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An e-Monitoring System for Patients with Non-Communicable Diseases:
A Case of Beni County in the Democratic Republic of Congo

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ABSTRACT

Non-Communicable Diseases (NCDs) are the leading causes of morbidity and mortality globally. 80% of these deaths occur in low- and middle-income countries whose fragile health systems are still grappling with a heavy burden of infectious diseases resulting in a duo burden of disease. While early detection increases the survival rate and ensures a favorable prognosis for most NCDs, about 80% of reported cases are detected at an advanced stage when little can be achieved in treatment. A few such patients are directed to palliative care in hospices. Some challenges include low awareness of NCDs' signs and symptoms, poor treatment, and inadequate early detection and monitoring services. Data collection was done through observation, personal experience, and interviews in the Beni, Democratic Republic of Congo population. The collected data was analyzed to identify the system requirements for a computer-based information system that supports the management of NCDs in rural areas. The findings propose an analytical application software that applies correlation and regression analysis techniques to analyze patients' vitals. This is to be used by community health workers/volunteers, administrators in health care facilities, and medical doctors to support the implementation of early interventions to prevent NCDs from getting worse at an avoidable rate. The system was developed based on an Object-Oriented Analysis and Design (OOAD) approach using the V-Shaped system development methodology. Functional testing was conducted to test the system, and the result for each functionality was successful.

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1. Introduction

According to reports from the World Health Organization (WHO), Non-Communicable Diseases (NCDs), also known as chronic diseases, rank first among the causes of death worldwide. More than 36 million people per year die from NCDs, such as cardiovascular diseases (48%), chronic respiratory diseases (12%), and diabetes (3%) [1][2]. The current challenges faced by health systems in controlling and responding to NCDs are especially difficult for low- and middle-income countries (LMICs) [3]. The Democratic Republic of Congo (DRC), one of the LMICs, has joined the list of countries facing the burden of NCDs. The number of cases and deaths is continuing to rise over time. Of the total deaths in the country, NCDs are estimated to account for 23% of the deaths.

High-impact and essential NCD interventions can be delivered through a primary healthcare approach that involves strengthening early detection and timely treatment [4]. Evidence shows such interventions are excellent economic investments because, if provided early to patients, they can reduce the need for more expensive treatment [5]. It is estimated that about 25% of deaths from NCDs can be prevented with regular monitoring of the patient's diagnostically important signs and symptoms and through systematic consultation with the treating physician [1]. Continuous management of NCDs is critical as it promotes early interventions required to control them.

Predictive analytics, considered a type of data mining, is an area of statistical analysis that extracts information from data and uses it to predict future trends and behavior patterns. Several predictive analytics approaches using data mining (decision trees, neural networks, regression, classification, clustering, etc.), machine learning, and deep learning techniques have been developed to predict the course of NCDs [6].

This study applied correlation and regression analysis techniques based on parameters defined as attributes or physiological risk factors. These include weight, height, blood pressure, cholesterol, blood sugar, and resting electrocardiographic results. In addition, the study's proposed analytical application software promotes regular monitoring of the diagnostically essential parameters. It ensures that patients get proper follow-ups from their treating physician, who can make an appointment if the patient is at risk or requires immediate medical treatment.

1.1. Current Challenges

In Africa, disability-adjusted life years due to non-communicable diseases (NCD) increased by 67% between 1990 and 2017. Even though primary care remains the first point of contact across LMICs, there is room for improvement in approaches to managing common NCDs, including hypertension and diabetes, through primary care [7]. Primary care is crucial for patients managing NCDs as they require long-term care. Providing effective medical care for NCDs in rural areas has proved difficult because of poor treatment adherence and the lack of continuous care and follow-up by healthcare providers (HCP). NCDs' monitoring services to patients are unavailable at health centers in rural areas, leaving patients making appointments and seeking care only when they feel sick or complications arise. For minor symptoms, they often self-refer to herbalists and traditional medicine vendors [8][9]. The lack of proper, real-time follow-up on NCD patients and timely, continuous, and effective primary care may lead to premature death. The study noted that systems for NCD patients are weak in remote areas, which is also the case for Beni County in the Democratic Republic of Congo (DRC) [10][11]. Most NCDs patients in Beni are economically disadvantaged. As a result, they cannot afford to leave their job or household work to visit the healthcare center routinely just for checkups.

The study noted that in most LMICs, monitoring of NCDs patients is done manually. Patients must go to healthcare facilities to assess their levels, manually record and track their health-related data at home, and present it to the physician in charge at the next visit. The lack of computer-based health information systems for managing patients with chronic conditions in rural areas. Their healthcare facilities limit their ability to effectively monitor the health conditions of patients with NCDs [12]. The study's main objective was to develop a remote monitoring system that helps healthcare facilities understand and manage their patient's health conditions, with a more constant stream of data that provides a much clearer picture of patients' health progression. This is expected to aid in visualizing what is happening with patients early, react to concerning trends quickly and effectively, and prevent further complications. Since Community Health Workers (CHWs) or Community Health Volunteers are the main links to healthcare in rural areas, they visit patients and capture their vitals from their households. Community health care workers can systematically collect patient data to support real-time disease monitoring across a county. This data will then be analyzed once it is stored in the database of the analytical application software. Results from the analysis will be accessible to healthcare providers (HCPs) to assess individual patients' health conditions and symptoms they are likely to develop and make appointments accordingly. This is expected to ensure NCD patients obtain the necessary health care on time. The following section presents various strategies implemented to monitor and follow up on NCD patients.

1.2. Related Works

In Malawi, patients' clinical and treatment information is collected and entered in real-time into the EMR (Electronic Medical Record) at each follow-up visit. During these visits, the patient is given the next appointment date, usually 1-3 months; every patient should be seen at least once a quarter. Medical prescriptions are administered from the clinic, and the data is entered into the EMR [13].

In 2009, The United Relief and Works Agency (UNRWA) for Palestine Refugees started an electronic health record system (E-health), which is operational in 6 primary health care clinics in Jordan [14]. The electronic health record system monitors NCDs, maternal health, child health, and general outpatients. The follow-up schedule for patients with diabetes is to see them at the clinic every three months. During the clinic visit, each patient's measurements are recorded: body mass index, urine for glucose and albumin, blood pressure, and the presence /absence of late complications [14].

CES (Compañeros en Salud), a non-governmental organization working in collaboration with the Mexican Ministry of Health in Chiapas, Mexico, provides comprehensive primary care and manages NCD patients based on national guidelines [15]. The medical doctor directs the care of NCD patients, including a monthly clinic visit, therapy with common oral medications for diabetes and hypertension, and community education. CES has designed the CHW-led intervention whereby CHWs serve as a bridge between medical doctors and patients. They conduct home visits and escort patients to clinic visits for follow-up.

In Chile, Accuhealth, a Remote Patient Monitoring system, is being used by healthcare institutions to monitor patients' health progress in the comfort of their own homes. The technology allows health providers to virtually assist patients through video chat and access patient information to provide medical assistance [10] efficiently.

The subsequent sections of the paper are organized as follows: Section 2 describes the methodology applied, Section 3 presents the study's findings, whereas Section 4 discusses what the findings mean. Section 5 then provides a conclusion based on the findings of the study.

2. Methodology

The number informed the research design of contacts with the study population, the reference period of the study, and the nature of the investigation [10]. The cross-sectional study design was best suited to define the number of contacts with the study population. It enabled us to evaluate the quality of primary care currently provided to NCD patients. This included the frequency of follow-ups from respective HCPs. The retrospective-prospective reference period enabled us to investigate existing records to identify correlated risk factors and project the probable outcome of applying an IT-based intervention in identifying additional correlated risk factors. Lastly, a comparative experimental design was used based on the nature of the investigation. This was appropriate as it supported the comparison of possible IT-based interventions.

The study conducted the collection of qualitative data through the use of observation, personal experience, and interviews. This data was used to evaluate the quality of primary care currently provided to patients with NCDs and define the system requirements of an IT-based intervention. The study population was Beni County in the Democratic Republic of Congo (DRC) in the East African Community (EAC) region. The observation and personal experience involved the researcher living in Beni County and interacting with the healthcare systems of Beni County. On the other hand, the interviews involved engaging senior physicians (Medical Doctors) working in Beni County. This provided an understanding of what potential users will require from an IT-based system that promotes early intervention through remote monitoring and follow-up of NCD patients.

3. Results

The developed system is made up of two modules: a mobile application for CHWs to collect patients' data and a web application for administrators and doctors to use the analyzed data. Android Studio was used to develop the mobile application by the community health workers to collect patients' data. JAVA was subsequently used as the main programming language, MySQL for managing the database, and XML for designing the layouts. The data collected through the study indicated that a mobile application was ideal for CHWs because their work requires them to be on the move as they visit patients' households in the community.

The web application was developed based on the MVC framework, which is an architectural framework that separates an application into three main logical components: a Model, a View, and a Controller. The model represents all the data-related logic that the system's user has to work with, whereas the view represents the presentation of data to the user. The controller, on the other hand, connects the model and the view. The controller responds to the user input and performs interactions on the data model objects. It converts inputs from the view to requests and then passes them to the model. Figure 1 graphically presents the MVC framework.

It was apparent from the data collected that the web application requires role-based access control for security purposes. The permissions to perform certain actions or operations were subsequently assigned to specific roles using middleware. Both administrators and medical doctors were directed to different screens upon authentication. Administrators were directed to the administrator dashboard (which can only be accessed by administrators), and the doctors were directed to the dashboard (which can only be accessed by doctors). A closer inspection of the data showed that the most important activities associated with a doctor require the ability to view patients' data and to book, cancel or postpone an appointment with a patient. Once the doctor makes an appointment, the study identified another system requirement: the need to send an SMS notification to the patient and the CHW assigned to the patient. The system made use of Vonage's SMS API to send SMS notifications. The functionality to create, update, and delete patients, doctors, and community health workers and their respective data were provided to the administrator. In addition, the functionality required to assign patients to doctors and community health workers that were provided to the administrator only to maintain the system's integrity. This is further depicted in Figure 2.

As depicted in the system architecture diagram presented in Figure 3, a mobile application used by CHWs to collect patients' data forms part of the system. This data collected is provided as input which is partitioned based on different attributes for storage and further analyzed. A web application used by doctors to retrieve results from the analysis of patients' data also forms a critical part of the system.

4. Discussion

The system applied correlation and regression analysis to process the data input by CHWs. The correlation was used to identify the degree of association between variables. The independent variables included the patient's age, sex, smoking status, and alcohol status. The dependent variables, on the other hand, included fasting blood sugar level in mg/dl, blood pressure in mmHg, weight in kg, cholesterol in mg/dL, body temperature in °C, and heart rate in bpm. The dependent variables were also used to classify patients, as shown in Table 1. Data analysis was done within the database server using database procedures, and the results were then displayed on the application from the database server. The system applied regression analysis to support the doctor and the CHW in making future projections on the probable state of the patient's NCD. If the need arises, appropriate interventions to prevent the worsening of the NCD can then be discussed with the patient during their medical appointment.

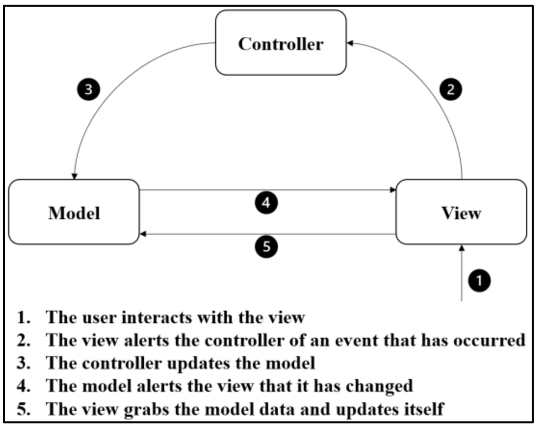

Figure 1 MVC Framework

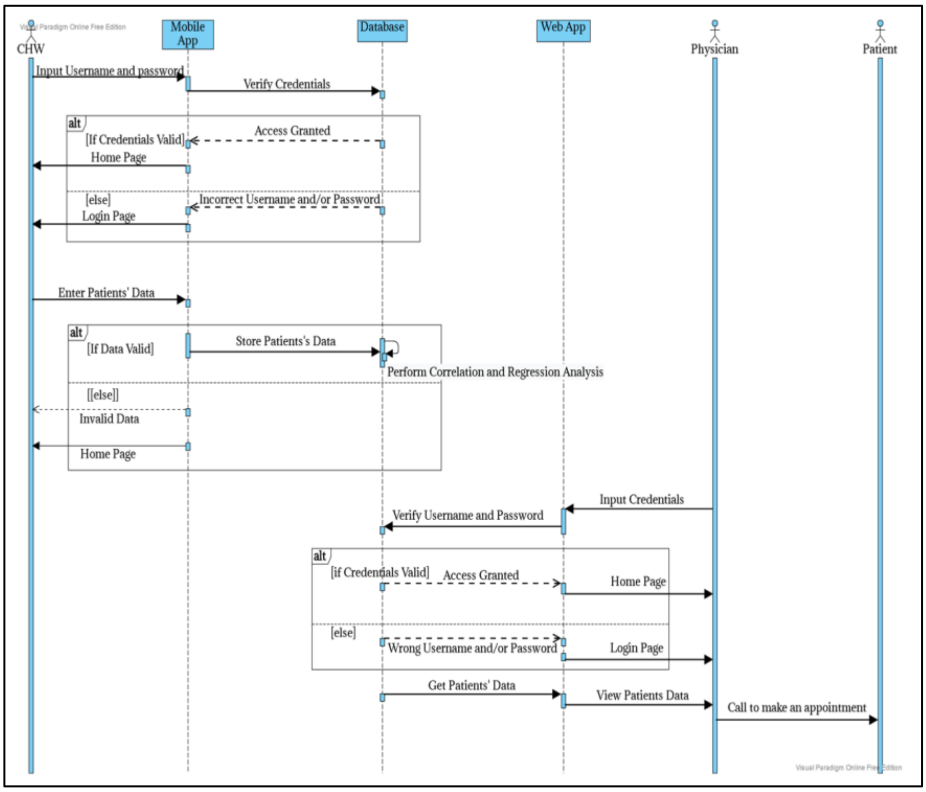

Figure 2 Sequence Diagram

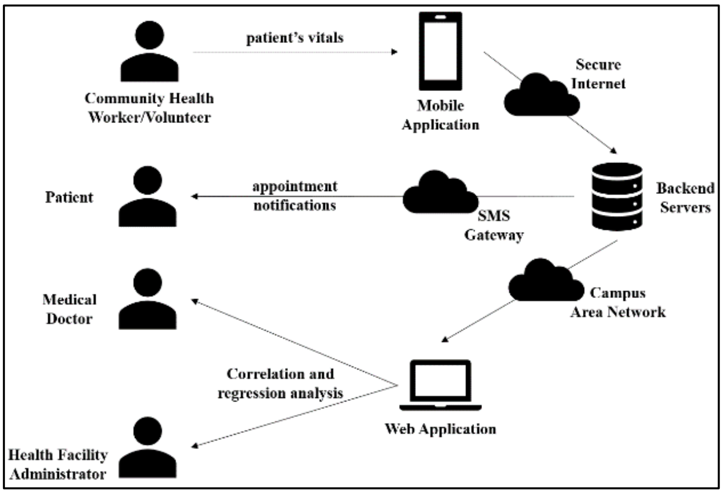

Figure 3 System Architecture

Table 1 NCD-Related Variables

No	Variable	Description	Value	Category
1	Age	Age of the patient in years	Age <= 40 40 < Age <= 60 Age > 60	Young Age Middle Age Old Age
2	Sex	Gender	1 0	Male Female

No	Variable	Description	Value	Category
3	BP	Blood Pressure in mmHg	BP < 80 80 <= BP < 90 BP >= 90 BP > 120	Normal High BP (stage 1) High BP (stage 2) Seek Emergency Care
4	Smoking	Smoker Patient	0 1	False True
5	Alcohol	Alcohol drinker	0 1	False True
6	Chol	Cholesterol	Chol <5.2 5.2<= Chol < 6.2 Chol >= 6.2	Normal High Severe
7	Heart Rate	Heart Rate in beats per minute (bpm)	HR <= 100 100< HR < 150 HR >= 150	Normal High Severe
8	FBS	Fasting Blood Sugar in mg/dl	80 <= FBS <=100 100 <FBS<=125 FBS > 125	Normal Pre-Diabetic Diabetic

Data is stored in a MySQL database and then analyzed using correlation and statistical regression techniques to determine the trends or changes in the patient's health condition with NCDs. The results of the correlation and regression analyses were then grouped based on predicted risk levels: no risk, low risk, medium risk, and high risk. These levels of risk were discussed with one of the senior physicians in charge of the management of NCDs to verify the accuracy of the results.

The study narrowed down its focus on NCDs to diabetes. This was done to provide a proof of concept to show the potential to apply the proposed solution in managing other NCDs. In as much as we can establish a positive correlation between independent and dependent variables, say a patient's cholesterol levels and serial measurements of Fasting/Resting Blood Sugar levels. It is useful to identify how a unit rise in the independent variable affects the dependent variable. Using coefficients is necessary to model the effect of an independent variable on a dependent variable in regression analysis.

Given that β represents the coefficient, the following hypotheses were used as starting points for performing a relevant investigation:

1. H_0: β age = 0
   H_a: β age > 0
2. H_0: β smoking = 0
   H_a: β smoking > 0
3. H_0: β alcohol = 0
   H_a: β alcohol > 0
4. H_0: β BP = 0
   H_a: β BP > 0
5. H_0: β Chol = 0
   H_a: β Chol > 0
6. H_0: β bpm = 0
   H_a: β bpm > 0

Also, given the basic form of a regression model as shown in Equation 1:

$$y = \beta\, x + \varepsilon \qquad \text{Equation 1}$$

For each independent variable, the null hypothesis states that the independent variable does not affect the dependent variable. Equation 2 provides an example.

$$H_0\text{: } \beta \text{ Chol} = 0 \qquad \text{Equation 2}$$

The application then applies statistics to decide whether to reject the null hypothesis in favor of the alternative hypothesis based on how significant the independent variable is. The alternative hypothesis states that the independent variable affects the dependent variable. For example, an increase in cholesterol will increase RBS/FBS, as shown in Equation 3.

$$H_a: \beta \text{ Chol} > 0 \quad \text{Equation 3}$$

A one-tailed (right-tail) t-test was applied periodically to compute the significance of the independent variables used to predict the dependent variables in the regression model. It was applied periodically to adapt the model based on new sample data. Regression analysis is widely used for prediction; however, effort must be made to justify why existing relationships have predictive power for a new context. The study addressed this by ensuring that the model was adaptive. Making the regression model adaptive implies that CHWs use the more the application, the more data it collects. As a result, the more accurate the regression model is expected to be.

The T-test was implemented as part of the application to provide a T-score which is a transformation of an individual score into a standardized form for easier comparison. The greater the difference between the calculated T-score and the tabular T-score, the more evidence there is that the independent variable is significant. This can be represented graphically for a one-tailed (right-tail) T-test, as shown in Figure 4.

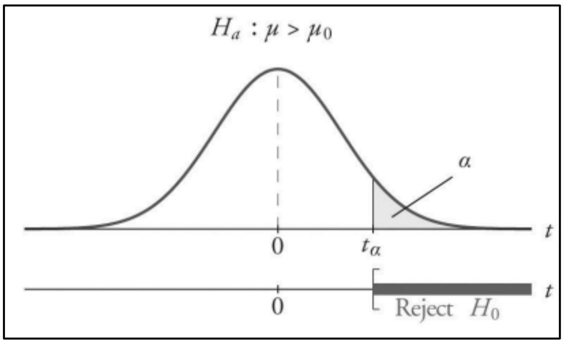

Figure 4 One-Tailed (Right-Tail) T-Test

The significance level of significance α was set to 0.05, meaning that the study was willing to take a maximum risk of 5% for rejecting the null hypothesis when it is true. This is represented as shown in Equation 4.

$$P\left(\mu > \mu_{H_0} \middle| H_0 \text{ is true}\right) < 0.05 \quad \text{Equation 4}$$

With the confidence level set as 95%, the application can determine the tabular T-score given the sample size. This is the point where the value of periodically re-sampling can be appreciated. The re-sampling is done periodically for the last 30 samples hence supporting the use of a T distribution based on the small sample size. The degrees of freedom required when determining the tabular T-score were as shown in Equation 5, where n = the sample size (n < 30).

$$n - 1 = 29 \quad \text{Equation 5}$$

The calculated T-score, on the other hand, was also calculated periodically in the application using the formula specified in Equation 6, where $\bar{x}$ is the sample mean, μ is a representation of the population mean, σ_s is the sample standard deviation, n is the sample size (n<30), and *d.f.* Represented the degrees of freedom

$$t = \frac{\bar{x} - \mu}{\sigma_s / \sqrt{n}}, \text{with degrees of freedom } (d.f.) = (n-1)$$

and Equation 6

$$\sigma_s = \sqrt{\frac{\sum(x_i - \bar{x})^2}{(n-1)}}$$

The application is expected to predict a worsening diabetic state based on current readings of statistically significant independent variables. A diabetes dataset was obtained from https://www4.stat.ncsu.edu/~boos/var.select/diabetes.tab.txt and randomly split into training (266 observations) and testing (176 observations) datasets. The application applied a multiple linear regression model to the training and test datasets to evaluate the models' prediction performance. We obtained an accuracy of 72% by applying an adaptive linear regression method. The Diabetes dataset from the Kaggle repository was used to evaluate the overall performance. Figure 5 and Figure 6 provide proof of implementation for web and mobile applications, respectively.

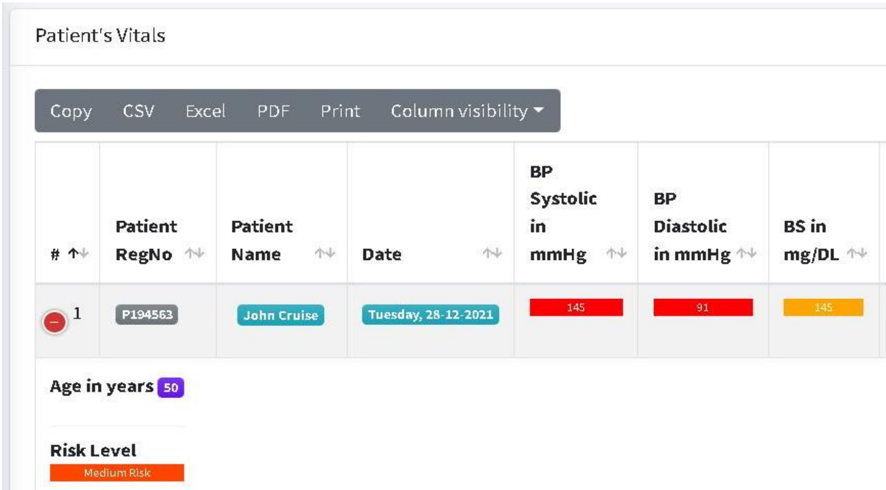

Figure 5 Screenshot of Web Application's Reports Page

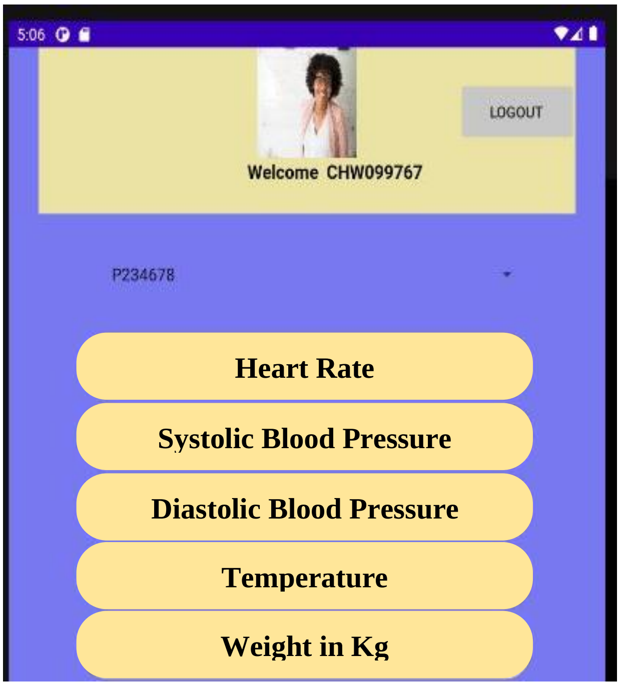

Figure 6 Screenshot of Mobile Application's Data Entry Page

5. Conclusion

This study aimed to address the challenge faced by patients living with NCDs in Beni County, DRC, in getting the quality care that is timely, efficient, and continuous. As indicated in the regression model's accuracy level presented in Section 4, the developed system has the potential to ease the burden on patients to keep track of their health records manually and to attend weekly or monthly in-person visits for screening physically. The system supports CHWs in regularly collecting and entering patient health data into the system from remote locations. This is especially useful for rural areas in low- and middle-income countries [16]. Using such a system, CHWs can sensitize patients and remind them of their next clinical visit based on appointments made by their doctors. Doctors or physicians, on the other hand, can see whether a patient is at risk or not based on the results from the regression analysis of data. If needed, a physician can initiate a timely intervention and make an appointment before the patient's condition worsens.

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