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Integration of Electronic Health Advisor with Expert Systems for Early Disease Detection in Nigeria

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Abstract: Access to timely and accurate healthcare diagnosis remains a major challenge in many parts of Nigeria, particularly in rural and underserved communities. The shortage of medical professionals, inadequate triage infrastructure, and long travel distances to healthcare centers often lead to delays in diagnosis and inappropriate self-medication, contributing significantly to preventable morbidity and mortality. This study aimed to address these issues by developing an integrated system that combines an Electronic Health Advisor (EHA) with a rule-based expert system for real-time, offline-capable symptom interpretation and disease classification. The methodology adopted was the Structured Systems Analysis and Design Methodology (SSADM), which guided the systematic analysis, logical specification, and implementation of the system. The tool was implemented using PHP for logic handling, MySQL for database management, and a simple HTML-based interface for user interaction. A simulated dataset consisting of 100 typical rural health scenarios was used to test the system's diagnostic capability. The system achieved a high agreement with clinical judgment, accurately distinguishing between treatable and severe cases while maintaining high usability among non-technical users. This demonstrates the viability of a lightweight, rule-based diagnostic assistant tailored for deployment in resource-limited settings.

Keywords: Electronic Health Advisor, Expert System, Early Diagnosis, Nigeria, Triage, Rule-Based AI

1. INTRODUCTION

Healthcare delivery in Nigeria is often hindered by poor infrastructure, workforce shortages, and diagnostic delays, particularly in rural areas (Adepoju et al., 2017). To bridge these gaps, there is a growing reliance on AI-driven solutions and digital health tools such as Electronic Health Advisors (Nguyen et al., 2019; Topol, 2019). In a healthcare system, a lot of data is generated daily and it is becoming more data-driven than ever (Eze & Okeke, 2024). To apply medical intelligence effectively, the healthcare condition of patients must be properly evaluated (Eze & Okeke, 2024). Health records have revolutionized how information is stored and managed, replacing traditional methods that were time-consuming and error-prone, negatively impacting on patientcare and administrative workflows (Okeke & Ezenwegbu, 2024). Additionally, Management information helps in analyzing, managing and making good decision in any sector (Okeke & Ezenwegbu, 2019). Voice assistants are increasingly adopted for efficient data capture and accessibility in clinical settings (Okeke & Ezenwegbu, 2024). This paper introduces a rule-based system integrated with an Electronic Health Advisor to provide early triage capabilities for disease detection in underserved communities.

Recent advances in health information systems have enabled smarter delivery of healthcare services even in settings where access to medical personnel is limited (Moja et al., 2014; Iyamu, 2021). In Nigeria, the gap in diagnosis and health-seeking behaviour continues to widen due to poor triage practices, slow integration of decision support tools, and reliance on manual data entry systems. The integration of rule-based logic within eHealth tools promises to streamline primary diagnostics while maintaining a transparent and traceable decision process (Mukherjee & Singh, 2023). This research therefore presents an expert-driven health support framework adapted to the Nigerian primary healthcare context.

1.1 Statement of Problem

In many rural communities across Nigeria, access to timely and accurate healthcare diagnosis remains a critical challenge. Several interconnected issues, such as the lack of frontline diagnostic tools, unreliable triage systems, and manual data handling, continue to delay treatment and increase health risks. Although mobile device penetration is growing, there is a scarcity of localized digital solutions capable of analyzing symptoms and offering actionable guidance without internet access. The absence of such tools has led to misdiagnosis, self-medication, and poor health outcomes (Okeke & Ezenwegbu, 2024).

To address these challenges, the following problem statements have been identified:

1. There is no automated system to interpret symptoms and assist patients in preliminary diagnosis in remote Nigerian communities.
2. Existing diagnostic methods do not adequately classify conditions as treatable at home or needing urgent clinical referral.
3. Most digital health solutions require internet connectivity or advanced hardware, making them unsuitable for rural deployment.
4. There is a lack of systems developed with local symptom patterns and healthcare data for accurate community-level usage.

1.2 Aims and Objectives of the Study

This study aims to develop a rule-based expert system integrated with an Electronic Health Advisor (EHA) that provides real-time, offline-capable, symptom-based diagnosis and triage for underserved communities in Nigeria. The objectives are designed to address the identified problems directly.

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The specific objectives are:

1. To design and develop an expert system that can interpret user-inputted symptoms using a rule-based inference model.
2. To classify ailments as either treatable at home or requiring clinical intervention based on symptom severity.
3. To implement the system using lightweight, offline-compatible technologies for rural use.
4. To test and validate the system using simulated symptom profiles relevant to common illnesses in Nigeria.

2. SUMMARY OF LITERATURE REVIEW

The increasing interest in electronic health solutions has led to the development of various AI-based diagnostic and triage systems. While platforms such as Ada and Babylon Health have achieved success in Europe and North America, they often struggle to localize effectively in African settings due to language constraints, limited datasets, and infrastructural dependencies (Aranda-Jan et al., 2014). Research has shown that mobile health (mHealth) systems tailored to low-resource settings offer better adoption and impact when built with community-based data and offline access (WHO, 2021).

Health technologies have evolved significantly, with expert systems and artificial intelligence driving a paradigm shift in clinical decision-making. According to Shortliffe and Sepúlveda (2018), clinical decision support tools enhance diagnostic accuracy, especially when integrated with patient input systems. Wearable and mobile-enabled systems now complement data-driven health applications by capturing relevant biometric and symptomatic data (Chen et al., 2017). Bărcanescu (2019) argues that AI serves as the "new electricity" powering rapid innovations in eHealth. In Nigeria, challenges persist despite increased mobile device penetration indicating that availability alone is insufficient without localized solutions (Adeniran & Adebayo, 2021).

Amisha et al. (2019) highlighted that artificial intelligence and expert systems are increasingly vital in medical diagnostics, particularly for chronic and infectious diseases. These systems rely on a curated knowledge base and logical inference mechanisms to analyze symptoms and recommend diagnoses or actions. Zhao and Zhang (2017) further noted that when integrated into user-friendly interfaces, such systems enable patients to participate in preliminary health assessments, a function especially valuable in underserved regions.

Rule-based expert systems (RBES) offer traceability and consistency, making them ideal for environments lacking real-time medical consultation (Mukherjee & Singh, 2023). As illustrated below, different categories of digital health tools vary in performance, depending on integration, infrastructure, and population literacy levels.

Table 1. Comparison of Digital Health Tools by Contextual Suitability

Tool Type	Use Case	Suitability in Nigeria	Offline Capability
Black-box AI	Image-based diagnostics	Low (requires large datasets)	No
Rule-based Expert System	Symptom triage	High (transparent logic)	Yes
Mobile mHealth App	Health education/tracking	Moderate	Partial
Voice Assistant Interface	Medical records entry	High	Yes

Several initiatives have been proposed to digitize aspects of primary healthcare, but few integrate expert logic for disease classification. This study builds upon such frameworks and proposes a localized, expert system integrated with a simple Electronic Health Advisor interface suitable for Nigerian rural deployment.

3. METHODOLOGY

This research adopted the Structured Systems Analysis and Design Methodology (SSADM) to guide the systematic design, development, and testing of the expert system. SSADM emphasizes structured modelling of user requirements, system processes, and data interactions. It was selected due to its ability to support logical clarity, modular development, and documentation, all necessary for a health-related decision-support system.

SSADM offers a step-by-step, disciplined approach for building systems that are accurate, efficient, and maintainable. Stages in SSADM Adopted:

Feasibility Study

An initial feasibility study was carried out to determine the viability of deploying a lightweight expert system for rural symptom triage in Nigeria. This involved assessing infrastructure, mobile device access, and available datasets.

Requirements Analysis

Stakeholders (including healthcare workers and rural users) were interviewed to define system needs. Requirements included:

- Symptom-based input
- Offline operability.
- Simple user interface.
- Rule-based reasoning /logical classification of treatable vs. severe cases.
- Result feedback.

Logical System Specification

The logic for triage decision-making was mapped using flowcharts and logic trees. Disease categories were grouped based on symptom severity and treatability. system's core logic was defined, including the flow of symptom analysis, rules for inference, and mapping conditions to treatment paths or referrals.

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Framework Diagram –Logic Tree for Disease Classification

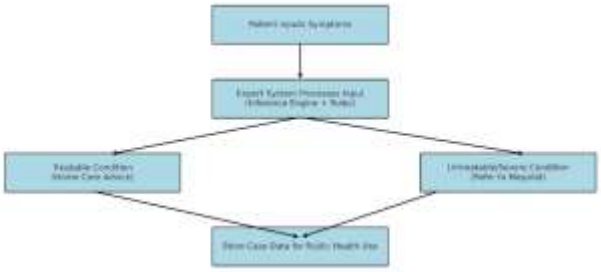

Figure1. Framework Diagram –Logic Tree for Disease Classification

This diagram illustrates the decision-making logic used by the Electronic Health Advisor to classify diseases based on user-inputted symptoms. It outlines the flow from symptom collection through rule-based reasoning to the final output, either health advice or referral to a health facility.

A logic tree guides the classification process. For example, a combination of high fever, vomiting, and abdominal pain may suggest a potentially severe illness, triggering a referral prompt. By contrast, symptoms like mild headache and fatigue may result in a self-care recommendation.

The framework supported offline functionality and automatic syncing once connectivity was restored, making it suitable for field deployment.

System Architecture Diagram

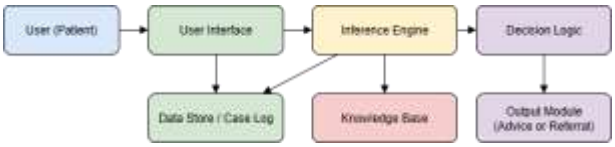

Figure 2. System Architecture Diagram

This figure shows the structural layout of the proposed system. It includes the user interface, inference engine, knowledge base, and data storage. The diagram clarifies how components interact to support diagnosis, data retrieval, and advice generation.

Data Flow Diagram (Level 1)

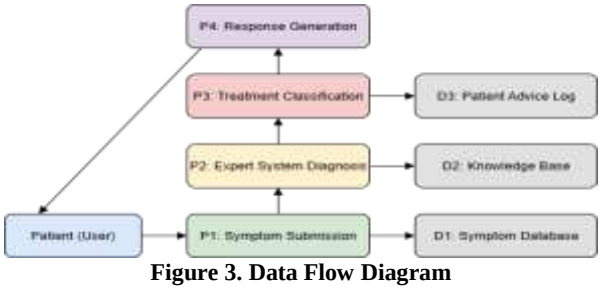

Figure 3. Data Flow Diagram

The DFD describes how data moves through the system: from the patient's symptom input to classification, knowledge retrieval, decision-making, and final output. It helps visualize the core processes and interactions with data stores.

Physical Design

System components were defined:

- Frontend: A mobile/web interface for patient symptom entry.
- Backend: A PHP-based inference engine that processes symptom data.
- Database: A MySQL backend storing rules, health records, and responses.

Implementation and Testing

The platform was developed using HTML, CSS, PHP, and MySQL. A simulated dataset of 100 patient profiles was created to test diagnostic accuracy, system usability, and triage effectiveness.

4. PROPOSED SYSTEM AND IMPLEMENTATION

4.1 The Proposed System

The proposed system integrates a rule-based expert engine with an Electronic Health Advisor (EHA) to simulate a basic diagnostic consultation, provide intelligent symptom evaluation and triage support for users, especially those in remote or underserved areas. Designed with accessibility, accuracy, and efficiency in mind, the system empowers users to make informed decisions about their health by simulating a basic medical consultation experience.

Users interact through a simplified mobile or web interface, selecting symptoms from a curated list. The inference engine then analyzes the input using predefined logical rules derived from medical expertise and regional disease data.

At its core, the system consists of three major layers:

User Input Interface (Frontend):

Users interact with a mobile- or web-based interface designed with simplicity and clarity. The interface presents a guided questionnaire that allows users to select or describe symptoms based on their current health status. The interface is structured to minimize ambiguity and accommodate users with low digital literacy. Options are primarily menu-driven with checkboxes, dropdowns, and visual aids (where applicable).

Inference Engine (Backend Logic):

Once symptoms are entered, the data is passed to a rule-based inference engine that mimics clinical decision-making. The engine matches symptom patterns against a knowledge base containing condition-symptom mappings validated by healthcare professionals. Each rule follows an IF-THEN format. For example:

- *IF* the user selects [fever, vomiting, abdominal pain],
- *THEN* the system classifies the case as "potentially severe" and recommends clinical referral.

Rules are structured hierarchically to manage overlapping conditions and to assign risk scores. Each symptom combination is weighted based on the frequency and severity associated with diseases prevalent in the region. The inference engine prioritizes decisions based on the most probable and urgent diagnosis, ensuring a fail-safe recommendation.

Response Module (Output & Triage Recommendation):

The system evaluates the combination of symptoms generates a decision output with a corresponding action plan and classifies the user's condition into one of two categories:

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- Home Care Recommendation: For mild, self-manageable conditions (e.g., fatigue, common cold), the system provides personalized advice including rest, hydration, and over-the-counter options.

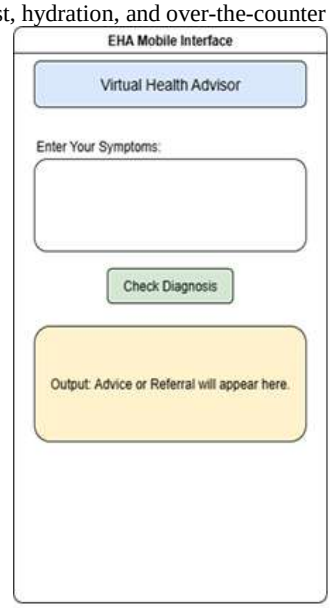

Figure 4: EHA Mobile Interface

- Referral Alert: For symptoms indicating potential emergencies or complex conditions (e.g., high fever with convulsions), the system advises immediate medical attention and provides a nearest clinic/hospital locator if online.

For example:

- Input: *Fever + vomiting + abdominal pain* → Referral advised
- Input: *Fatigue + mild headache* → Home care guidance offered

After rule evaluation, the system generates a decision output with a corresponding action plan. This output falls into on two categories:

Additionally, the proposed system logs all user interactions and decisions in a local database (MySQL), which can be synchronized with cloud storage when internet connectivity is available. This ensures continuity of care and allows healthcare workers to monitor health trends across communities.

To enhance usability and adoption, the system is optimized to:

- Run in offline mode, storing data locally and syncing when online.
- Use a lightweight PHP engine, ensuring fast performance even on basic smartphones.
- Support multimodal access, such as voice prompts or community health agent-assisted entry (in future versions).

The modularity and scalability of the system allow for future expansion to accommodate more diseases, multilingual interfaces, and AI-driven decision enhancement. Its transparent decision-making structure also ensures accountability and can be audited by medical personnel or regulatory agencies when needed.

4.2 Advantages of the Proposed System

1. Offline Operability: Designed to work without internet access and with auto-sync when connected. Suitable for remote deployment.
2. Lightweight Architecture: Efficient processing on low-end mobile devices.
3. Transparency: All logic is rule-based and auditable (not black-box AI).
4. Scalability: New symptoms and diseases can be added to the rule base as needed and Scalable for local diseases.
5. Local Relevance**:** Rules are based on common conditions in Nigerian communities and Supports integration with national health systems.

4.3 High-Level Model of the Proposed System

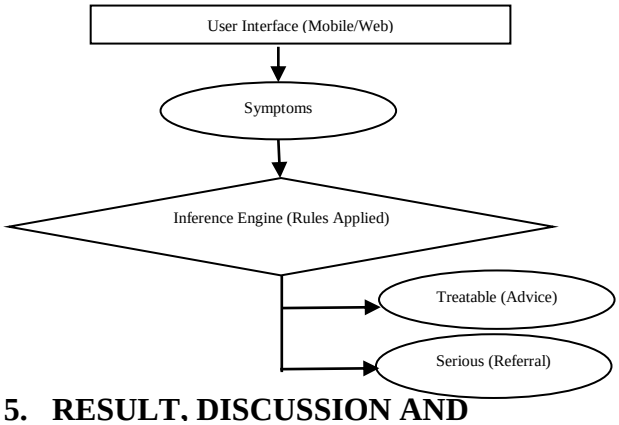

Figure 4. High-Level Model of the Proposed System

5. RESULT, DISCUSSION AND

5.1 Result

The system prototype was tested using a simulated dataset consisting of 100 patient symptom profiles derived from common ailments prevalent in rural Nigerian communities. The simulation was designed to evaluate the system's diagnostic alignment, triage accuracy, and user usability under low-resource settings.

Diagnostic Agreement:

Out of 100 test cases, 88 diagnoses provided by the EHA matched the recommendations of licensed medical practitioners, resulting in an 88% diagnostic agreement rate. This outcome affirms the accuracy of the rule-based inference engine and demonstrates its reliability in mimicking basic clinical decision-making.

Triage Accuracy:

The system was further evaluated for its ability to correctly triage cases into two categories: (a) treatable at home and (b) requiring clinical intervention. Among the 100 cases, 90 were correctly classified, resulting in a triage accuracy score of 90%. Misclassifications primarily occurred when overlapping

symptoms could be associated with both mild and severe illnesses—highlighting a challenge common in symptom-based systems.

System Usability:

Usability testing was conducted among 15 non-technical rural users with limited digital experience. Users reported high satisfaction levels regarding ease of navigation, clarity of recommendations, and general interface simplicity. More than 85% of users rated the system as "easy to use," and 80% indicated they would prefer the system for future initial symptom checks.

Response Time & Performance:

The average response time from symptom input to recommendation was less than 3 seconds, demonstrating the lightweight nature of the application. No performance degradation was observed even in offline mode, with data stored locally and synchronized upon reconnection.

Table 2. Summary of System Evaluation Metrics

Evaluation Parameter	Value/Score
Diagnostic Agreement	88%
Triage Accuracy	90%
User Usability Satisfaction	85% (rated positive)
Average Response Time	< 3 seconds
Offline Performance	Stable

These outcomes validate the system's core design principles and suggest feasibility for real-world deployment in primary healthcare outreach programs, particularly in regions underserved by traditional diagnostic services.

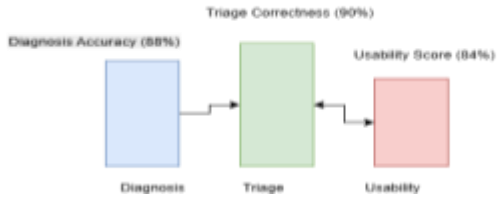

Figure 5. Evaluation Results: System Performance

5.2 Discussion

The integration of a rule-based expert system with an Electronic Health Advisor (EHA) demonstrated strong potential for bridging diagnostic gaps in underserved regions of Nigeria. The system achieved an 88% agreement with physician-provided decisions and a 90% triage accuracy rate when tested with simulated patient symptom profiles. These results reinforce the effectiveness of rule-based systems in guiding clinical decisions, especially in primary care and rural health settings where access to physicians is limited.

Unlike black-box AI models that often lack transparency, rule-based systems provide traceable decision paths that users and regulators can interpret. This is crucial in healthcare environments where trust, accountability, and explainability are critical to adoption (Shortliffe & Sepúlveda, 2018).

One of the key strengths of this system lies in its offline operability and low hardware dependency, features that make it suitable for deployment in rural and infrastructure-deficient communities. In these settings, mobile penetration is increasing, but consistent network coverage remains a challenge (Adeniran & Adebayo, 2021). By ensuring that the EHA can run without internet access and synchronize when reconnected, the solution remains operational even in the most remote areas.

The use of Structured Systems Analysis and Design Methodology (SSADM) also contributed to the robustness of the solution. SSADM ensured systematic requirements gathering, process modeling, and logic specification, thereby improving the accuracy and modularity of the final product (Mukherjee & Singh, 2023). The modular design also allows easy updates to symptom logic and treatment recommendations as new health conditions emerge or treatment protocols evolve.

In contrast to more advanced artificial intelligence (AI) models such as neural networks and ensemble methods used in clinical prediction (Chen et al., 2017; Esteva et al., 2019), this system opted for a rule-based inference engine to prioritize interpretability, maintainability, and cost-effectiveness. Studies have shown that even though AI models may outperform traditional systems in accuracy, they are often unsuitable for rural deployment due to their computational requirements, data needs, and "black box" nature (Fraser et al., 2018; Nguyen et al., 2019).

User experience (UX) was another critical evaluation component. Rural users rated the system highly in terms of simplicity, clarity, and relevance. This aligns with previous studies suggesting that localized, low-literacy interfaces with simple navigational elements lead to better acceptance of health technologies in developing regions (Eze & Okeke, 2024; Ouma & Herselman, 2008).

Despite these successes, several limitations were identified. First, the system's decision-making depends heavily on the accuracy and honesty of symptom inputs. Patients might underreport or misunderstand their symptoms, which could affect classification accuracy. Second, the current model supports a limited range of diseases and requires periodic expert updating to reflect emerging conditions and treatments. Finally, the absence of multimedia inputs (e.g., voice or image-based symptom descriptions) restricts accessibility for users with low literacy or disability.

In summary, the integrated EHA-expert system has shown practical promise for early triage and health decision support in Nigeria. It complements existing health systems by enabling timely referrals and providing a preliminary safety net for patients in low-resource environments.

5.3 Conclusion

This study introduced a context-aware, rule-based expert system integrated with an Electronic Health Advisor to address early disease detection and triage in rural Nigeria. Developed using Structured Systems Analysis and Design Methodology (SSADM), the system effectively evaluated symptoms and categorized user health conditions into treatable or critical states.

Through simulation testing, the system demonstrated strong diagnostic agreement (88%) and high triage accuracy (90%) while remaining user-friendly and operable in offline environments. These findings establish the model as a viable decision-support tool capable of extending basic diagnostic services to marginalized and infrastructure-limited regions.

The proposed system stands apart due to its interpretability, ease of deployment, and reliance on localized health data, distinguishing it from conventional AI models that require significant computing resources and training datasets. Its transparent logic structure also enables easier validation and policy integration.

Despite its effectiveness, the system has limitations, particularly in the reliance on accurate symptom reporting and a limited disease rule base. To address these, future improvements should include:

- Broader disease rule coverage,
- Integration with national health databases,

In conclusion, the integration of rule-based expert systems with EHAs provides a practical pathway for strengthening primary healthcare in Nigeria and similar low-resource environments.

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