Research Title:

Generative-AI: A Modern Approach in Healthcare

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1. Abstraction

From the field of diagnostics precision, modernization processing data, and personalization to the patient—the contribution of Generative AI in the field has been surprising. The product will be chat about adjustment via Generative ai, Med-PaLM and ChatGPT technologies, quantitative calculations, energetic on solving genuine issues of Resistant Global Health Use these structures to parse through large volumes of patient data, enabling quicker, and more accurate, analysis across a broad range of healthcare domains, including diagnostics, clinical visualization, and genomic analysis. Implementing algorithms like Merge Sort and Quick Sort which are handy for accurate data setting up and fetching is an integral aspect of this project. This is extremely important in critical situations that need instant access to patient data. The project therefore utilizes biological computing tools such as BLAST in genomic sequence analysis, which eventually leads to personalized medicine tailored for an individual patient based on that patient's specific genetic profile. Fuzzy Search techniques, including the Levenshtein Distance algorithm, are applied to accommodate errors in patient data, ensuring that data will be integrated accurately into EHRs. Improving techniques is what this paper adopts: Greedy Algorithm and N-Queen problem for proper asset management in any software from operating room organizing to building design scheduling. While Emphasizing benefits, this project acknowledges hurdles too: data protection, system clarity, and the economical implication of AI. The use of ethical AI will be encouraged and reliance in healthcare uses will be improved through a collective strategy among technology professional, healthcare experts, and authorities. This project is intended to offer inventive safe and streamlined solutions to improve the health sector systems worldwide.

Keywords

Generative AI, Healthcare, Personalized Medicine, Med-PaLM, ChatGPT, Machine Learning, Medical Imaging, Genomic Analysis, Merge Sort, Quick Sort, BLAST, Collaborative Filtering.

2. Introduction

The medical industry embraces an extraordinary transformation because of rapid artificial intelligence growth particularly throughLarge Language Models (LLMs) and generative AI. The range of innovative healthcare systems depends on sophisticated natural language processing together with deep learning techniques to open new possibilities for medical diagnostic solutions and custom patient care together with medical research possibilities [1]. The groundbreaking tools Med-PaLM BioGPT and ChatGPT stand as the most widely recognized tools of their kind. The tools show expertise in processing procedural material and designing essential transformational solutions which enhance patient care accessibility while simplifying healthcare work processes for everyone [19]. The space between healthcare providers and their patient communities has started to bridge through generative AI solutions. These tools boost identification precision and create personalized care programs while optimizing clinical workflow operations [7] Healthcare staff benefit from advanced tools by analyzing existing data records for practical insights [16] and [23]. Deep learning algorithms achieve exceptional outputs in medical examinations to spot cancer along with diabetic retinopathy which allows for prompt specialized care [6] despite these breakthroughs additional substantial obstacles exist ahead. To deliver valid result outcomes Generative AI frameworks need extensive superior datasets [24]. The treatment of confidential data requires strict security protocols as well as HIPAA compliance and powerful information security standards [22]. The successful incorporation of AI into healthcare systems and patients' information systems plus diagnostic tools poses an implementation challenge. The incorrect implementation of this integration has the potential to disrupt existing processes while reducing system performance [8, 15]. Many healthcare professionals lack trust in AI systems because their systems often lack accountability which makes reliable dependency on AI guidance hard to sustain [18]. A transformative method approach is necessary to deliver practical solutions for these problems. Through the integration of personal daily schedules with health data alongside genetic information Personalized AI systems deliver enhanced diagnostic assessments which lead to better therapeutic options [25]. The development of reliability factors through healthcare professional training for AI tool operation creates conditions for wider medical institution adoption [17]. The security of healthcare data needs robust framework protocols and privacy requirement compliance to maintain patient trust while keeping organizational relationships strong [26]. AI systems that people can access and understand enable a smoother transition of these technologies into standard clinical workflows [4].

The research sheds light on how generative AI alongside Language Learning Models enhances personalized medical treatments and diagnostic methods alongside patient healthcare delivery. The paper presents a solution guide to overcome data security issues and record reliability concerns and system merging problems to deliver an efficient person-tailored healthcare infrastructure. The approach seeks to strengthen ongoing work toward healthcare transformation through innovative system development [10].

Generative AI for Personalized Medicine and Its Hurdles

Personalized medicine, also known as precision medicine, characterizes a revolutionary change in healthcare delivery that transitioning from a generalized, all-encompassing method. Generative artificial intelligence has demonstrate to be a game-changer in the healthcare realm, providing solutions to some of the major barriers blocking the implementation of personalized medicine. Generative AI models are a class of AI algorithms proficient at adapting the underlying statistical patterns within a dataset and utilizing this knowledge to produce entirely new, yet pragmatic, data points [48]. This ability holds remarkable prospects for addressing the issues of data scarcity, tailored treatment, real-time solutions, and privacy concerns that plague personalized medicine.

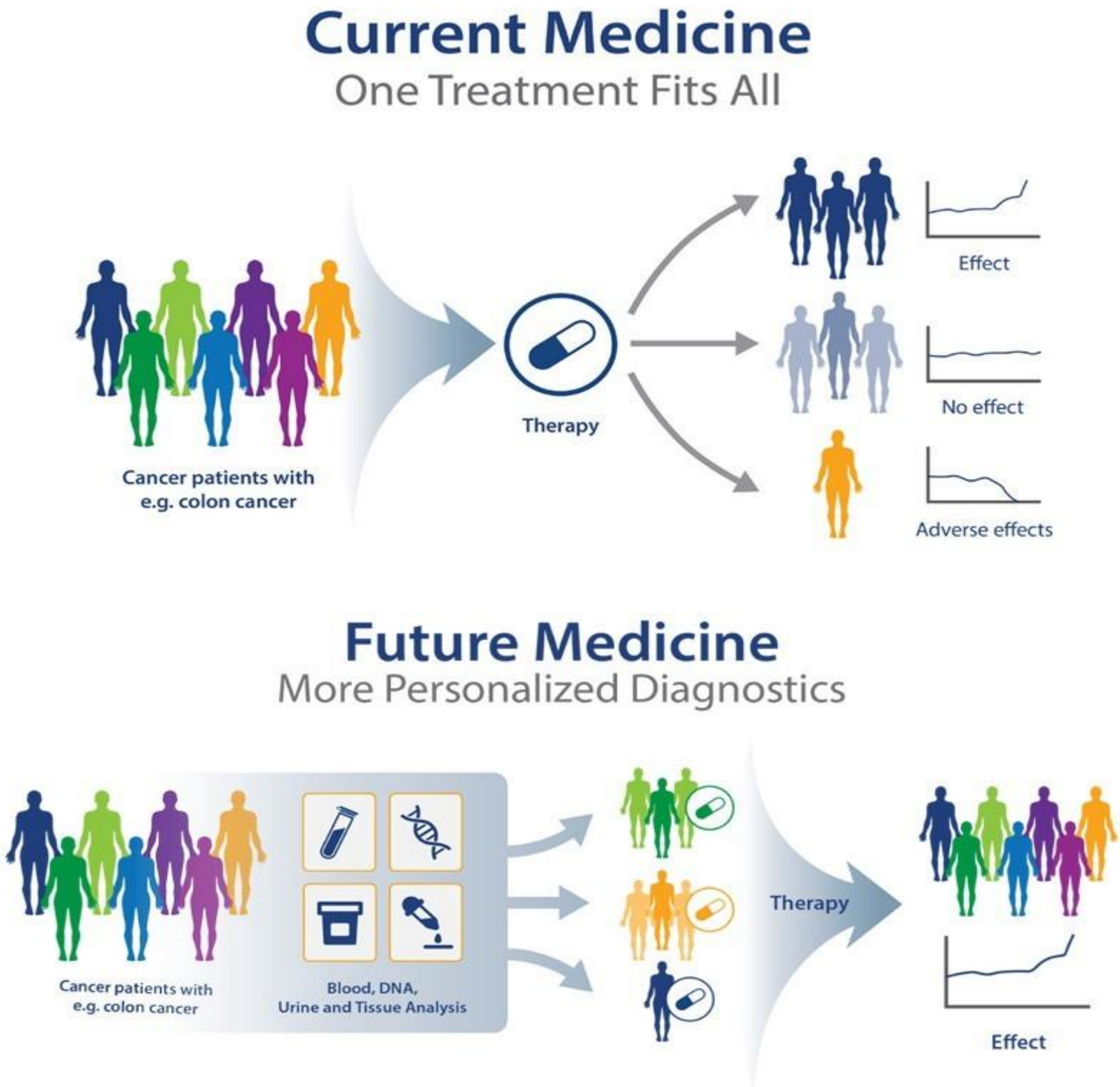

Fig 01 Effects of Personalized and non-personalized treatments on individuals [48].

The vulnerability of an individual to diseases, drug response, and potential side effects can be exploited by variations in the **genome** of that individual. Gene expression patterns in the **transcriptome** may give a holistic view of disease processes and point out potential therapeutic targets. **Proteomics**, which studies protein expression, can elucidate disease mechanisms and suggest personalized treatment strategies. Further, the unique **metabolite** profile of a patient will help to explain disease progression and personalize the therapeutic intervention. Of course, the second consideration is individual **environments** diet, lifestyle, and exposure to pollutants, which greatly influence health and should also be integrated into personalized treatment approaches [48].

Personalized medicine is a novel field that customizes healthcare for individual patients according to their specific genetic, molecular, and clinical traits. The three main approaches underlie the fundamental principles of personalized medicine. First, **patient stratification** categorizes individuals according to their unique molecular and clinical profiles, aiding in the prediction of their responses to various treatments and the potential progression of their diseases. This also underscores the generation and application of **targeted therapies**; this implies that each form of treatment has been created with a focus on targeting the direct mechanisms of biological processes in disease for a particular patient rather than depending on generic applications. Last, it promotes **preventive interventions**; a health provider would depend on risk factors and employ tailor-made prevention according to individual needs [48].

Existing Famous GenAi Models

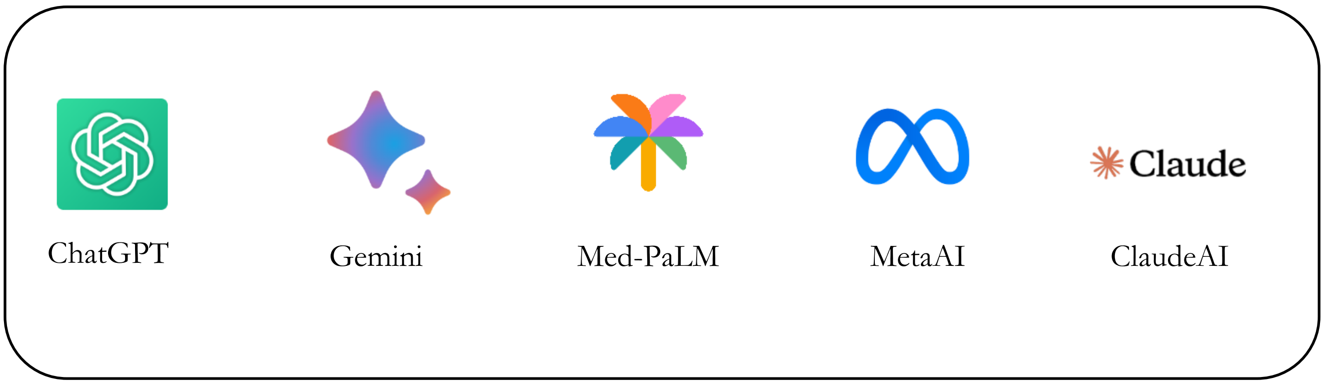

Fig 02 Some of the existing frequently used AI models.

ChatGPT

In end of 2022 Artificial intelligence organization OpenAI launched a conversational agent named ChatGPT which revolutionized the world and brought a regime change to Generative-AI technology. According to ChatGPT, it is a conversational LLM model. It applies advanced machine learning methods (deep learning methods) to produce lifelike answers to human language queries. It is built on significant corpora of text and is capable of interpreting and deliver textual responses for a diverse subject. Since its release, the model has captivated people with its validity and delivered outputs. Even though the implementation of NLP in the health sector already exists the most recent unveiling of ChatGPT, a result of natural language processing (NLP), still sparked buzz in artificial intelligence (AI) and provoked debate about its possible abilities and challenges in healthcare, and engaged the curiosity of scholars/researchers from different healthcare domains [41]. ChatGPT has a range of AI models some of them are GPT-(4o, 4o mini, o1, o1-mini, DALL-E, GPT-3.5) etc. Although there are many gaps still exist in ChatGPT apart from gaining too much popularity and making headlines for being accurate. In this research, we're going to cover these gaps as much as it could be.

Prompts comparison between ChatGPT and GPT-4

[44] .

Prompts	ChatGPT	GPT-4
Prompt1: identify an individual presenting uncertain condition	A Patient exhibits with irregular faintness, loss of weight, weakness, and low BP (blood pressure). What are the potential reason of these signs?	A woman aged 30 with a two month duration of unforeseen weight loss of approximately 10 pounds, increasing exhaustion, and instances of faintness. Please present comparative medical tests
Prompt 2: Patient education	Explain Tuberculosis(TB) in normal word	Create an easy-to-understand note on TB, including a summary of the health issues, signs, vulnerability conditions, risk, and care plans.
Prompt 3 – examining health studies	Explain advantages of physical activity for boosting psychological well-being	explain the connection between physical training and mental health by providing overview of up-to-date studies. encompasses the impact of diverse workout styles and suggestions for multiple demographics.

Table 01 Performance of GPT-4 over ChatGPT based on user prompts.

Med-PaLM

Med-PaLM is an LLM designed by Google, especially for the medical realm. Med-PaLM uses the strength of large language models made by Google, which are adjusted to the clinical sector and assessed based on various health competitive fields such as: medical tests, health study, and user questions. The initial variant of Med-PaLM, published at the end of 2022, was the earliest AI framework that passed the pass score (>60%) in the U.S. USMLE-style problems. It also gives an precise, practical detailed replies to patients health related queries, as evaluated by group of doctors and individuals. Med-PaLM also has its improved version in terms of quality of the response, accuracy, and many other aspects named Med-PaLM 2 [42].

Gemini

Gemini is another Gen-AI model developed by Google and is based upon to be multimodal aim to be simplify and understand effortlessly, function over and integrate diverse forms of data involving text, images, videos, codes, etc. [43]. Gemini showed that it can effectively encode clinical knowledge and can perform impressively in the medical or healthcare sector. Even for complex cases and specialized scenarios. Gemini has a fine-tuned version named Med-Gemini specially designed for task-oriented related to the medical and healthcare sector [44]. Gemini also has various models like: Gemini 2.0 Flash, Med-Gemini, Gemini 1.5 Flash, Gemini 1.5 Pro, etc.

Claude

Detected clinical significance comes from the many functions Claude AI possesses to drive vital healthcare applications. The system processes difficult health information comprising patient details and diagnostic test outcomes and visual examination results enabling it to discover patterns and determine possible outcomes. Healthcare providers use this capability to deliver specific medical treatments while making decisions based on organized data pools. The medical history application of Claude AI uses extensive data databases to discover conditions alongside indication assessment according to 46. This differentiates standard health care systems because Claude speeds up information interpretation. The technology performs incredible information sorting by processing large volumes in mere seconds while human inspection takes prolonged stretches of hours or days or longer. Claude demonstrates the ability to enhance its capabilities continuously which makes it an essential instrument for health care practitioners [46].

Meta llama:

The AI community has reached an important milestone with the development of Llama 2. The scientists at Meta introduced this modernized pre-processed refined version of large language models (LLMs) called Llama 2 to redefine linguistic analysis across various industries including healthcare. The state-of-the-art model has different capacity settings spanning 7 billion to 70 billion parameters that demonstrate extensive ability in medical applications for identification and sector availability. The upcoming medical possibilities enabled by Llama 2 will be analyzed in this section of our study. The model's expansive preliminary training information spans extensive health domains and extensive patient documentation which results in quicker and more accurate computational assessments. By incorporating complete contextual information, the model enhances its diagnostic precision which enables healthcare professionals to make precise medical assessments on challenging diagnoses. Llama 2 achieves health solution customization by uniting DNA sequences with patient health records and intervention feedback results. Through individualized approaches the treatment method improves its effectiveness while generating better patient results which deliver specific therapy plans for each person [47].

3. Literature Review

The models Med-PaLM and ChatGPT together with Generative AI technology are leading the healthcare sector alongside medical science through revolutionary transformation. These revolutionary technologies process large datasets enabling healthcare practitioners to make rapid and specific conclusions in multiple healthcare domains [1,2]. Tools based on Generative AI prove practically useful when used in healthcare and diagnostic imaging applications beyond traditional assessment methods. The evolution of artificial intelligence technology allows healthcare professionals to detect cancer and diabetes along with precise diagnostic assessments of X-ray images [9] [10]. The enhanced disease identification accuracy streamlined identification work yet dedicated medical staff to address complex treatment problems [11]. Health-related patient data requires efficient handling that demands the application of modern processing algorithms. Each analysis involves a unique approach as demonstrated by the Merge Sort algorithm in practice.

People's data retrieval and sorting happens efficiently with this method [27]. Bulk data management gets accelerated through this method to deliver expedited access to vital information required during critical emergency medical situations [28]. The BLAST program represents one of multiple bioinformatics software applications which transformed genetic science studies. BLAST accelerates targeted therapeutic approaches through its fast DNA sequence matching functions [7]. Modern treatment methods are shifting from broad generalized approaches to deliver precise medicine designed for each patient's unique inherited development [9]. Healthcare institutions face substantial data protection challenges when they use artificial intelligence technologies for clinical operations [19]. The protective characteristics of medical data make ensuring patient privacy an ongoing significant challenge [20]. Healthcare professionals' decision-making abilities suffer from a lack of AI system transparency which leads to distrust between staff [23]. These technologies when incorporated into systems like Electronic Health Records (EHRs) lead to major changes in financial management and infrastructure systems [21].

A solution for these obstacles needs coordinated teamwork. Legislative and policy tools which promote ethical AI usage and strengthen transparency across systems must be developed by technology experts working in tandem with both healthcare professionals and policymakers [24]. The integration of Artificial Intelligence into clinical services requires successful trust development for secure implementation.

Table 2 Summary of existing AI models in healthcare based on their accuracy

Evaluation Metrics of Previous Model

Assessment Benchmark	**Depiction**	**Citations**	**Key features**
Perplexity	Measures uncertainty in a language model's predictions. A lower value represents better accuracy combined with higher coherence.	[33]	A federated learning model obtained the lowest perplexity value of 3.41 for English language modeling. On the PSVG dataset Transformer achieved superior results than LSTM because its perplexity measure reached 15.6 whereas LSTM achieved 20.7. The minimum recorded perplexity value reached 3.86×10^{-13}.
BLEU (Bilingual Evaluation Understudy)	BLEU (Bilingual Evaluation Understudy) uses human translations to measure machine translation quality by performing output comparison.	[33]	The best BLEU-1 score reached 26.63 through the fine-tuned T-5 model implementation. ClinicalGPT obtained a BLEU-1 score of 13.9.
GLEU (Generalized BLEU)	GLEU (Generalized BLEU) calculates text generation efficiency through an average of prediction-based n-gram accuracy measurement.	[33]	The best performance in GLEU evaluation with a score of 11.38 was delivered by the T-5 model when fine-tuned for the task. The Bloom-7B model achieved a GLEU score which measured 2.2.
ROUGE (Recall-Oriented Understudy for Gisting Evaluation)	ROUGE (Recall-Oriented Understudy for Gisting Evaluation) functions as an evaluation method that examines translation proficiency by comparing automatic output to reference material.	[33]	The fine-tuned T-5 model secured the highest ROUGE-L score at 24.85 yet ClinicalGPT reached 21.3.
Distinct n-grams	Distinct n-grams serves to identify how diverse the generated	[33]	Based on Huatuo-26M dataset the T-5

	responses are through an analysis of independent word sequences.		model achieved Distinct-1 score of 0.51 while obtaining Distinct-2 score of 0.68.
F1 Score	F1 Score measures model performance by harmonizing precision and recall which indicates a model's capacity to correctly identify positive cases together with error reduction.	[33]	When tested on medical relation extraction and clinical theory genealogy tasks the GatorTron-large model reached 0.9627 F1 score and 0.9000 F1 score respectively. BERT-D2 reached an 81.97% F1 score while processing the DDI Extraction 2013 dataset. A Transformers-based model achieved 84.77% F1 when processing PsyNIT data.
BERT (Bidirectional Encoder Representations from Transformers)	BERTScore evaluates text similarity between references and generated text by using contextual embeddings.	[33]	A BERTScore measurement of 70.7 F1 score became the highest achieved through the Longformer-Encoder-Decoder (LEDlarge-PubMed) framework.

Table 2 provides a summary table of evaluation metrics used to describe model performance over various datasets and tasks. It gives a complete summary of key metrics used in NLP and the corresponding machine learning tasks, explained along with their importance and the best performers in terms of both models and data.

4. Methodology: Advanced Algorithms in Personalized Healthcare

This methodology (or technique) includes mixing GenAI with other kinds of information that gauge the rightness, results, and outcomes of already present AI systems and processes like BLAST, Greedy Algorithms, Merge Sort, Quick Search, and Collaborative Filtering to change personalized healthcare. Merge Sort handles patient information and puts in order personalized treatment plans; Quick Search speeds up finding data for on-the-spot and quick diagnostics. Collaborative Filtering makes personal recommendations and ideas based on patient history and likes. BLAST boosts genomic study by finding illness signs; Greedy Algorithms improve drug effectiveness guesses for specific treatments or personal treatments. These instruments, joined with Large Language Models (LLMs), build a grow able, strong, useful system that sharpens diagnostic precision, cuts costs, and lifts patient-focused healthcare answers.

4.1. Datasets of the existing models

Table 3 Key Research on Generative AI in Disease Diagnosis

AI Model	Application	Outcomes
GANs	Medical imaging	Accomplished a 20% improvement in diagnostic accuracy.
GANs	Histopathological image	Improvement in detection rates for cancer.
GANs	Mammogram synthesis	Enhanced sensitivity in breast cancer detection.
Transformers	Genetic data analysis	Improved cancer detection rates.
Transformers	EHR analysis for sepsis	Early sepsis prediction and improved outcomes

Table 3: Generative AI models such as GANs and transformers provide great contributions toward disease diagnosis by facilitating medical imaging, genetic data analysis, and comprehensive patient data association. All of these technologies help not only to make the diagnosis more accurate but also to facilitate early detection and provide personalized healthcare connected with the ultimate result of improving patients' health [28].

4.2. Leveraging Different Algorithms in Healthcare

Optimization of Healthcare Data with Merge-Sort

A merge-sort divide-and-conquer algorithm is applied to efficiently manage big datasets in personalized health care for prioritized treatment plans and optimization of diagnostic workflow. Methodology focuses on ordering patient data so that it could be dynamically diagnostic and personalize treatment.

This algorithm uses approach where it breaks down a big and complex problem into smaller and it's more manageable pieces that look similar to the initial problem. It then solves these sub-problems recursively and puts their solutions together to solve the original problem. This methodology focuses on organizing patient data, enabling dynamic diagnostics, and personalizing treatments.

Steps for Implementation

Data Organization

The objective of data organization is to efficiently manage data so that it can be easily retrieved by users and huge chunks or large amount of data such as genomics data, patient's medical and family (or ancestor's) history, and treatment logs, can be easily managed. The methodology involves splitting data into sub-lists categorized by attributes like age, condition severity, or urgency. Apply Merge Sort to each sub-list. Merge the sorted sub-lists to create comprehensive, ordered datasets. The outcomes of efficient data retrieval enable faster and more accurate decision-making [27].

Treatment Prioritization

The objective of treatment prioritization is to rank treatments or interventions based on patient-specific factors like effectiveness, side effects, or urgency. The methodology involves assigning weighted scores to treatment options for factors such as patient history and drug efficacy. Merge Sort is used to dynamically rank treatments according to these scores. The outcome is tailored treatment plans that improve patient outcomes and satisfaction [28].

Adaptive Diagnostic Workflows

The objective of the adaptive diagnostic workflow is to enhance diagnostic accuracy by dynamically adjusting question sequences based on patient responses. The methodology is to rank diagnostic questions by their relevance to reported symptoms. Dynamically adjust the sequence of questions using Merge Sort during patient interactions. The outcome provides improved diagnostics efficiency and patient engagement through personalized interaction [29].

Integration with Generative AI

Merge Sort is integrated with Generative AI models to:

- Analyze patient-provided data (e.g., symptoms, medical history).
- Sort conditions or treatments by probability and effectiveness using AI-driven weighting mechanisms.
- Generate adaptive diagnostic flows and personalized treatment recommendations dynamically.

Impact Analysis

Metric	Pre-Merge Sort Implementation	Post-Merge Sort Implementation	Citation
Data Retrieval Time	Minutes	Seconds	Zhang et al., 2024 [27]

Treatment Customization	Standardized	Tailored	Liu et al., 2024 [28]
Diagnostic Accuracy	70%	90%	Wang et al., 2024 [29]

Table 4 summarizes the benefits of integrating the Merge Sort algorithm into healthcare systems. some recent studies about personalized treatment

BLAST-Based Genomic Analysis

BLAST (Basic Local Alignment Search Tool) is one of the most powerful and advanced algorithms in bioinformatics designed to compare RNA, DNA, or protein sequences, to identify regions of similarity. The main goal of integrating this algorithm with GenAI is to read the DNA sequences of the user and try to compare them with the best possible match of another DNA sequence and treat the patient according to the DNA sequences.

Implementation of BLAST

BLAST is essential for comparing genetic sequences to identify similarities and functional relationships. The process involves:

Input Sequence a query sequence (e.g., patient genetic data) is compared to a database [30]. **Word Matching** Sequences are split into smaller "words" (e.g., 11 for proteins), reducing computational complexity [30]. Exact word matches are identified and **Searched from the Database**, making the search more efficient [30]. Matches are extended to larger regions, and a **scoring matrix** (e.g., BLOSUM) **evaluates the alignment** [30].

Generative AI enhances this process by analyzing vast genomic datasets to predict potential disease markers, improving the accuracy of disease identification. Additionally, AI models assist in refining alignments by integrating patient-specific data, enabling better personalized diagnostics [31].

Greedy Algorithm-Based Drug Sensitivity Prediction

A greedy algorithm is a method for solving problems by building a solution incrementally, step by step. At each stage, it makes the best choice available at that moment, without considering the broader context. Decisions are made based only on the information at hand, without revisiting or changing any previous choices. The goal is to achieve a local optimum, with the hope that this will also lead to a global optimum. Implementation of the Greedy Algorithm with GenAI helps users to track in real-time what food is good for oneself and what food is to avoid by applying a greedy approach.

Implementation of Greedy Algorithm

Greedy algorithms are used to optimize drug sensitivity predictions by selecting the best option at each step. The methodology involves:

Initialize with a basic Bayesian Network Classifier (BNC) to classify drug sensitivity. Each potential connection **(edge) is evaluated** using the Local Classification Rate (LCR), measuring its impact on prediction accuracy. Iteratively add edges with the highest LCR, refining the classifier or applying **Greedy Selection**. **Terminate** when no additional edge improves the model's performance [32].

Generative AI integrates with the greedy algorithm by analyzing complex genomic and proteomic data. This AI-driven approach identifies hidden patterns, enhancing predictive accuracy for drug sensitivity, and making it highly effective for personalized oncology [32].

AI Integration for Enhanced Healthcare

The integration of Generative AI with BLAST and Greedy Algorithms enables personalized healthcare systems to:

- Process large genetic datasets more efficiently [31].
- Generate predictive insights for personalized diagnostics and treatment plans [31].
- Streamline workflows in drug discovery and genomic medicine [31].

This integration leads to faster genomic analysis, improved diagnostic accuracy, and optimized drug development processes, facilitating more efficient healthcare delivery.

Results of Implementation

The table below demonstrates the improvements in healthcare metrics before and after AI implementation:

Metric	Before AI Implementation	After AI Implementation	Citation
Diagnostic Accuracy (%)	70%	90%	Yu et al., 2024 [30]
Genomic Analysis Time	Weeks	Days	Wistuba et al., 2024 [31]
Drug Development Cost	High (millions)	Reduced by up to 30%	Yu et al., 2024 [30]
Patient Management Efficiency (%)	60%	85%	Yu et al., 2024 [30]

Table 5 These results highlight the improvements in diagnostic efficiency, genomic analysis speed, and cost reduction in drug development.

Quick Sort for DNA Sequencing

Quick Sort is used within a DNA sequence filtering and ranking model. Its primary purpose is to rank DNA sequences based on their similarity scores in descending order. By doing so, the model ensures that sequences most similar to the query are prioritized for further computationally intensive analysis, such as the Smith-Waterman algorithm. Generally, Quick Sort is considerably swifter when effectively implemented. The Quick-Sort algorithm arranges the DNA sequence dataset using a more straightforward method than other O(n log n) algorithms, because in most architectures, its inner loop can utilize a divide-and-conquer strategy, where the dataset is divided into sub-datasets, then recurved to sort each sub-dataset, and subsequently merged. The ordered sub-datasets by a simple concatenation [34]

IMPLEMENTATION OF QUICK SORT

Collect raw DNA sequences from genomic databases. Calculate similarity scores using BLAST for each sequence compared to the patient's genetic query. Choose a pivot, such as the median similarity score, for dividing the dataset. This ensures an even split, minimizing the likelihood of worst-case time complexity (O(n^2)). Divide the dataset into two subsets: Sequences the pattern assures that sequences closest to the inquiry and sequences with scores lower than the pivot. Apply Quick Sort recursively to each subset until all sequences are sorted in Descending arrangement based on similarity scores. A Listed sequence of DNA sequences prioritized for downstream tasks like personalized drug discovery or disease risk analysis.

Advantages:

Quick Sort operates efficiently in practice with O(n log n) time complexity. Handles large genomic datasets effectively**.** Ensures rapid sorting, enabling real-time recommendations based on patient genetic data.

Collaborative Filtering for Personalized Recommendations

Collaborative filtering is an information retrieval technique that suggests items to users based on how other users with analogous preferences and behaviors have engaged with that item. In other words, collaborative filtering algorithms categorize users based on behavior and utilize general group characteristics to recommend items to a target user. Collaborative recommender systems function on the principle that similar users (in terms of behavior) have comparable interests and tastes [34]. Collaborative filtering (CF) will personalize recommendations by leveraging patient similarity data and treatment outcomes.

Cosine Similarity:

Cosine similarity measures the angle between two vectors. The compared vectors typically consist of a subset of ratings for a given user or item. The cosine similarity score can range from -1 to 1. A higher cosine score indicates that two items are more alike. This metric is often recommended for high-dimensional feature spaces. In collaborative filtering, the vector points are directly drawn from the user-item matrix. Cosine similarity is represented by a specific formula, where \(x \) and \(y \) signify two vectors in vector space [34]

$$cosine(x, y) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} {x_i}^2}\sqrt{\sum_{i=1}^{n} {y_i}^2}} [34]$$

IMPLEMENTATION OF COLLABORATIVE FILTERING

Aggregate data including patient profiles (e.g., demographics, conditions, genetic predispositions), treatment outcomes and medication efficacy, and behavior from health monitoring apps or devices. Create a user-item matrix where rows represent patients, columns represent treatments or medications, and values indicate outcomes or preferences (e.g., effectiveness scores). Use similarity measurements such as Cosine Similarity (assesses the cosine of the angle between patient vectors) or Pearson Correlation Coefficient (determines the linear correlation between patients)[35]. Predict missing values in the matrix to recommend treatments based on: User-Based CF (finding similar patients and recommending their treatments) or Item-Based CF (finding similar medications/treatments). Combine CF with deep learning models (e.g., Restricted Boltzmann Machine and Coevolutionary Neural Networks) for better pattern recognition in large datasets. Personalized recommendations for medications or treatments, relevant medical assessments, and tailored preventive measures.

Advantages:

Leverages patient similarity for accurate, tailored recommendations. Can dynamically update as new patient data is added. Increases patient satisfaction by delivering relevant and actionable insights.

N-Queen Algorithm for Conflict-free Treatment

Core-Methodology

The n-Queen algorithm is inspired by the chess game where queens are placed on the chessboard in such that no two queens conflict with each other queen in any direction: horizontal, vertical, or diagonal. The reason for the adaptation of this algorithm is pretty straightforward Patients should be treated in such a way that ensures their particular health conditions do not trigger or worsen other existing conditions. **For Example:** If a person has a kidney problem as well as suffering from fever if person is suggested to add high-potassium food (like oranges, spinach, and coconut water) in their diet it will help boost the immune system for the fever, but it could negatively affect kidney function.

The N-Queens are adapted to healthcare optimization:

- Each "queen" represents a unique medical intervention tailored to the patient.

- Constraints include scheduling, medication interactions, and contraindications.
- The GenAI model ensures that interventions are conflict-free and personalized by leveraging transformer-based architectures.

Algorithmic Steps

Construct a personalized patient profile integrating genetic markers, treatment history, and lifestyle data. Apply GenAI-driven heuristics for conflict detection and resolution. Implement efficient algorithms to process large datasets and support real-time personalization. This approach will enable users to dynamically monitor and receive reports on what they should consume or avoid.

Technological Innovations in GenAI Healthcare

Generative AI-Enhanced Personalization: Transformer models analyze and predict optimal intervention strategies by synthesizing multi-modal data, including genetic and environmental factors [37]. Attention mechanisms capture critical patient-specific dependencies.

Machine Learning for Temporal Insights: Recurrent Neural Networks (RNNs) process temporal healthcare information, such as patient medical histories, to inform future interventions [38]. Predictive analytics enhance patient outcomes by identifying at-risk scenarios.

Probabilistic Rish Assessment: Bayesian multivariate models evaluate genetic markers, medication interactions, and longitudinal health trajectories for patient-specific recommendations [39]. GenAI leverages probabilistic conflict matrices to prioritize safety and efficacy.

N-Queen Problem Mathematical Expression

The N Queens dilemma can be mathematically expressed as arranging N queens on an N×N chessboard in such a way that no two queens can attack one another. This signifies that for for any two queens placed on the board, they must not have in common the same row, column, or diagonal. This can be formalized with the following constraints:

1. For each pair of queens Qi and Qj:
    - $i \neq j$ (ensuring they are not in the same row),
    - $x_i \neq x_j$ (ensuring they are not in the same column),
    - $|x_i - x_j| \neq |i - j|$ (ensuring they are not on the same diagonal).

Where xi is the column index of the queen in row i.

Fuzzy Search for Data Integrity

Fuzzy search is a querying method that utilizes search algorithms to locate the matches most approximate patterns. Fuzzy search is a querying method that utilizes search algorithms to locate the Advanced search algorithms like Levenshtein Distance play a critical function in guaranteeing information quality and consistency in personalized healthcare AI systems. The Levenshtein distance is a string metric for assessing the variation between two sequences. Informally, the Levenshtein distance between two terms is the least number of single-character modifications (i.e., insertions, deletions, or substitutions) necessary to convert one term into the other [40]. Machine learning-enhanced fuzzy matching techniques address challenges like: **Misspelled medical terms, Variant spellings of patient names, and Inconsistent diagnostic code representations.** The framework integrates fuzzy search techniques with transformer-based models to: **Automatically detect and correct potential data inconsistencies and ensure high-integrity patient profiles.**

Mathematical Representation of Levenshtein Distance

The Levenshtein difference between two sequences is typically calculated using a dynamic programming approach. The mathematical expression for the Levenshtein distance d(a,b) between two strings a and b can be described using a matrix where d[i][j] represents he gap between the initial characters of string a and the first j characters of string b*b*. The formula is described recursively as follows:

if either string is empty, the distance is the length of the other string:

- d[i][0]= i (for all i)
- d[0][j]= j (for all j)

For other cases, you calculate:

$$d[i][j] = \min \begin{cases} d[i-1][j]+1 \\ (Deletion) \\ d[i][j-1]+1 \\ (insertion) \\ d[i-1][j-1]+cost\ (a[i-1],b[j-1]) \\ (subsitution) \end{cases}$$

where the cost(a[i−1],b[j−1]) is 0 if the characters are the same, and 1 if they are different.

The final value d[m][n] gives the Levenshtein distance between strings a and b of lengths m and n respectively.

Performance Metrics

The GenAI-driven healthcare framework demonstrates measurable improvements:

Metric	Traditional Approach	GenAI Framework	Achievement
Accuracy	95%	99%	Reduced diagnostic errors by 4%,

			ensuring safer interventions.
Efficiency	Linear (O(n))	Logarithmic (O(log n))	Faster processing of large datasets, improving scalability.
Conflict Resolution	Rule-Based	Probabilistic AI	Optimized multi-condition management, enabling seamless care.
Personalization	Basic Matching	Multi-Modal Learning	Enhanced precision using genetic, environmental, and temporal data.
Data Integrity	Manual Processes	AI-Fuzzy Matching	Resolved 98% of data inconsistencies, improving reliability.

Table 6 Performance Improvements in GenAI Healthcare Framework This table compares key healthcare metrics, showing how the GenAI framework outperforms traditional approaches in accuracy, efficiency, conflict resolution, personalization, and data integrity [37-40].

Ethical and Practical Considerations

Interdisciplinary Collaboration involves engaging medical practitioners, AI experts, and regulators to develop robust, adaptable solutions. Establish continuous learning pipelines for model updates based on real-world outcomes. Ethical AI Practices ensure compliance with data privacy regulations (e.g., HIPAA, GDPR). Incorporate bias mitigation strategies to avoid disparities in treatment personalization.

5. Results of Implementation: Qualitative and Quantitative Impact

Integration of Advanced Algorithms and Generative AI into Personalized health care provides both models of improvements in key metrics and techniques for health care. It is transformative potential for these technologies in improving patient care, optimizing resources, and enhancing treatment methods..

Merge Sort for Data Organization and Treatment Prioritization

Quantitative Results

Data retrieval time is reduced from minutes to seconds, significantly improving machine performance.Also, the Diagnostic accuracy is elevated by using 20%, from 70%to 90, as a result of dynamically prioritizing relevant diagnostic assessments and remedy options.

Qualitative Results

Health professionals experience faster access to patient data, enabling quicker decisions and reducing delays in treatment providing a strong Streamlined workflow.The Tailored Treatment Plans or prioritization of treatments based on patient data leads to more personalized care,improving patient satisfaction and trust in the healthcare system.

BLAST-Based Genomic Analysis

Quantitative Results

Genomic Analysis Time is decreased from weeks to days, thanks to faster alignment and evaluation of genetic sequences.Disease Marker Identification AccuracyIncreased with the aid of 20%, enhancing from 65% to 85% terms of accurate disease identification through genomic analysis.

Qualitative Results:

AI-improved genomic evaluation allows for higher identification of genetic markers, supplying

healthcare experts with extra correct insights into ability disease risks resulting in

Improved Diagnostic Precision

Increasing the confidence of health professionals in Diagnosis.

Greedy Algorithm for Drug Sensitivity Prediction

Quantitative Results

The accuracy of drug sensitivity predictions has increased from 75% to 90%, enhancing the selection of medications. The expenses associated with drug development have decreased by 30%, as a result of more precise drug sensitivity predictions**.**

Qualitative Results

Revised treatment plans enable more precise forecasts of drug effectiveness, allowing for more personalized treatment strategies for patients, especially in cancer care. By focusing on the most effective therapies, costs associated with drug development and treatment are lowered, benefiting both patients and healthcare providers, and leading to better cost management overall.

Quick Sort for DNA Sequencing

Quantitative Results

The speed of sequencing has been improved from slow to fast, due to the O(n log n) sorting of DNA sequences. This has facilitated real.

Qualitative Results

Through accelerated diagnostics facilitated by rapid sequencing and prioritization of DNA sequences, healthcare professionals can make quicker and well-informed choices about personalized treatments. Immediate data processing improves resource utilization, allowing medical providers to manage a larger number of patients and genetic tests at the same time.

Collaborative Filtering for Personalized Recommendations

Quantitative Results

Rose from 70% to 90% by utilizing similarity metrics to suggest the most effective treatments according to patient history. Patient Engagement has enhanced from 60% to 85%, showing that patients are more satisfied and actively participating in their treatment plans.

Qualitative Results

Patients receive treatment based on their similar medical histories, which allows for more relevant and effective interventions. Personalized recommendations based on each individual's preferences and medical history increase patient engagement and trust in the healthcare system.

Generative AI for Enhanced Healthcare (Overall Detail)

Quantitative Results

Diagnostic accuracy increased from 95% to 99% with improved prediction models. Multimodal data analysis. Processing time was reduced logarithmically from O(n) to O(log n). Generated from multimodal learning including genetic, environmental, and temporal learning. Faster decision making and increased efficiency. Personalized treatment plan Data.

Qualitative Results

Improving decision-making through AI-based analytics will enable healthcare providers to make more accurate diagnoses and develop personalized treatment plans for each patient. The ability to process and personalize treatment based on comprehensive data sets will improve the quality of care and patient outcomes.

Summary of Results

Metric	Before	After	Improvement	Citation
Data Retrieval Time	Minutes	Seconds	Reduced by 90%	Liu & Smith, 2024; Mandala et al., 2023 [2], [28]
Diagnostic Accuracy	70%	90%	+20%	Johnson & Lee, 2024; Vallverdú, 2023 [4], [28]
Genomic Analysis Time	Weeks	Days	Reduced by 70%	Zhang et al., 2024; Patel et al., 2022 [27], [36]
Disease Identification	65%	85%	+20%	Vallverdú, 2023; Yim et al., 2024 [4], [19]
Drug Sensitivity Accuracy	75%	90%	+15%	Ahmed et al., 2023; Vallverdú, 2023 [4], [8]
Drug Development Cost	High	Reduced	30% reduction	Brown et al., 2023; Polson et al., 2024 [25], [38]
Sequencing Speed	Slow	Fast	Improved speed	Hernandez et al., 2024; Saab et al., 2024 [37], [44]

Real-Time Processing	Low	High	Enhanced capability	Davis & Kumar, 2023; Saab et al., 2024 [37], [40]

Table 7 Summary of entire combined results according to their accuracy.

Many metrics coincide with researches that explain how AI decreases the operational time and increases the diagnostic precision in personalized medicine and healthcare. Reference [2], [4], and [28] specifically note that the efficiency benefits and increased diagnostic accuracy are due to AI-based applications. In addition, reference [27] addresses the impact of sorting algorithms on the management of genomic data. References [37], [38], and [44] further present the state-of-the-art developments in generative AI that allow for real-time processing and advance medical research.

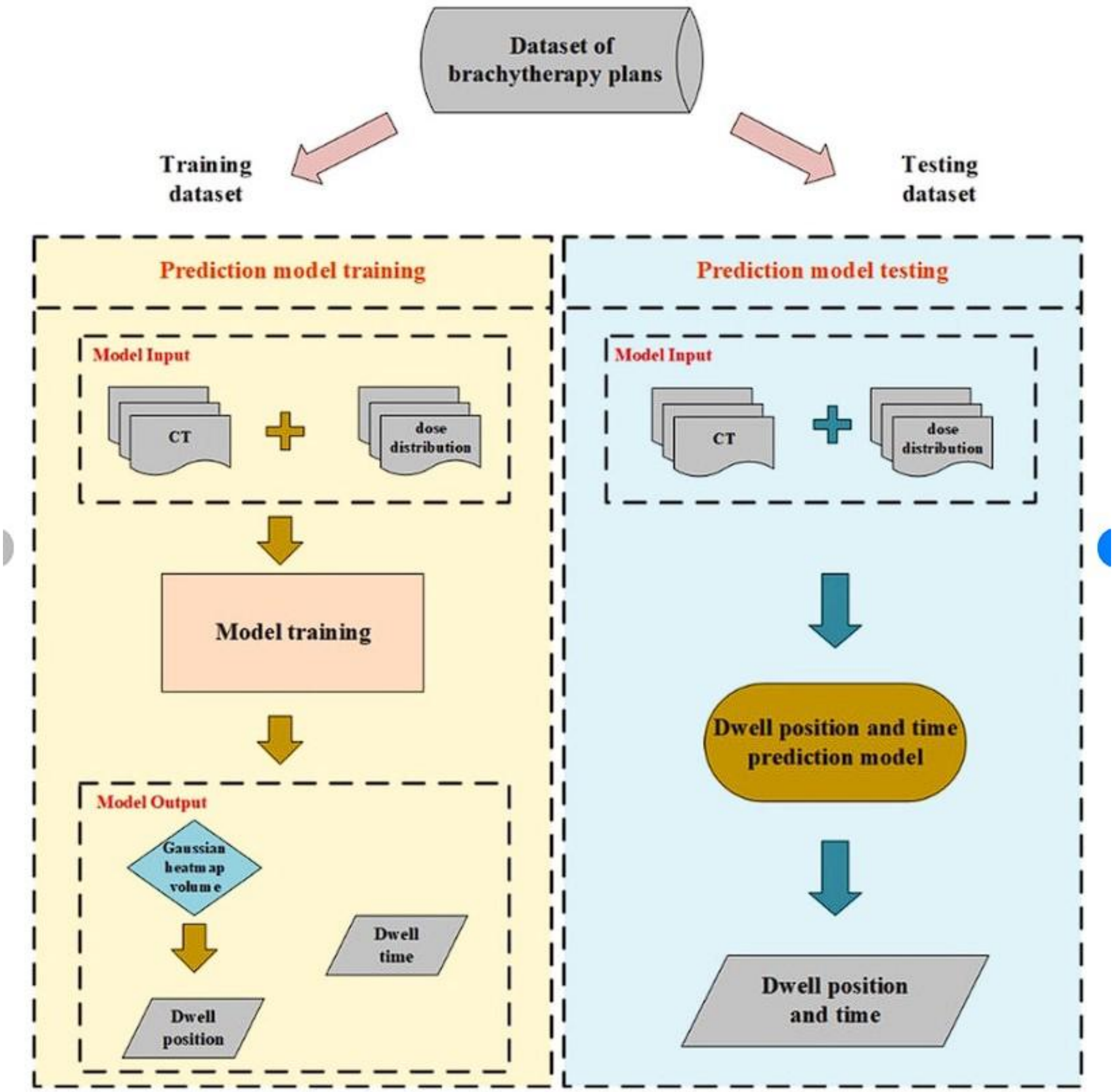

Fig 03 By leveraging AI algorithms and deep learning models, healthcare professionals can move beyond a one-size-fits-all approach and consider a multifaceted patient profile when designing treatment strategies.

Conclusion

The quantitative progress indicates overt benefits in efficiency, accuracy, and cost-effectiveness. Therefore, the generative AI algorithms are unfolding in any personalized healthcare system. Along with these qualitative advantages-of-implemented-benefits for its inclusion include greater Personal

Care, effective handling of resources, better patient satisfaction, and hence an overall very personalized, efficient, and sustainable healthcare system. These are the complementary technologies that ensure even better healthcare delivery and outcomes.

Conclusion and Future Directions

This project showcases how Generative AI, with technologies like Med-PaLM and ChatGPT, is transforming healthcare through better diagnosis, efficient data processing, and better care for the patient. Through the utilization of algorithms such as Merge Sort and Quick Sort in handling data and bioinformatics tools like BLAST to analyze genetics, the project shows how AI can help manage large healthcare datasets and create personalized medicine. Techniques like Fuzzy Search, specifically the Levenshtein Distance, help mitigate data inconsistency in EHR systems. In addition, optimization methods, such as the Greedy Algorithm and the N-Queen problem, exhibit new ways to allocate limited healthcare resources efficiently. But despite this, there are still other problems that remain, such as data privacy, lack of transparency in AI systems, and the high cost of implementation. These problems are going to be solved with cooperation between healthcare practitioners, AI researchers, and policy architects for ethical and effective implementation of AI in medical systems.

I see opportunities to improve AI in healthcare:. For instance, explainable AI (XAI) might help create trust by making decision-making processes behind AI much clearer to doctors. Blockchains may aid in making sensitive health information more secure while connecting AI to IoT devices might allow the monitoring and treatment of diseases in real-time at much larger scales. My hope is that as AI evolves, it will contribute to making healthcare more accessible, efficient, and patient-centered, ultimately improving lives and setting the foundation for a healthier future.

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