pp. 1-12.

[3] AL-NAMANKANY, A., 2023. Influence of Artificial Intelligence-Driven Diagnostic Tools on Treatment Decision-Making in Early Childhood Caries: A Systematic Review of Accuracy and Clinical Outcomes. Dentistry Journal, 11(9), pp. 214.

[4] ARJMANDNIA, F. and ALIMOHAMMADI, E., 2024. The value of machine learning technology and artificial intelligence to enhance patient safety in spine surgery: a review. Patient Safety in Surgery, 18, pp. 1-6.

[5] ASAN, O., CHOI, E. and WANG, X., 2023. Artificial Intelligence–Based Consumer Health Informatics Application: Scoping Review. Journal of Medical Internet Research, 25(1),.

[6] ATCEKEN, Z., CELIK, Y., ATASOY, C. and PEKER, Y., 2023. The Diagnostic Utility of Artificial Intelligence-Guided Computed Tomography-Based Severity Scores for Predicting Short-Term Clinical Outcomes in Adults with COVID-19 Pneumonia. Journal of Clinical Medicine, 12(22), pp. 7039.

[7] BHAGAT, S.V. and DEEPIKA, K., 2024. Navigating the Future: The Transformative Impact of Artificial Intelligence on Hospital Management- A Comprehensive Review. Cureus, 16(2),.

[8] CHANH, H.Q., MING, D.K., NGUYEN, Q.H., DUC, T.M., AN, L.P., TRIEU, H.T., KAROLCIK, S., HERNANDEZ, B., PEREZ, VAN NUIL, J., LYLE, N.N., KESTELYN, E., THWAITES, L.,

GEORGIOU, P., PATON, C., HOLMES, A., CHAU, N.V.V. and YACOUB, S., 2023/07//. Applying artificial intelligence and digital health technologies, Viet Nam. World Health Organization.Bulletin of the World Health Organization, 101(7), pp. 487-492.

[9] CHANNA, R., WOLF, R.M., ABRÀMOFF, M.D. and LEHMANN, H.P., 2023/12//. Effectiveness of artificial intelligence screening in preventing vision loss from diabetes: a policy model. NPJ Digital Medicine, 6(1), pp. 53.

[10] CHEN, K.A., NISHIYAMA, N.C., KENNEDY NG, M.M., SHUMWAY, A., JOISA, C.U., SCHANER, M.R., LIAN, G., BEASLEY, C., ZHU, L., BANTUMILLI, S., KAPADIA, M.R., GOMEZ, S.M., FUREY, T.S. and SHEIKH, S.Z., 2024. Linking gene expression to clinical outcomes in pediatric Crohn's disease using machine learning. Scientific Reports (Nature Publisher Group), 14(1), pp. 2667.

[11] DARLEY, S., COULSON, T., PEEK, N., MOSCHOGIANIS, S., SABINE N VAN, D.V., WONG, D.C. and BROWN, B.C., 2022/10//. Understanding How the Design and Implementation of Online Consultations Affect Primary Care Quality: Systematic Review of Evidence With Recommendations for Designers, Providers, and Researchers. Journal of Medical Internet Research, .

[12] DI MARTINO, F. and DELMASTRO, F., 2023/06//. Explainable AI for clinical and remote health applications: a survey on tabular and time series data. The Artificial Intelligence Review, 56(6), pp. 5261-5315.

[13] FERRARA, M., BERTOZZI, G., FAZIO, N.D., AQUILA, I., FAZIO, A.D., MAIESE, A., VOLONNINO, G., FRATI, P. and RUSSA, R.L., 2024. Risk Management and Patient Safety in the Artificial Intelligence Era: A Systematic Review. Healthcare, 12(5), pp. 549.

[14] GALA, D., BEHL, H., SHAH, M. and MAKARYUS, A.N., 2024. The Role of Artificial Intelligence in Improving Patient Outcomes and Future of Healthcare Delivery in Cardiology: A Narrative Review of the Literature. Healthcare, 12(4), pp. 481.

[15] GOMEZ-CABELLO, C., BORNA, S., PRESSMAN, S., SYED, A.H., HAIDER, C.R. and FORTE, A.J., 2024. Artificial-Intelligence-Based Clinical Decision Support Systems in Primary Care: A Scoping Review of Current Clinical Implementations. European Journal of Investigation in Health, Psychology and Education, 14(3), pp. 685.

[16] HALLBERG, S. and HARRISON, D., 2021/10//. Telemedicine via Continuous Remote Care: A Proactive, Patient-Centered Approach to Improve Clinical Outcomes. JMIR Diabetes, 6(4),.

[17] HORAN, M.R., JIN-AH SIM, KRULL, K.R., NESS, K.K., YASUI, Y., ROBISON, L.L., HUDSON, M.M., BAKER, J.N. and I-CHAN, H., 2023. Ten Considerations for Integrating Patient-Reported Outcomes into Clinical Care for Childhood Cancer Survivors. Cancers, 15(4), pp. 1024.

[18] HYO, J.L., JUNG-KYU, L., PARK, T.Y., EUN, Y.H., KIM, D.K. and HYUN, W.L., 2024. Clinical outcomes of long-term inhaled combination therapies in patients with bronchiectasis and airflow obstruction. BMC Pulmonary Medicine, 24, pp. 1-11.

[19] ISTASY, P., WEN, S.L., IANSAVICHENE, A., UPSHUR, R., GYAWALI, B., BURKELL, J., SADIKOVIC, B., LAZO-LANGNER, A. and CHIN-YEE, B., 2022/11//. The Impact of Artificial Intelligence on Health Equity in Oncology: Scoping Review. Journal of Medical Internet Research, .

[20] JUNET, V., MATOS-FILIPE, P., GARCÍA-ILLARRAMENDI, J.M., RAMÍREZ, E., OLIVA, B., FARRÉS, J., DAURA, X., MAS, J.M. and MORALES, R., 2023/07//. A decision support system based on artificial intelligence and systems biology for the simulation of pancreatic cancer patient status. CPT: Pharmacometrics & Systems Pharmacology, 12(7), pp. 916-928.

[21] KASTRUP, N., BJERREGAARD, H.H., LAURSEN, M., VALENTIN, J.B., JOHNSEN, S. and JENSEN, C.E., 2023/12//. An AI-based patient-specific clinical decision support system for OA patients choosing surgery or not: study protocol for a single-centre, parallel-group, non-inferiority randomised controlled trial. Trials, 24(1), pp. 24.

[22] KOSOWICZ, L., TRAN, K., TOAN, T.K., DANG, T.H., PHAM, V.A., KIM, H.T.T., HOANG THI, B.D., TRAN, D.N., PHUONG, A.T., LE, T.H., TA, V.A., WICKRAMASINGHE, N., SCHOFIELD, P., ZELCER, J., TUAN, P.L. and NGUYEN, T.A., 2023. Lessons for Vietnam on the Use of Digital Technologies to Support Patient-Centered Care in Low- and Middle-Income Countries in the Asia-Pacific Region: Scoping Review. Journal of Medical Internet Research, 25(1),.

[23] KOTOVICH, D., TWIG, G., ITSEKSON-HAYOSH, Z., KLUG, M., SIMON, A.B., YANIV, G., KONEN, E., TAU, N., RASKIN, D., CHANG, P.J. and ORION, D., 2023/12//. The impact on clinical outcomes after 1 year of implementation of an artificial intelligence solution for the detection of intracranial hemorrhage. International Journal of Emergency Medicine (Online), 16(1), pp. 50.

[24] KRZESIŃSKI, P., 2023. Digital Health Technologies for Post-Discharge Care after Heart

Failure Hospitalisation to Relieve Symptoms and Improve Clinical Outcomes. Journal of Clinical Medicine, 12(6), pp. 2373.
[25] LAMMONS, W., SILKENS, M., HUNTER, J., SHAH, S. and STAVROPOULOU, C., 2023. Centering Public Perceptions on Translating AI Into Clinical Practice: Patient and Public Involvement and Engagement Consultation Focus Group Study. Journal of Medical Internet Research, 25(1),.
[26] LAURENT, A., PARODIS, I., DEVILLIERS, H. and CHASSET, F., 2024. Clinical trial outcomes for SLE: what we have and what we need. Lupus Science & Medicine, 11(1),.
[27] LEON-FERRE, R., CARTER, J.M., ZAHRIEH, D., SINNWELL, J.P., SALGADO, R., SUMAN, V.J., HILLMAN, D.W., BOUGHEY, J.C., KALARI, K.R., COUCH, F.J., INGLE, J.N., BALKENHOL, M., CIOMPI, F., VAN DER LAAK, J. and GOETZ, M.P., 2024. Automated mitotic spindle hotspot counts are highly associated with clinical outcomes in systemically untreated early-stage triple-negative breast cancer. NPJ Breast Cancer, 10(1), pp. 25.
[28] LOBIG, F., SUBRAMANIAN, D., BLANKENBURG, M., SHARMA, A., VARIYAR, A. and BUTLER, O., 2023/12//. To pay or not to pay for artificial intelligence applications in radiology. NPJ Digital Medicine, 6(1), pp. 117.
[29] MALIK, O.O., FATIMA, E., MUHAMMAD, A.M., DAVE, T., IRFAN, H., FARIHA, F.N.U., MARBELL, A., UBECHU, S.C., GODFRED, Y.S. and ELEBESUNU, E.E., 2024/01//. Impacts of the advancement in artificial intelligence on laboratory medicine in low- and middle-income countries: Challenges and recommendations—A literature review. Health Science Reports, 7(1),.
[30] MARASCIO, N., GIUSEPPE GUIDO, M.S., ROMEO, F., CICINO, C., TRECARICHI, E.M., QUIRINO, A., TORTI, C., MATERA, G. and RUSSO, A., 2023. The Role of Gut Microbiota in the Clinical Outcome of Septic Patients: State of the Art and Future Perspectives. International Journal of Molecular Sciences, 24(11), pp. 9307.