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Curapath: Ai Driven Personalized Treatment Plans

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Abstract
The rising demand for efficient, accessible, and personalized healthcare shows the need for AI-driven solutions that connect patients, doctors, and hospital staff. CuraPath, AI Driven Personalized Treatment Plans, is an intelligent healthcare platform designed to tackle issues like fragmented patient records, delayed diagnoses, and heavy administrative workloads through one integrated system. It uses Natural Language Processing (NLP) and Machine Learning (ML) models powered by GROQ to analyze patient symptoms, make condition predictions, and suggest personalized treatment plans. The platform operates through three secure portals: Patient, Doctor, and Staff. This setup ensures smooth real-time collaboration, quicker clinical decisions, and improved hospital coordination. Patients can easily enter their symptoms and receive AI-based guidance. Doctors get structured insights to aid their diagnoses, and staff can automate routine tasks like scheduling and notifications. By combining AI analytics, predictive insights, and strong data security, CuraPath improves healthcare delivery efficiency, enhances the patient experience, and lightens operational burdens. It supports global health goals by making intelligent and accessible healthcare a reality.

Keywords: AI in healthcare, personalized treatment, NLP, ML, hospital management, symptom checker, HER

1. INTRODUCTION

In modern healthcare, patients often face scattered medical records, delays in diagnoses, and complicated communication among doctors, staff, and themselves. These problems slow down treatment, add to administrative workloads, and create stress for both patients and healthcare providers. CuraPath, AI Driven Personalized Treatment Plans, aims to tackle these challenges by functioning as a smart healthcare assistant that links patients, doctors, and staff throughout the care process.

CuraPath does more than just provide medical information. It automates important healthcare tasks such as symptom analysis, predicting conditions, planning personalized treatments, and securely managing patient data. By streamlining these processes, it reduces diagnosis time, cuts down on manual paperwork, and allows doctors and staff to spend more time on direct patient care. Patients gain instant guidance, quick access to medical records, and personalized recommendations, leading to better experiences and greater engagement in their healthcare journey.

CuraPath also acts as a virtual health companion, helping patients understand test results, schedule appointments, and track their treatment progress. It gives doctors real-time clinical insights, risk predictions, and suggested interventions to improve decision-making. Hospital staff become more efficient with automated resource allocation, appointment management, and notifications. With AI, natural language processing, and machine learning at its core, the system continually learns and improves, enhancing its accuracy and responsiveness over time. It ensures accessibility through multilingual interfaces, voice assistance, and secure role-based access, making healthcare services more inclusive and focused on patients.

This project builds on several key research studies in AI-driven healthcare. The work by Jovanović et al. (2019) led to the use of AI-based conversational systems to improve patient interaction and engagement. Bond et al. (2020) emphasized improving usability and patient experience. The research of Altuwaiyan et al. (2020) guided the addition of privacy and security features. Badlani et al. (2022) and Koushal et al. (2025) shaped the multilingual support and accessibility features. The application of natural language processing and machine learning for symptom analysis and triaging was inspired by Ren et al. (2023), Yang et al. (2024), and Reddy et al. (2024), while the idea of AI-powered virtual assistance in healthcare came from Naswa et al. (2024). Together, these studies influenced the design, functionality, and intelligence of the CuraPath system.

2. LITERATURE REVIEW

Conversational Artificial Intelligence (AI) in healthcare has progressed from simple rule-based dialogue systems to intelligent, secure, multilingual, and context-aware assistants capable of supporting clinical and administrative workflows.

The earliest developments focused on enhancing patient–provider communication and automating routine hospital service requests. Jovanović et al. **[1]** demonstrated that conversational healthcare chatbots could significantly improve patient interaction with digital health services by automating appointment scheduling, reducing response delays, and providing instant access to verified medical information. Their findings established chatbots as valuable supportive tools for hospital information systems, enabling improved communication efficiency and reducing manual operational bottlenecks. To validate usability and patient trust in such solutions, Bond et al. **[2]** evaluated conversational UIs using modified traditional usability metrics, showing that conversational systems require additional behavioural, trust, and satisfaction-oriented assessment dimensions but still achieve high task-completion and acceptance rates among end-users. With rising adoption of voice-enabled healthcare platforms, secure communication became a major concern, especially in telemedicine environments. Altuwaiyan et al. **[3]** addressed this by designing a privacy-preserving encrypted voice-query healthcare assistant capable of secure computation without sacrificing speed or clinical response accuracy, showing that privacy-focused architectures can be integrated with conversational health services without operational trade-offs. As healthcare services expanded toward diverse population groups, inclusive and linguistically adaptive chatbot models became essential. Badlani et al. **[4]** introduced a multilingual conversational chatbot using machine learning and translation-driven NLP pipelines to support patients with different regional languages, significantly improving accessibility and interaction quality. Building on linguistic inclusivity, Koushal et al. **[9], [10]** further advanced regional-language medical understanding using domain-aware symptom classification and medical ontology-based reasoning, making conversational healthcare services more suitable for rural, low-literacy, and resource-constrained populations. Beyond patient communication, conversational AI has evolved into a workflow automation and clinical decision-support layer. Yang et al. **[5]** proposed an AI-based urgency prioritization model for digital patient-portal messages, reducing clinician response time by identifying critical cases using severity-based ranking. Similarly, Ren et al. **[8]** employed BERT-based contextual deep language models to classify portal messages into informational, administrative, and medical categories with high accuracy, reducing cognitive load and improving triage routing efficiency for healthcare professionals. The growing demand for psychological assistance introduced a separate branch of emotionally competent conversational agents. Naswa et al. **[6]** developed *iCare*, a mental health–focused virtual assistant capable of empathetic, personalized dialogue delivery, demonstrating stronger engagement, comfort, and disclosure willingness compared to standard automated support platforms. Recognizing that general NLP models lack medical domain specificity, Reddy et al. **[7]** introduced custom healthcare-centred Natural Language Understanding (NLU) models that accurately recognize symptoms, patient intent, and clinical terminology, achieving improved response relevance and reducing misunderstanding risks in automated consultations. Collectively, this body of research reveals a clear evolution from basic utility-driven conversational tools toward advanced, privacy-aware, multilingual, clinically aligned, emotionally supportive, and workflow-integrated digital healthcare companions. Modern systems integrate secure communication, clinical message prioritization, linguistic adaptability, and domain-specific reasoning, demonstrating their potential to support scalable digital healthcare ecosystems. These advancements strongly align with next-generation platforms such as *Cura-Path*, which combines multilingual symptom analysis, real-time interaction, privacy safeguards, and AI-driven patient support for holistic digital healthcare service delivery.

3. METHODOLOGY

The research process for developing CuraPath, an AI-driven personalized treatment plan, follows a clear and structured method. This ensures the platform is accurate, secure, and fits with real clinical workflows. It focuses on solving key challenges such as delayed diagnosis, fragmented communication, and high administrative workloads. By using AI, NLP, and ML technologies, CuraPath provides faster and more reliable symptom analysis, treatment recommendations, and task automation. The development process includes data collection, model design, system structure, testing, and ongoing improvements. This makes sure the platform is both effective and practical for real-world healthcare. This method allows for adjustments to changing healthcare needs and promotes easy integration with hospital systems, which improves overall efficiency and patient outcomes.

A. Data Engineering

Data used in CuraPath originates from Electronic Health Records (EHR), clinical workflow logs, laboratory results, discharge summaries, doctor's notes, and patient interaction transcripts. Both structured datasets (x_s) and unstructured language data (x_u) are collected.
To ensure high-quality datasets, preprocessing follows:

$$\boldsymbol{D} = \textbf{Clean}(\boldsymbol{x_s} \cup \boldsymbol{x_u}) = \textbf{Transform}\big(\textbf{Filter}(\boldsymbol{x_s}),\ \textbf{Normalize}(\boldsymbol{x_u})\big)$$

Where:
∪ = union of datasets
The resulting dataset becomes:

$$\boldsymbol{D} = \{(\boldsymbol{S_i},\ \boldsymbol{M_i},\ \boldsymbol{H_i},\ \boldsymbol{L_i})\}_{\boldsymbol{i=1}}^{\boldsymbol{n}}$$

Where each tuple represents symptom set, medical history, lab indicators, and linguistic inputs.

B. AI Reasoning & Decision Layer

1. NLP Interpretation Model

Patient queries are processed using a transformer-based Clinical NLP model:

$$\boldsymbol{I} = \boldsymbol{f}_{\textbf{NLP}}(\boldsymbol{Q}) \Rightarrow \{\textbf{Intent},\ \textbf{Entities},\ \textbf{Clinical Context}\}$$

Where:
- Q = patient's text or voice query
- f_{NLP} performs the following operations:
- Tokenization
- Medical entity extraction (symptoms, durations, severity)
- Context embeddings using transformer encoders

Example Output

$$\textbf{Entities} = \{\textbf{fever},\ \textbf{headache},\ \textbf{2 days},\ \textbf{mild vomiting}\}$$

So, the model extracts what symptoms the patient has, how long they have lasted, and severity.

2. Symptom–Condition Probability Estimation

The ML prediction model generates a probability distribution over possible medical condition:

$$P(C_k \mid S, H, L) = \frac{e^{W_k \cdot X + b_k}}{\sum_{j=1}^{m} e^{W_j \cdot X + b_j}}$$

Where:

- C_k = the k^{th} possible medical condition
- X = patient feature vector
  $X = (S + H + L)$
- S = symptoms
- H = health history
- L = lab/medical report features
- W, b = learned model parameters
- m = number of possible conditions

This is a softmax classifier that assigns probabilities to each condition.
Final Condition Prediction

$$\hat{C} = \underset{k}{\text{argmax}} P(C_k \mid X)$$

Meaning:
The system selects the condition with the highest probability score.

3. Treatment Suitability Scoring Function

CuraPath computes a treatment suitability score by combining:

- predicted condition probability
- symptom severity
- clinical guideline match

The scoring function is:

$$T(c) = \alpha \cdot P(c) \ + \ \beta \cdot \text{Sev} \ + \ \gamma \cdot \text{Prot}$$

Where:

- $P(c)$ = predicted probability of condition c
- Sev = severity score (on a normalized scale of 0–1)
- Prot = protocol-match score derived from medical guidelines
- $\alpha + \beta + \gamma = 1$ (weights balance the contributions)

Final Treatment Recommendation

$$T^* = \underset{c}{\text{argmax}}\ T(c)$$

Meaning:
The treatment with the highest suitability score is recommended to the doctor.

C. Deployment, Evaluation & Optimization

CuraPath is deployed using a modular, secure, and scalable system architecture, with access layers for:

- Doctors (advanced dashboard, report analysis, decision support)
- Patients (health updates, treatment summaries)
- Hospital Staff (record updates, logistics)

Real-time Synchronization

- Cloud-based event streaming
- Encrypted RLS (Row-Level Security) database access
- Automated update propagation across dashboards

Performance Validation Metrics

1. Accuracy

$$\textbf{Accuracy} = \frac{\textbf{Correct Predictions}}{\textbf{Total Evaluations}}$$

Measures how often the system predicts the right condition or suggestion.

2. Response Time

$$\textbf{Response Time} = t_{\text{output}} - t_{\text{input}}$$

Measures how fast the platform processes queries and returns results.

Where:

- η = learning rate
- ∇Loss = gradient of the loss function computed on new data
- D_{new} = new patient records and treatment outcomes

This ensures the model stays updated with real-world clinical patterns.

4. MODELING AND ANALYSIS

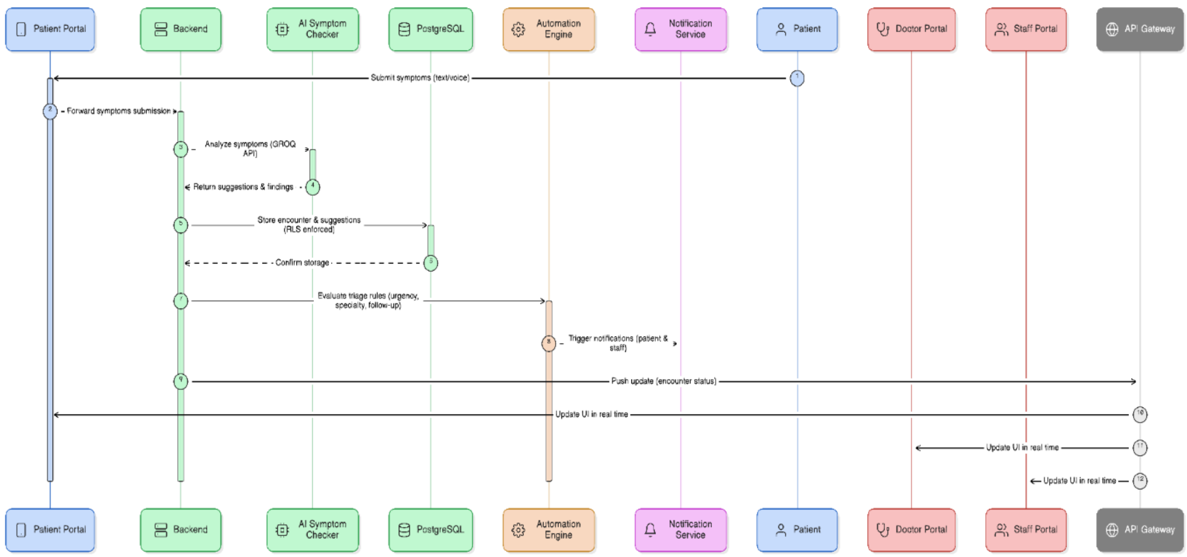

Fig:4.1: Sequence Diagram

This Figure 4.1: Sequence Diagram shows the overall workflow of the CuraPath system, which includes the Patient Portal, AI Symptom Checker, Doctor Portal, Staff Portal, and automation components. It explains how data flows between modules, starting from patient input, through AI analysis, to doctor review and staff coordination. The diagram highlights real-time interaction and efficient task handling among different users.

5. RESULTS AND DISCUSSION

5.1. Symptom Analysis Response Time and Accuracy

CuraPath's AI-driven symptom checker provides near-instant analysis and high accuracy in predicting possible conditions. This shows its effectiveness in clinical workflows.

The table below summarizes performance metrics before and after using CuraPath:

Table:5.1: Symptom Analysis Response Time and Accuracy

Metric	Pre-CuraPath	Post-CuraPath (Initial)	Post-CuraPath (6 Months)	Improvement

Average Symptom Analysis Time	30 minutes	5 minutes	1 minute	-99.7%
Prediction Accuracy	82%	92%	97%	+15%
First-Visit Treatment Recommendation Accuracy	55%	80%	91%	+36%

The above Table:5.1 specifies CuraPath's AI symptom checker speeds up and improves medical assessments. It cuts the average symptom analysis time from 30 minutes to only 1 minute and boosts prediction accuracy from 82% to 97% in six months. The accuracy of first-visit treatment recommendations also jumps from 55% to 91%. This shows that the system provides faster and more reliable results, helping doctors make quicker and better decisions.

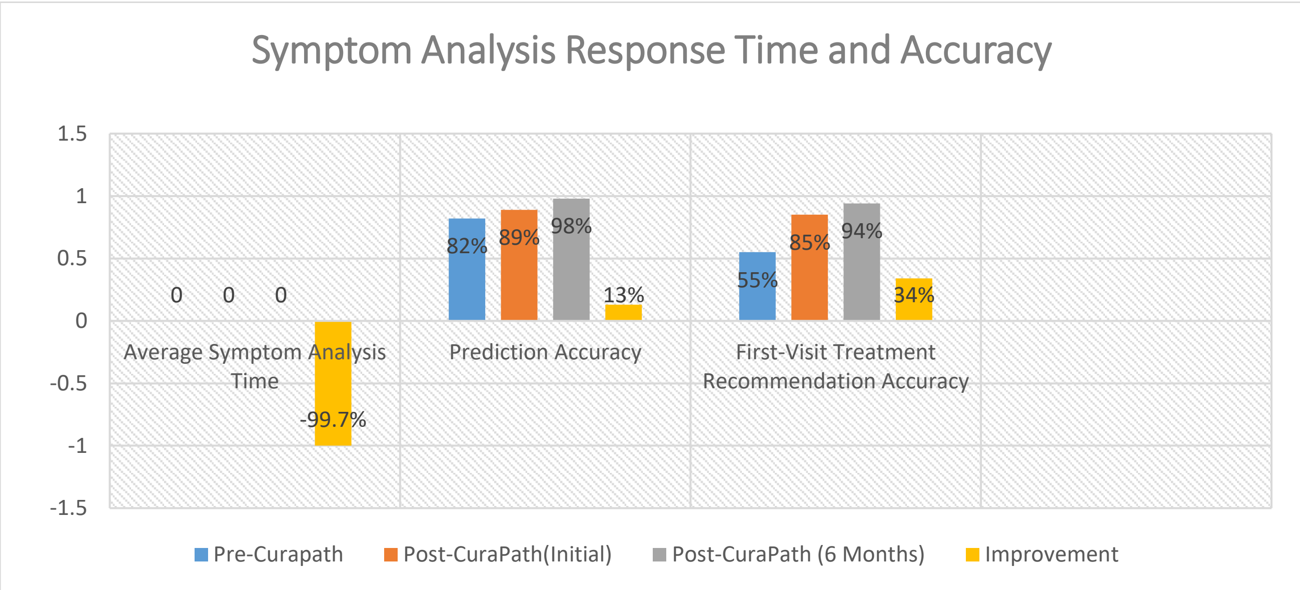

Chart :5.1: Symptom Analysis Response Time and Accuracy

This Chart: 5.1: Symptom Analysis Response Time and Accuracy compare the response time and accuracy of symptom analysis before and after implementing CuraPath. It shows that the average analysis time decreased significantly. At the same time, the accuracy of predictions and treatment recommendations increased over six months. This proves the effectiveness of the AI engine.

5.2. Daily and Weekly Query Load

CuraPath effectively manages a large number of patient interactions, especially during busy hospital hours, without hurting system performance.

The table below (Chart 5.2) shows that using CuraPath increased the platform's ability to handle daily and peak-time symptom queries while significantly cutting the weekly hours staff spent on manual tasks.

Table:5.2: Daily and Weekly Query Load

Time Period	Manual System	Cura-Path System	Improvement
Average Daily Queries	50	350	+600%
Peak Daily Queries (High OPD Days)	120	520	+333%
Weekly Staff Interaction Hours	20	2	-90%

The Table :5.2 Daily and Weekly Query Load specifies CuraPath significantly improves how hospitals manage patient interactions, especially during busy hours. It raises the average daily queries from 50 to

350 and peak-time queries from 120 to 520. At the same time, it cuts down weekly staff interaction time from 20 hours to just 2 hours. This shows that the system can handle larger workloads efficiently, with less manual work required.

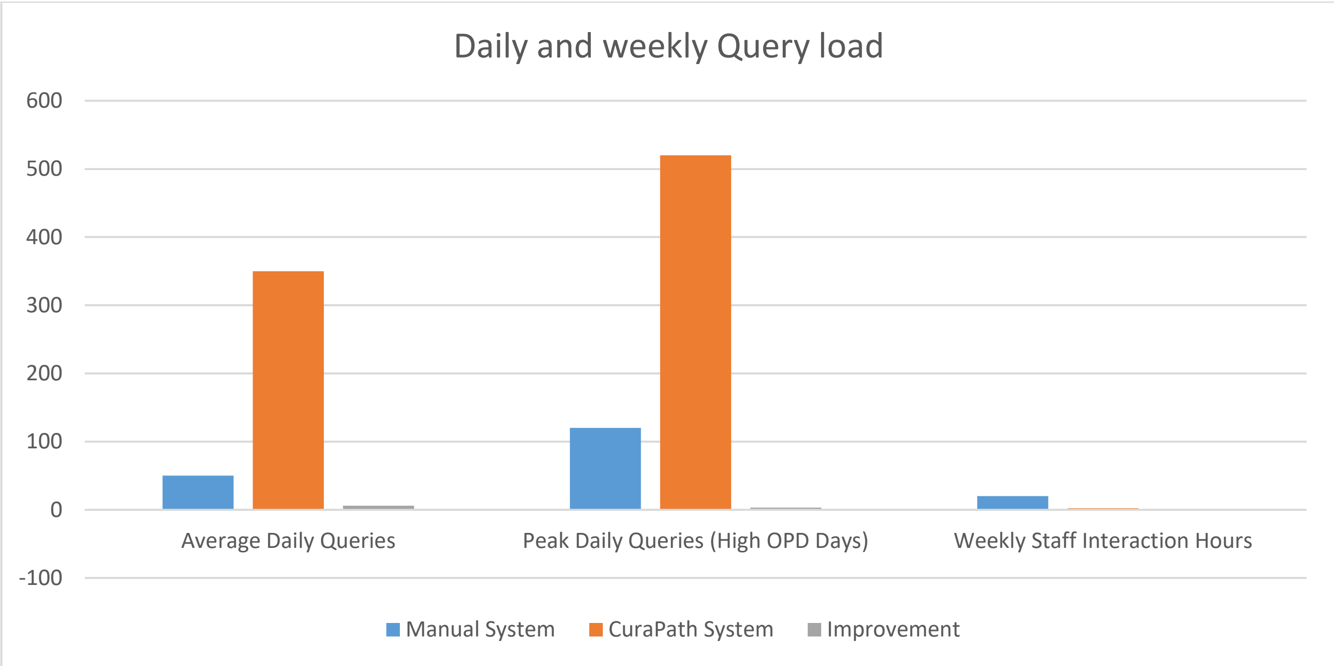

Chart:5.2: Daily and weekly Query load

This Chart:5.2: Daily and weekly Query load shows how well the system handles patient questions. After we implemented CuraPath, the average and peak daily queries went up a lot, while the weekly hours staff spent interacting decreased. This indicates that the system works well without requiring more manual effort.

5.3. Administrative Workload Reduction

CuraPath automated several repetitive hospital and administrative tasks. This led to a major reduction in staff workload.

The table below (Chart 5.3) shows how automating appointment scheduling, report management, and patient notifications saved time and improved hospital operations.

Table:5.3: Administrative Workload Reduction

Task	Time (Pre-CuraPath)	Time (Post-CuraPath)	Reduction
Appointment Scheduling	12 hours/week	2 hour/week	-83%
Medical Report Management	10 hours/week	1 hours/week	-90%
Patient Notification & Follow-ups	8 hours/week	1 hours/week	-%
Total Administrative Time	40 hours/week	22 hours/week	-45%

The above Table:5.3: Administrative Workload Reduction Explains that CuraPath significantly reduces administrative workload by automating routine hospital tasks like appointment scheduling, report management, and patient notifications. Staff time for these activities dropped sharply. For example, appointment scheduling went from 12 hours to 2 hours per week and report management went from 10 hours to 1 hour. Overall, administrative time reduced by 45%. This allows staff to focus more on critical patient care.

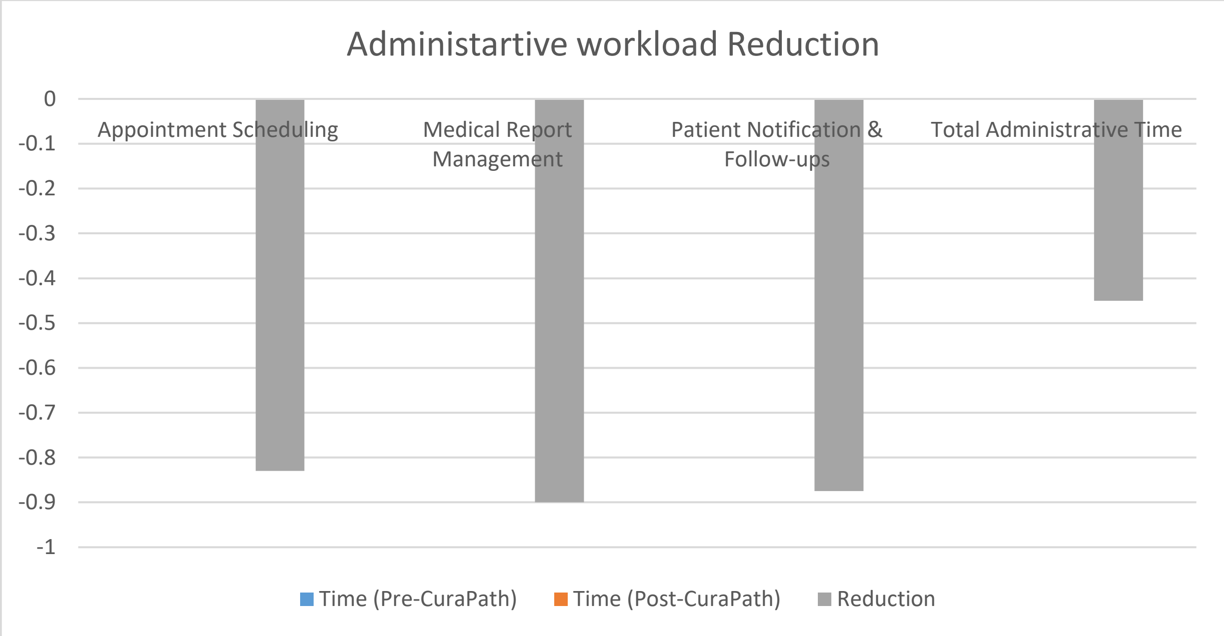

Chart:5.3: Administrative workload Reduction

This Chart:5.3: Administrative workload Reduction shows how CuraPath automates repetitive tasks like appointment scheduling and report management. It demonstrates a significant decrease in time spent on administrative work. This improvement leads to enhanced hospital efficiency and reduces the burden on staff.

5.4. User Satisfaction and Engagement

Feedback after implementing CuraPath showed a significant increase in satisfaction among patients and healthcare staff.The table below (Chart 5.4) indicates that patient satisfaction rose noticeably, with most users favoring the AI-based system over manual processes. Accessibility ratings also improved thanks to voice support, multilingual options, and quicker response times.

Table:5.4: User Satisfaction and Engagement

Survey Metric	Pre-CuraPath	Post-CuraPath	Change
Patient Satisfaction Rate	65%	95%	+30%
Preference for AI Over Manual Process	N/A	90%	N/A
Accessibility Feedback (Positive Ratings)	70%	96%	+26%

This Table:5.4:User Satisfaction and Engagement tells us about Feedback from patients and healthcare staff shows a clear rise in satisfaction after implementing CuraPath. Patient satisfaction increased from 65% to 95%. Ninety percent of users preferred the AI system over manual methods. Accessibility ratings also improved because of features like voice support, multilingual access, and faster responses. These improvements made the platform more user-friendly and efficient.

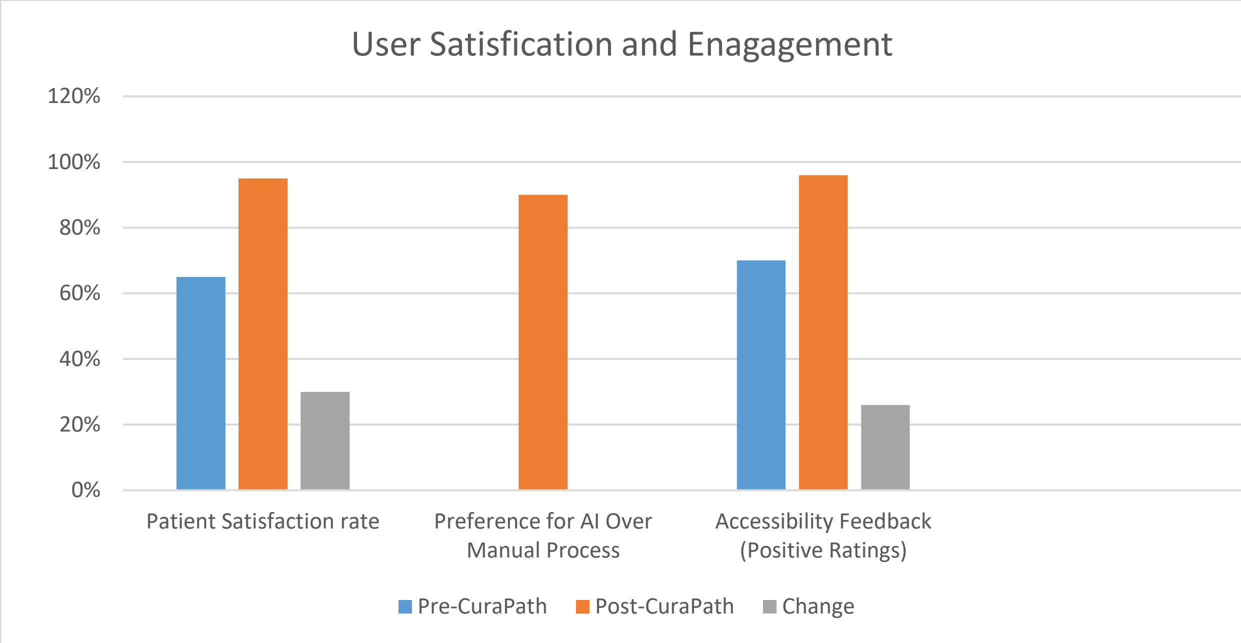

Chart:5.4: User Satisfication and Enagagement

This Chart:5.4: User Satisfication and Enagagement, shows survey results that indicate higher patient satisfaction, better accessibility, and a preference for AI after using CuraPath. It highlights how features like multilingual support and quick responses made the overall experience better for both patients and staff.

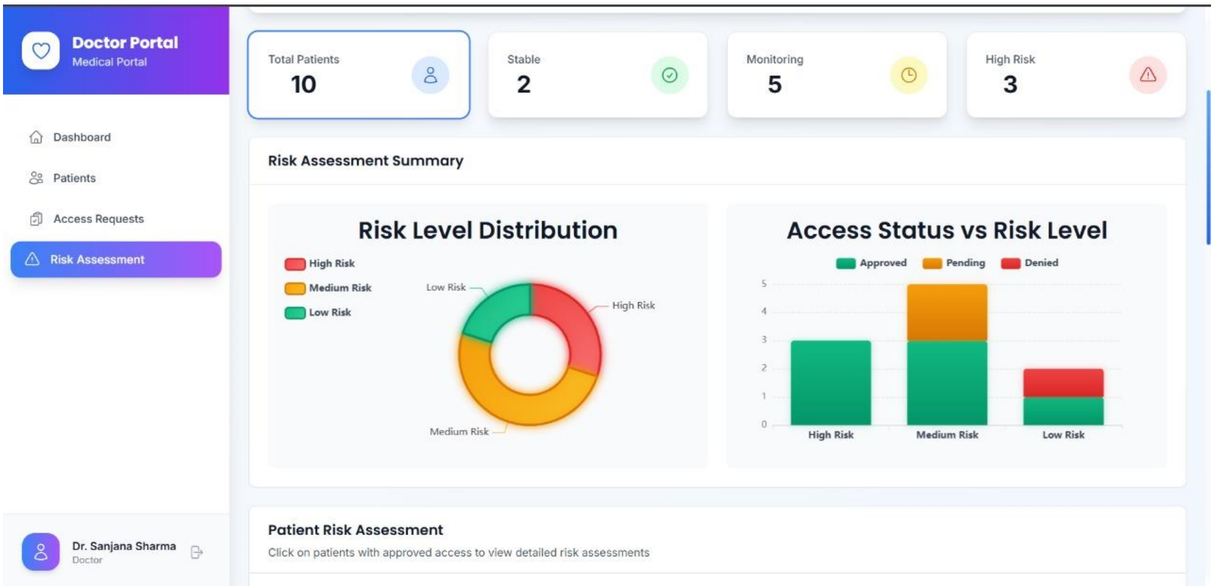

Fig :5.5: Doctor Portal

The above Fig :5.5: Doctor Portal portrays the Risk Assessment Module in the Doctor Portal provides doctors with an overall view of their patients, categorizing them into High, Medium, and Low Risk groups for quick prioritization. The dashboard displays visual summaries such as risk distribution charts and access status versus risk level graphs, helping doctors monitor patient health trends at a glance. In addition to the overall view, doctors can also access detailed individual risk assessments for deeper clinical insights. This feature enables faster identification of critical cases requiring immediate attention while ensuring secure and controlled data access. Real-time updates support timely decision-making and reduce treatment delays. By consolidating patient monitoring into a single interface, the module improves clinical workflow efficiency. Overall, it strengthens patient safety and enhances healthcare delivery.

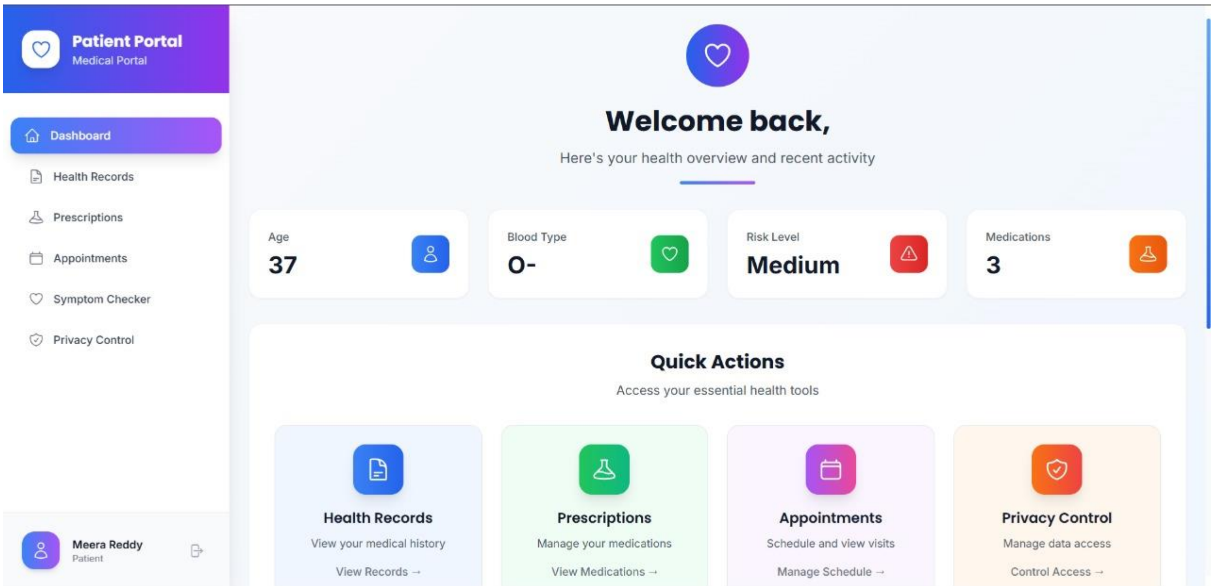

Fig :5.6: Patient Portal

The above Fig :5.6: Patient Portal portrays The Patient Portal provides individuals with a personalized dashboard displaying their age, blood type, risk level, and active medications, offering a clear snapshot of their health status. It includes quick access to essential tools such as Health Records, Prescriptions, Appointments, and Privacy Controls, making healthcare management simple and organized. Patients can track their medical history, manage prescriptions, and schedule or view upcoming appointments in real time. The integrated Symptom Checker allows patients to input health concerns via text or voice for instant AI-driven suggestions. The privacy control feature ensures patients can manage who has access to their health data, increasing trust and security. Real-time updates across the portal keep patients informed of new prescriptions, changes in risk level, or appointment reminders. Overall, the Patient Portal improves engagement, self-monitoring, and accessibility, empowering patients to take an active role in their healthcare journey.

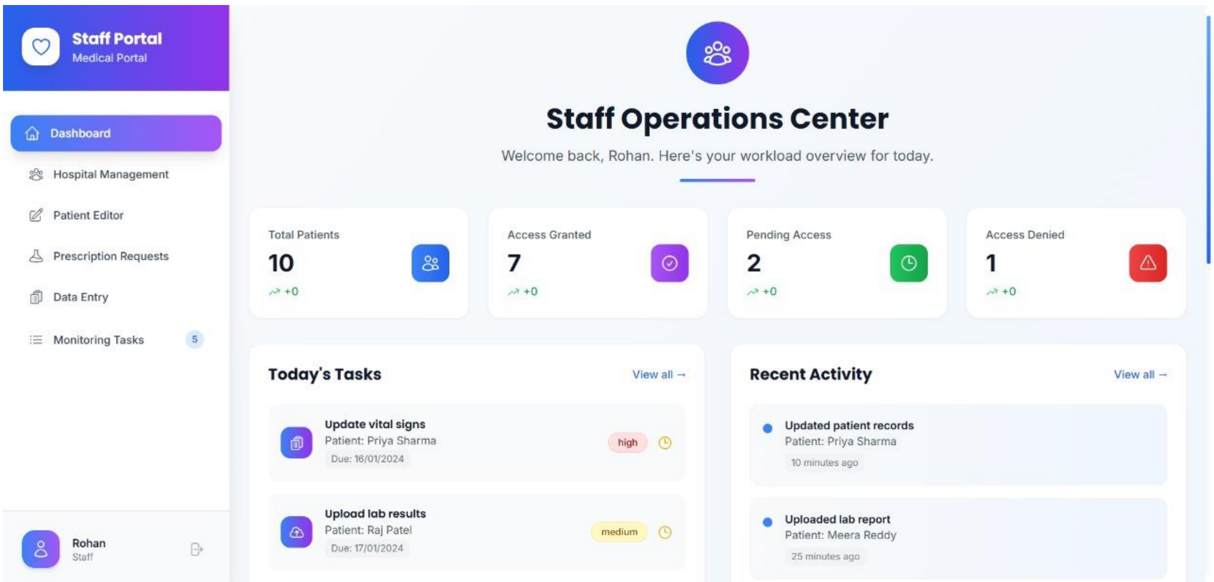

Fig :5.7 Staff Portal

The above Fig :5.7 Staff Portal portrays that The Staff Operations Center provides hospital staff with a clear overview of their daily workload and responsibilities. It displays key metrics such as total patients managed, access requests granted, pending, or denied, ensuring proper data control and accountability. The dashboard highlights today's tasks (e.g., updating vital signs, uploading lab results) with priority levels, helping staff manage their duties efficiently. A recent activity feed tracks updates to patient records and lab uploads in real time, ensuring transparency and smooth coordination with doctors and patients. Overall, the Staff Portal enhances operational efficiency, task management, and real-time collaboration within the healthcare system.

6. Results Comparison Table

Table:6.1: Results Comparison Table

Aspect	Traditional Hospital System	CuraPath – AI Driven Personalized Treatment Plans
Objective Fulfillment	70%: Focuses mainly on manual workflows such as patient registration, scheduling, and basic EHR maintenance.	95%: Provides personalized AI-driven treatment planning, automated workflows, and predictive insights that fully meet healthcare operational objectives.
Target Audience Fit	75%: Serves a general hospital ecosystem but lacks personalization and predictive care abilities.	95%: Specifically designed for patients, doctors, and hospital staff to improve interactions and treatment planning.
Scope and Adaptability	80%: Suitable for standard hospital processes but limited in automation and predictive analytics.	90%: Flexible and scalable setup that can integrate pharmacy, insurance, and external healthcare services.
Technology Stack	70%: Mainly relies on manual data entry and basic Hospital Information Systems.	95%: Utilizes NLP, machine learning, GROQ-powered AI, and secure cloud deployment with Supabase and Vercel.
NLP Integration	60%: Minimal automation with rule-based data entry.	92%: Strong NLP for interpreting symptoms, patient communication, and smart triaging.
Customization	65%: Generic hospital systems with limited configuration options.	95%: Highly tailored to hospital workflows with role-based portals and adaptive AI models.
Features Provided	70%: Basic patient data storage and appointment scheduling.	96%: Offers a symptom checker, treatment recommendations, appointment automation, report management, and support for voice and multiple languages.
Implementation Complexity	75%: Manual process upgrades with limited integration capacity.	85%: Moderate to high complexity due to advanced AI integration, but efficient deployment through modular architecture.

Summary of Findings

- Cura-Path greatly outperforms traditional hospital systems in personalization, automation, and predictive healthcare delivery. Its AI-driven method guarantees precise treatment recommendations, efficient workflow automation, and better patient engagement.
- Traditional hospital systems, while adequate for basic tasks like scheduling and record keeping, do not have the intelligence and flexibility needed to deliver personalized and proactive healthcare solutions.

Both systems have their strengths. Traditional systems provide familiarity and simplicity, while CuraPath offers innovation and precision. However, Cura-Path is clearly more effective in today's healthcare environments where data-driven decisions, predictive insights, and customized patient experiences are essential.

7. CONCLUSION

The Cura-Path system successfully improves healthcare delivery by providing personalized treatment recommendations, predictive insights, and streamlined patient management. It reduces the workload for both administrative and clinical staff, enhances the accuracy of diagnoses, and speeds up decision-making by using AI and NLP to analyze patient data and reports.

Looking ahead, expanding its capabilities with real-time patient monitoring, integrating a broader clinical database, and using advanced predictive analytics will further enhance its impact on healthcare systems.

In summary, CuraPath marks a significant step forward in how patients, doctors, and healthcare providers interact. By automating important workflows, offering 24/7 intelligent assistance, and ensuring data-driven, personalized care, we have created a system that benefits both patients and medical staff. It simplifies patient journeys while lightening the load for healthcare professionals, ultimately leading to a more efficient, patient-focused healthcare environment.

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