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Efficacy of using a digital health intervention model using community health workers for primary health services in Bangladesh: a repeated cross-sectional observational study

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Abstract

Objective This study aims to evaluate the effectiveness of a digital health intervention model by observing people's health conditions in a rural area of Bangladesh. Through a repeated cross-sectional design, health outcomes were assessed at six-month intervals over 18 months.

Methods The data presented in this paper are obtained from the model's pilot implementation in one catchment area in Bangladesh. The model involved community health workers (CHWs) using a smart health kit and Artificial Intelligence(AI)-based mobile application to provide monthly doorstep health education, screenings, risk assessments, and digital referrals. Socio-demographic and health measurement data are presented as proportions with 95% confidence intervals (CIs). Multivariate logistic regression was used to analyze the association between diseases and their respective risk factors. We compared health vitals across three consecutive periods to determine the effectiveness of the model in improving health outcomes over time.

Results The model served 32,581 people from 7,090 households during this operation. We found that 21.76% of the served population were overweight, 8.18% had prehypertension, 16.45% had high blood glucose, and 11% children were malnourished. From the analysis of risk factors, we found that people aged > 40 were associated with developing hypertension, diabetes, and cardiovascular diseases(CVD). CVD was associated with hypertension and stroke. A comparative analysis of different periods showed an improvement in BMI, BP, and MUAC. Blood glucose measurements did not show significant improvement.

Conclusion This study highlights the feasibility and effectiveness of digital health interventions in enhancing primary healthcare in rural settings. Integration of AI-driven decision support with CHW-led health education and screenings can improve early detection, intervention and management of non-communicable diseases (NCDs). Scaling up this model through public-private partnerships offers a cost-effective approach to bridging healthcare gaps and promoting universal health coverage.

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Keywords Digital health inclusion, Digital health intervention model, Clinical decision support system (CDSS), Artificial intelligence, Non-communicable diseases (NCD), Community health workers (CHWs), Primary healthcare, Health equity, Universal health coverage, Sustainable development goals

Introduction

Primary health care (PHC) is an integral part of the health care system that addresses a community's basic health problems. However, primary healthcare in rural areas of Bangladesh needs to catch up with healthcare facilities in urban regions. Some reasons for this situation are- the shortage of healthcare professionals in rural areas compared with those in urban areas [1], the health-seeking behaviour of rural people [2], and the unawareness of health conditions and outcomes. Rural people often practice self-care and self-medication for treatment. They seek health services from local pharmacists, religious healers, and "witches" [3, 4]. As people lack access to quality healthcare, these are the only sources of medical services they have.Besides, due to the absence of proper health education, they are often ignorant of the severity of chronic diseases. Consequently, these patients suffer from these diseases at an advanced stage.

The recent shift in disease burden from communicable diseases to noncommunicable diseases (NCDs) has raised concerns about the preparedness of health facilities for many low-and middle-income countries (LMICs), including Bangladesh [5]. A total of 73.4% of global deaths are due to NCDs and 77% of all NCDs deaths occur in LMICs [6, 7]. Currently, in Bangladesh, NCDs are responsible for approximately 67% of total deaths [8]. The current healthcare system in Bangladesh, especially in rural areas, is yet to be well equipped to address such a load of fatal diseases.

Digital health has become a new standard for the 21 st century. Like many other developing countries, Bangladesh has adapted digital technologies to improve its health system management in the last decade by introducing national eHealth policies in 2011 [9]. Consequently, many organizations have launched digital health solutions. In 2014, 26 eHealth and mHealth services were reported to operate in Bangladesh, including government and private initiatives [10]. Recently, some digital healthcare service providers have excellently transformed the healthcare industry [11, 12]. These operators focus on telemedicine, online consultation services, sample collection from home, report and medicine delivery, etc. [13–15]. Even though these initiatives offer excellent health services to the people, rural people's access to these services has not been assessed [16]. Most specialized health services are only available in urban areas, so the importance of digitalizing health care in rural demographics is often neglected.

"CMED Health", a leader in healthcare services in Bangladesh, proposed and implemented a digital health intervention model of community health workers (CHWs) integrated with digital technologies to provide comprehensive, preventive, and primary healthcare services to the rural people of Bangladesh [17, 18]. The model was designed aligning with the latest ideas of digital health technologies. These concepts included- easy access to information, digital diagnostic devices, telemedicine services, data-centric service models, etc. [19]. Digital health interventions also provide cost-effective ways to promote healthy behavior [20]. In the 21 st century, new IoT, big data, and data-driven decision-making systems trends have emerged in the era of smart healthcare [21]. Thus, data-driven decision-making for risk assessment was also incorporated into the model.

CMED partnered with Palli Karma-Shahayak Foundation (PKSF), an organization working for the development of rural Bangladesh [22], and launched this model in the Somvag Union (the smallest administrative unit of a rural area) in Bangladesh [23]. Faruque et al. conducted a feasibility study to assess the usability and efficacy of the model in preventing NCDs. They reported ease and increased speed in data collection by health workers while delivering services [24]. Similarly, recent research in Bangladesh also has recommended community-led approach to improve healthcare [25]. Under this project, people in this area were provided doorstep health services, vital health measurements, consultation, and digital referrals if required. The services were designed to focus on preventive care, particularly on prevention and management of NCDs.

In this paper, we analyzed the data from the operation of this project. We performed a descriptive analysis of vital health measurements to understand the health conditions of the populations. NCD risk factors were identified by applying a multivariate logistic regression. To measure the effectiveness of the intervention model in improving health outcomes, we performed a comparative analysis of three consecutive periods during the 18 months following the operation.

Methodology

System design

In this study, we used a repeated cross-sectional observational study design to evaluate the impact of the digital health intervention model on the health outcomes of Bangladesh's rural population. The model used a bottom-up approach, with patients moving from the household level to the upper level. Community health workers (CHWs) visited each household once a month to collect their health vitals and input them into their digital profile through the "Enriched Sastho" application.

The study began with a baseline assessment, where community health workers (CHWs) collected demographic and health-related data, including blood pressure, blood glucose, BMI, SpO_2, and MUAC for child nutrition assessment, using the Enriched Sastho application. Additionally, Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs) were conducted to understand existing healthcare gaps. For every 500 households, there is one community health worker. So, to cover 7090 households, we deployed 14 community health workers (CHWs). These CHWs were privately employed by CMED Health and are called Health Assistants (HAs). As HAs, their primary responsibilities included conducting household visits to provide doorstep health services, collecting vital health measurements, and providing essential health consultations. The HAs had at least eight years of schooling. They underwent a two-week training program for data collection using the smart health kit, operating the Enriched Sastho mobile application for data entry and AI-based risk assessment, and delivering preventive health consultations focusing on non-communicable disease (NCD) risk factors.

After conducting the health screening, health workers assessed health risks using an AI-based clinical decision support system (CDSS). The patients were provided with digital referrals to medical assistants or GP doctors based on risk assessment. Medical assistants were trained professionals who received Medical Assistant Training School (MATS) certification and could provide limited interventions, including prescription of over-the-counter (OTC) medication. GP doctors provide comprehensive treatment, including available diagnostic tests and medicines, over telemedicine or in person. Upon requirement, GP doctors also referred patients to secondary and tertiary care facilities. At the end of each six month period, follow-up data were collected to measure changes in health indicators, and additional FGDs and KIIs were conducted to evaluate the intervention's effectiveness, service usability, and patient adherence. Figure 1 illustrates the architecture of the implemented system in the Somvag union.

Served population

This paper presents data collected from July 1, 2018, to December 31, 2019, during which time the digital health intervention model provided services to all households (7,090 in total) within the Somvag Union, reaching a served population of 32,581 individuals.

Data variables

The key variables considered in this study are presented in Table 1

Data collection instruments

The CHWs were equipped with a smart health kit (Fig. 2) provided by CMED for data collection. The kit contained analogue and smart measurement devices for measuring height, weight, temperature, oxygen saturation (SpO_2), blood pressure (BP), blood glucose, and electrocardiogram (ECG). A digital profile was created during the initial visit, and CHWs subsequently updated health vitals

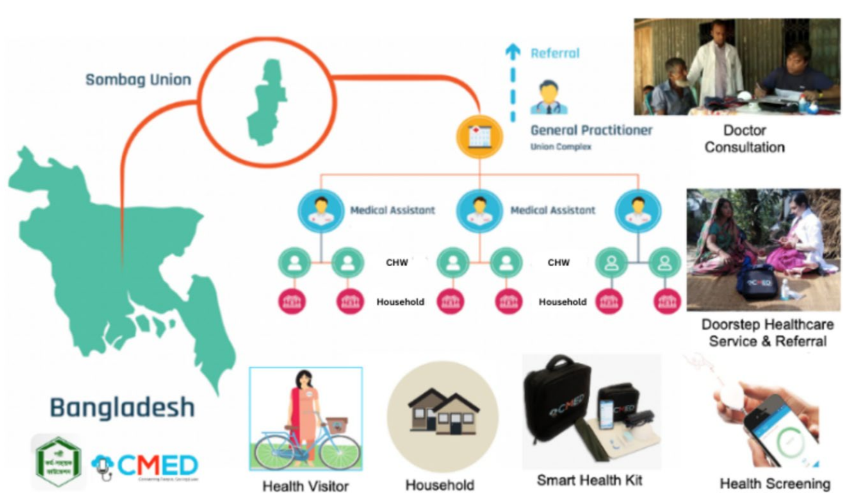

Fig. 1 CMED digital health interventions model and system architecture

Table 1 List of collected key variables

Group	Variables
Socio-Demographic	Member ID, Mobile Number, Living, Primary Occupation, Household ID, Head of Household, Member's Name, Birthplace, Religion, Secondary Occupation, Elderly Allowance, Total Male Members of Household, Gender, Nationality, Marital Status, Union ID, Pregnancy, Total Female Members of Household, Age, Birth Certification Card, Freedom Fighter, Village, Father's Name, Relation with Head of the Household, Blood Group, National ID, Educational Qualification, Ward Number, Mother's Name, Health Visitor ID
Health Related	Diabetes, High Blood Pressure, Stroke, CVD, Total Patients in the Household, Mental Health, Low Blood Pressure, Normal Diabetes, Genetic High Blood Pressure, SpO_2, Hygienic Sanitary Pad User, Blood Glucose, Pulse Rate, Excessive Diabetes
Nutrition Related	BMI, MUAC, Height, Weight, Vitamin A Capsule Takes, Iodinated Salt, Worm Medicine, Mineral Salt Intake
Economic	Health Card, Monthly Income of Family, Monthly Expense of Family, Other Medical Expenses, Prosperous Home, Cultivates Vegetables in the Yard
Occupation	Housewife, Other Expert Worker, Student, Farmer, Banker, Labourer, Merchant/Shopkeeper, Weaver, Engineer, Agriculturist, Teacher, Other Inexpert Worker, Unemployed, Expatriate, Disabled/Age Related, Farmer and Shared Crop, Garments Worker, Carpenter, Rickshaw Puller/Auto-rickshaw Driver, Small Businessman, Private Employee, Retired, Accountant, Driver, Fisherman, Handyman, Government Employee, Labor, Tailor, Cook, Executive/Manager/Officer, Doctor, Electrician, Barber, Cleric (Imam/Brahmmachari), Police, Housemaid, Architect, Village Doctor, Watchman, Poultry/Fishery/Nursery/Dairy Farm Worker, Manager, Hawker/Small Business, Beggar, Nurse/Midwife/Paramedics/Health Assistant/SACMO, Driving Helper, Goldsmith/Big Business/Industrialist, Document Writer, Inspector, Lawyer, Blacksmith/Potter, Jute Worker, Cleaner, Kabiraj, Contractor/Supplier, Veterinarian, Journalist, Mechanic, Paramedic, Laundry Man, Ayurvedic/Homeopath Doctor, Restaurant Business, Advocate, Jewelry Business, Witch-doctor, Merchandiser, Engraver

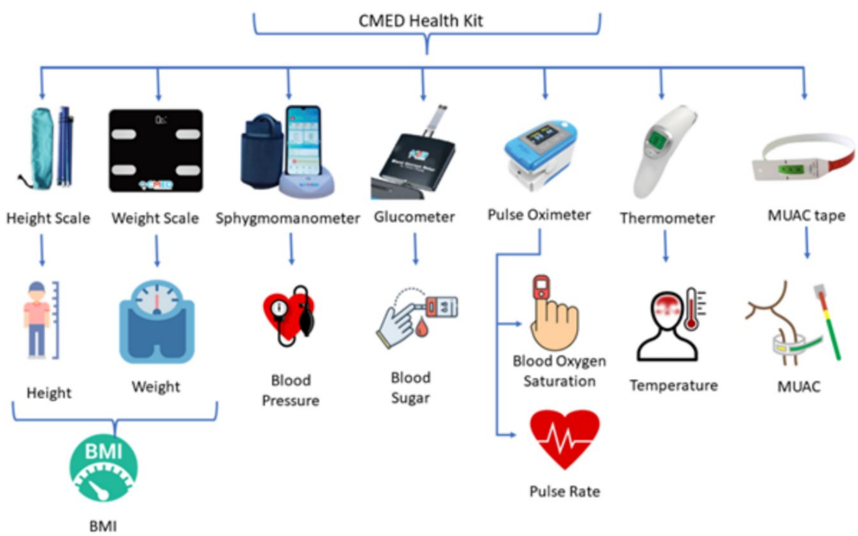

Fig. 2 Smart Health Kit

in the "Enriched Sastho" application, which was installed on their smartphones to store patient information.

Data collection procedure

Community health workers (CHWs) visited the households and took several measurements. The measurement data presented in this paper are body mass index (BMI), blood pressure (BP), blood glucose, and mid-upper arm circumference (MUAC). BMI was calculated by dividing the weight in kilograms by the square of the height in meters. To measure height, each participant was asked to remove their footwear and headgear, stand straight with their feet together and heels on the floor, and look straight ahead with their eyes and ears at the same level. A standard height scale was used to measure height in centimetres (cm). Weight was measured in kilograms (kg) using a digital weighing scale. Each participant stood still on the scale, wearing light clothing and barefoot. BP was measured using an IoT-enabled sphygmomanometer, which automatically entered the data into the Enriched Sastho app. CHWs used a single lancet to draw blood from patients' fingertips, which was analyzed using an IoT-enabled glucometer to measure blood glucose levels. MUAC was measured for children under the age of seven, using a standard measuring tape, with the arm hanging straight down at the midpoint between the olecranon process and acromion. Participants were also asked if they had any prior history of hypertension, diabetes, cardiovascular disease, and stroke. After all the tests, the data were stored in the mobile application.

Data analysis

The data collected through the "Enriched Sastho" app were kept in the Amazon Web Service (AWS). We collected the data as a dump file from the AWS and stored them in the MySQL server. Subsequently, MySQL (a structured query language) was applied to extract our data. Then, the data were processed and analyzed using Python in a Google Colaboratory environment [26]. We used conditional logic to clean the data for invalid observations, inconsistencies, and outliers. For a better understanding of the behaviour trends of the population, the collected data were divided into three periods based on operation time: the first period from July 1, 2018, to December 31, 2018; the second period from January 1 to June 30, 2019; and the third period from July 1 to December 31, 2019. Since the assessments were conducted monthly, each participant had multiple instances of health measurements. For the analysis, we only considered the latest instances of each period. Descriptive statistics were used to understand the characteristics of the study population. Socio-demographic data and measurement results were segregated by sex and age. Categorical frequencies and proportions were calculated using 95% confidence intervals (CIs). To determine the association of diseases and their respective predictors, we performed multivariate logistic regression and calculated the odds ratio (OR) along with the 95% CIs. We compared the measurement results between periods one, two, and three to evaluate the outcomes of the intervention. Numerical variables were tested for normality using the D'Agostino and Pearson's test. The normally distributed variables were subsequently analyzed using the Student's t-test. The Wilcoxon signed-rank test was applied to compare non-normal distributions. Statistical significance was defined as a p-value less than 0.05 for all comparative analyses using Welch's t-test. Two proportion z test was performed to compare the percentage of a categorical variable across different periods.

Results

Sociodemographic characteristics of the study population

Table 2 shows the served population (32,581 people) segregated by age group. The number of male and female participants was almost equal. Ages 18–35 were the most prevalent age group, accounting for 32.25% of the total served population.

Health measurement results

Health measurements of BMI, BP, blood glucose, and MUAC are shown in Table 3, segregated by sex. Excluding MUAC, all measurements in this table are for people aged 18 years or older. The cut-off values of the categories are provided in the supplementary material.

MUAC was measured for only children under the age of seven years. Total measurements of different health vitals were BMI 14670, BP 15549, blood glucose 1775, and MUAC 1009. 68.02% had normal BMI, but 21.76% were overweight. Among the women, 24.16% were overweight. 78.19% of people had normal blood pressure. 70.65% had normal blood glucose, and 16.45% had high blood glucose. 87.61% of children were nourished, and 11% were malnourished.

Table 2 Age-wise distribution of the served population

	Male (%)	95% CI (Male)	Female (%)	95% CI (Female)	Total (%)	95% CI (Total)
Total population	16508(50.67)	50.13–51.21	16073(49.33)	48.79–49.87	32581	
Age group						
0–6	2135(12.93)	12.42–13.44	1996(12.42)	11.91–12.93	4131(12.68)	12.32–13.04
7–17	3260(19.75)	19.14–20.36	2931(18.24)	17.64–18.84	6191(19.00)	18.57–19.43
18–25	1974(11.96)	11.46–12.46	2591(16.12)	15.55–16.69	4565(14.01)	13.63–14.39
26–35	2906(17.6)	17.02–18.18	3037(18.90)	18.29–19.51	5943(18.24)	17.87–18.66
36–45	2417(14.64)	14.1–15.18	2108(13.12)	12.60–13.64	4525(13.89)	13.51–14.27
45–55	1709(10.35)	9.89–10.81	1446(9.00)	8.56–9.44	3155(9.68)	9.36–10.0
56–65	1193(7.23)	6.83–7.63	1187(7.39)	6.99–7.79	2380(7.3)	7.02–7.58
66–75	660(4.00)	3.70–4.30	530(3.30)	3.02–3.58	1190(3.65)	3.45–3.85
>= 75	254(1.54)	1.35–1.73	247(1.54)	1.35–1.73	501(1.54)	1.41–1.67
Total	16508		16073		32581	

Table 3 Summary of Health Metrics for Participants

Category	Male	95% CI (Male)	Female	95% CI (Female)	Total	95% CI (Total)
BMI (age ≤ 18)	8474 (40.3)	39.64 - 40.96	12552 (59.4)	59.04 - 60.36	21026	
Underweight	294 (5.82)	5.17 - 6.47	493 (5.13)	4.69 - 5.57	787 (5.36)	5.00 - 5.72
Normal	3752 (74.25)	73.04 - 75.46	6225 (64.75)	63.80 - 65.70	9979 (67.27)	67.02 - 68.77
Overweight	869 (17.20)	16.16 - 18.24	2323 (24.13)	23.30 - 25.02	3192 (21.09)	21.76 - 22.43
Obesity	114 (2.26)	1.85 - 2.67	482 (5.01)	4.57 - 5.45	596 (4.06)	3.74 - 4.38
Highly Obese	19 (0.38)	0.21 - 0.55	68 (0.71)	0.54 - 0.88	87 (0.59)	0.47 - 0.71
Morbid Obesity	5 (0.10)	0.01 - 0.19	24 (0.25)	0.15 - 0.35	29 (0.20)	0.13 - 0.27
BP (age ≥ 18)	5677		9872		15549	
Low	208 (3.66)	3.17 - 4.15	604 (6.12)	5.65 - 6.59	812 (5.22)	4.87 - 5.57
Normal	4453 (78.44)	77.37 - 79.51	7705 (78.05)	77.23 - 78.87	12158 (78.54)	77.54 - 78.84
Mild High	373 (6.57)	5.93 - 7.21	637 (6.45)	5.97 - 6.93	1010 (6.50)	6.11 - 6.89
Moderate High	89 (1.57)	1.25 - 1.89	154 (1.56)	1.32 - 1.80	243 (1.56)	1.37 - 1.75
Severe High	23 (0.41)	0.24 - 0.58	31 (0.31)	0.20 - 0.42	54 (0.35)	0.26 - 0.44
Prehypertension	531 (9.35)	8.59 - 10.11	741 (7.51)	6.99 - 8.03	1272 (8.18)	7.75 - 8.61
Blood glucose (age ≥ 18)	649		1126		1775	
Low (Hypoglycaemia)	8 (1.23)	0.38 - 2.08	36 (3.20)	2.17 - 4.23	44 (2.48)	1.76 - 3.20
Normal	447 (68.88)	65.32 - 72.44	807 (71.67)	69.04 - 74.30	1254 (70.65)	68.53 - 72.77
High	109 (16.80)	13.92 - 19.68	183 (16.25)	14.10 - 18.40	292 (16.45)	14.73 - 18.17
High (Borderline)	40 (6.16)	4.31 - 8.01	50 (4.44)	3.24 - 5.64	90 (5.07)	4.05 - 6.09
Pre-Diabetic	13 (2.00)	0.92 - 3.08	14 (1.24)	0.59 - 1.89	27 (1.52)	0.95 - 2.09
Diabetic (need confirmation)	32 (4.93)	3.26 - 6.60	36 (3.20)	2.17 - 4.23	68 (3.83)	2.94 - 4.72
MUAC (age < 7)	512		497		1009	
Nourished	456 (89.06)	86.36 - 91.76	426 (85.72)	83.08 - 89.16	884 (87.61)	85.58 - 89.64
Malnutrition	52 (10.16)	7.54 - 12.78	59 (11.87)	9.03 - 14.71	111 (11.00)	9.07 - 12.93
Severe Malnutrition	4 (0.78)	0.02 - 1.54	10 (2.01)	0.78 - 3.24	14 (1.39)	0.67 - 2.11

Analysis of risk factors

We performed a multivariate logistic regression analysis of NCDs (hypertension, diabetes, CVD, and stroke) and their risk factors. Sex, age over 40, and obesity were selected as the risk factors. We also analyzed the associations of hypertension and diabetes with other diseases. Among the total served population, hypertension patients were 2384, diabetic 940, CVD 95, and stroke patients were 84. The results in Table 4 show association of risk factors and diseases in the form of odds ratios. Age ≥40 years of age was associated with hypertension (OR: 13.56; CI 95%: 12.06–15.24) and diabetes (OR: 3.96; CI 95%: 3.35–4.69). CVD was strongly associated with hypertension (OR: 12.50 CI 95%: 7.45–20.73). Stroke and CVD were associated with each other (OR: 8.12 CI 95%: 3.76–17.54). Hypertension and diabetes were also associated with each other (OR: 7.16 CI 95%: 6.13–8.36).

Comparison of nutritional assessment

In periods one, two, three, 15144, 12309, and 9426 people took BMI measurement services respectively. This included people both over and under the age of 18. We presented the percentage of people with different BMI levels during three different periods in Fig. 3. It shows that the proportion of underweight people had decreased, and normal BMI increased over time. Two-proportion z-tests showed a statistically significant increase in the normal BMI percentage and a decrease in the underweight percentage. Cutoff values are given in Supplementary material (Table 1).

Comparison of blood pressure measurement results

Figure 4 shows the percentages of people with different blood pressure levels in three periods. 14288, 11134, and 8593 people took blood pressure measurement services in periods one, two, and three respectively. It was observed that the proportion of people with normal blood pressure had increased over time. In addition, the proportion of people with prehypertension and mild high blood pressure also decreased. Wilcoxon signed-rank test revealed significant increase in diastolic BP (p-value < 0.001) and a substantial decrease in systolic BP (p-value < 0.006) between periods one and three. The two-proportion z-test revealed that the proportion of people with normal BP significantly increased over time and that the

Table 4 Analysis of risk factors

Disease	Factor	B	Odds ratio	*P*-value	95% CI for OR	
					Lower bound	Upper bound
Hypertension	**Sex**					
	Female	0.98	2.67	< 0.01	2.42	2.95
	Male (*Ref.*)					
	Age					
	≥40	2.61	13.56	< 0.01	12.06	15.24
	< 40 (*Ref.*)					
	Diabetes					
	Diabetic	2.00	7.35	< 0.01	6.30	8.59
	Non-Diabetic (*Ref.*)					
	Obesity					
	Obese	0.92	2.51	< 0.01	2.18	2.88
	Not Obese (*Ref.*)					
Diabetes	**Sex**					
	Female	0.02	1.02	0.74	0.89	1.18
	Male (*Ref.*)					
	Age					
	≥40	1.38	3.96	< 0.01	3.35	4.69
	< 40 (*Ref.*)					
	Hypertension					
	Hypertensive	1.97	7.16	< 0.01	6.13	8.36
	Non-Hypertensive (*Ref.*)					
Cardiovascular Disease	**Sex**					
	Female	0.57	1.77	< 0.05	1.16	2.71
	Male (*Ref.*)					
	Age					
	≥40	1.48	4.41	< 0.01	2.35	8.29
	< 40 (*Ref.*)					
	Hypertension					
	Hypertensive	2.53	12.50	< 0.01	7.54	20.73
	Non-Hypertensive (*Ref.*)					
	Diabetes					
	Diabetic	0.66	1.94	< 0.05	1.16	3.24
	Non-Diabetic (*Ref.*)					

Table 4 (continued)

Disease	Factor	B	Odds ratio	*P*-value	95% CI for OR	
					Lower bound	Upper bound
Stroke	**Sex**					
	Female	0.24	1.28	0.29	0.82	2.00
	Male (*Ref.*)					
	Age					
	≥40	1.77	5.90	< 0.01	3.10	11.21
	< 40 (*Ref.*)					
	Hypertension					
	Hypertensive	1.76	5.82	< 0.01	3.49	9.72
	Non-Hypertensive (*Ref.*)					
	Diabetes					
	Diabetic	0.50	1.64	0.11	0.90	3.01
	Non-Diabetic (*Ref.*)					
	Obesity					
	Obese	– 0.59	0.55	0.17	0.23	1.30
	Not obese (*Ref.*)					
	CVD					
	CVD	2.09	8.12	< 0.01	3.76	17.54
	No CVD (*Ref.*)					

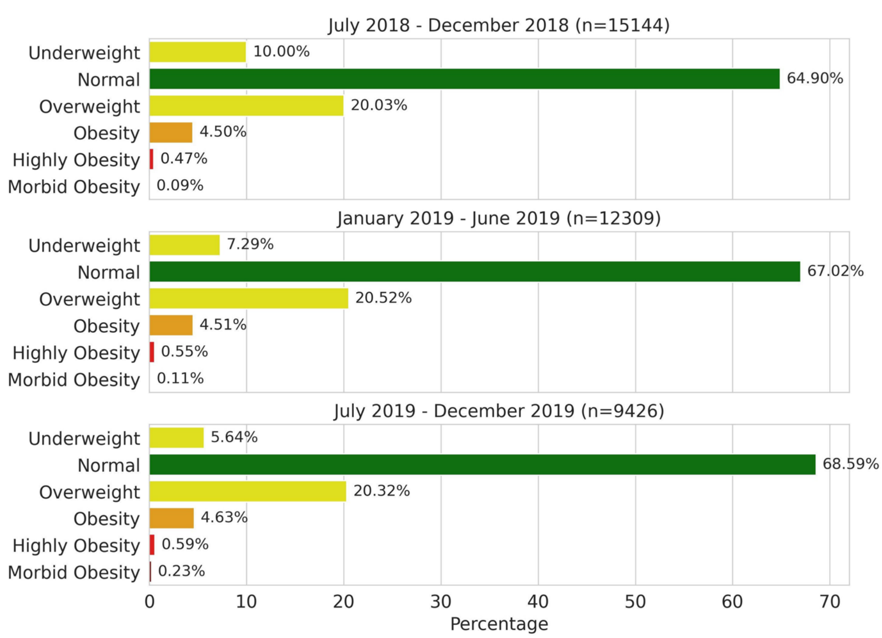

Fig. 3 Nutritional assessments across three periods

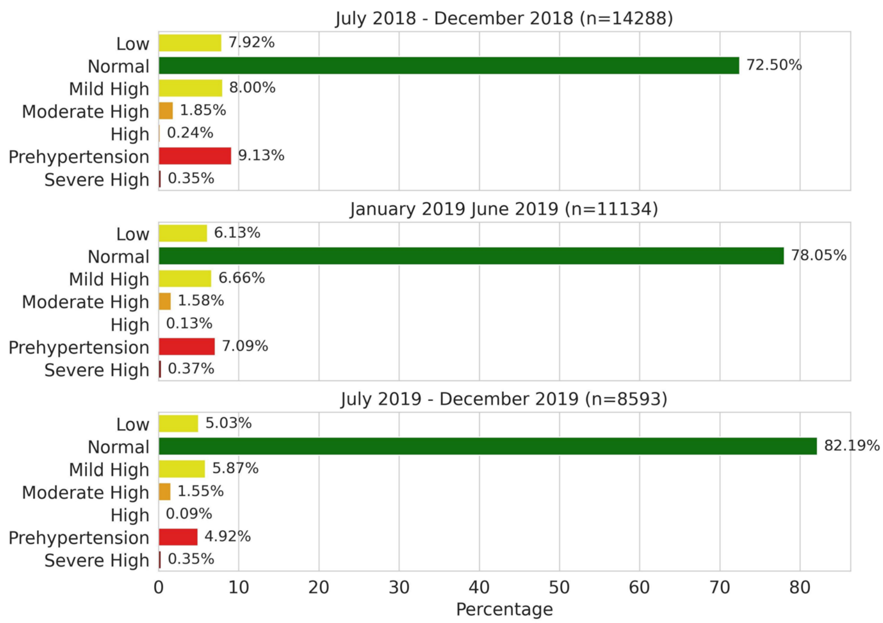

Fig. 4 Blood pressure measurement results across three periods

proportion of prehypertensive patients decreased. Cutoff values are given in supplementary material (Table 2, 3).

Comparison of blood glucose measurement results

Figure 5 shows the proportional distribution of blood glucose measurement results over three periods. The number of people whose blood glucose levels were measured in periods one, two, and three was 1442, 435, and 220 people, respectively. We observed an increase in the percentage of people with high blood glucose and a drop in the rate of people with normal blood glucose

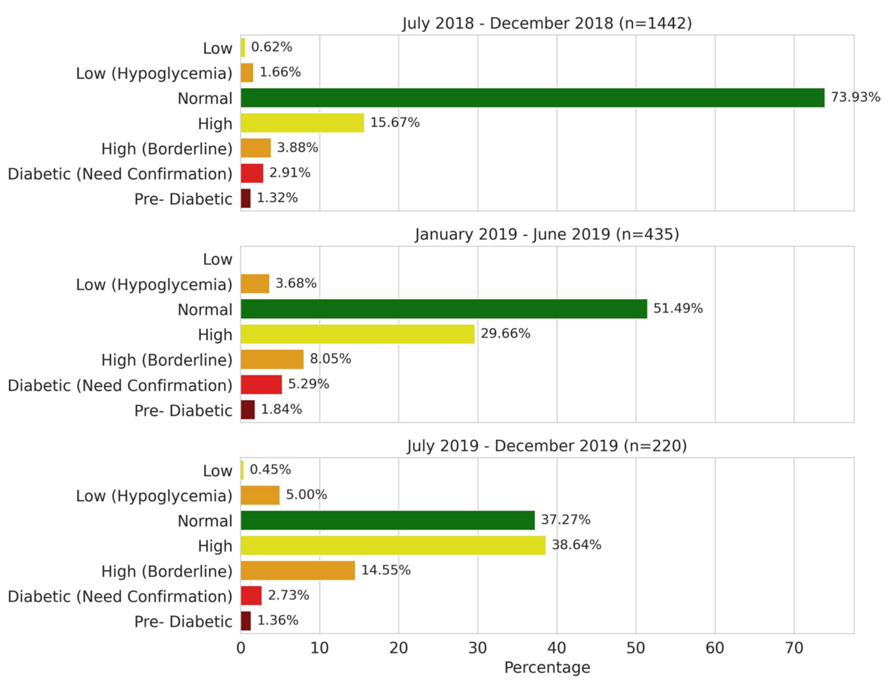

Fig. 5 Blood glucose measurement results across three periods

levels. Cutoff values are given in Supplementary material (Table 4, 5).

To investigate why, we identified the people who measured blood glucose and categorized them into diabetic and non-diabetic. We found that in period one, most people who measured blood glucose did not know whether they had diabetes. So, when they found they had normal blood glucose levels, most of them thought it unnecessary to keep taking the blood glucose measurement service. In the following periods, the majority of the people who took this service had confirmed diabetes. And since they had diabetes, they had uncontrolled blood glucose levels, which was reflected in Fig. 5 where the percentage of high blood glucose patients increased in period two and three. Two proportion z tests showed that the percentage of normal blood glucose decreased, and the percentage of high blood pressure increased over time

Comparison of nutritional status

Periods one, two, and three had MUAC measurements of 689, 383, and 410 children (aged less than seven), respectively. Over time, the proportion of nourished children increased, whereas the proportion of malnutrition and that of children with severe malnutrition decreased (Fig. 6). This trend indicates the increase in general awareness of children's nutritional status in the family and the positive outcome of the intervention.

Two proportion z tests showed that the percentage of nourished children increased while the percentage of malnourished children decreased significantly. Cutoff values are given in Supplementary material (Table 6).

Discussion

The CMED digital health intervention model provided health services to 32,581 people in 18 months of operation. Based on data collected from all registered users at the end of the service time, we provided descriptive findings of the served population and the vital health measurements. From the self-reported data of hypertension, diabetes, CVD, and stroke, we calculated the association of different risk predictors of NCDs, such as sex, age over 40, and obesity. We also calculated the association among the NCDs, as they are related to each other. Finally, we conducted a comparative analysis of the vital health measurements to evaluate the model's performance.

The descriptive analysis of the served population revealed that almost 64% of the served population were under the age of 35. That means a large proportion of people were still in their reproductive age, indicating an expansive population progression. This large population would require access to quality healthcare in the future.

The results of the measurement analysis from Table 3 showed that the majority of the participants over 18 years who took these services were women (59.70%). This skewness of the data can be explained by the time the health measurements were conducted. Since the services were provided during the day, mostly women were at home while men were at work. Similar trends have been observed in previous studies on digital health interventions in Delhi's Aam Aadmi Mohalla Clinics [27]. From BMI analysis, we found 21.76% overweight and 4.06% obese patients. This is similar to findings from a national study on the prevalence of overweight and obesity prevalence, which are reported to be 18.90% and 4.60%

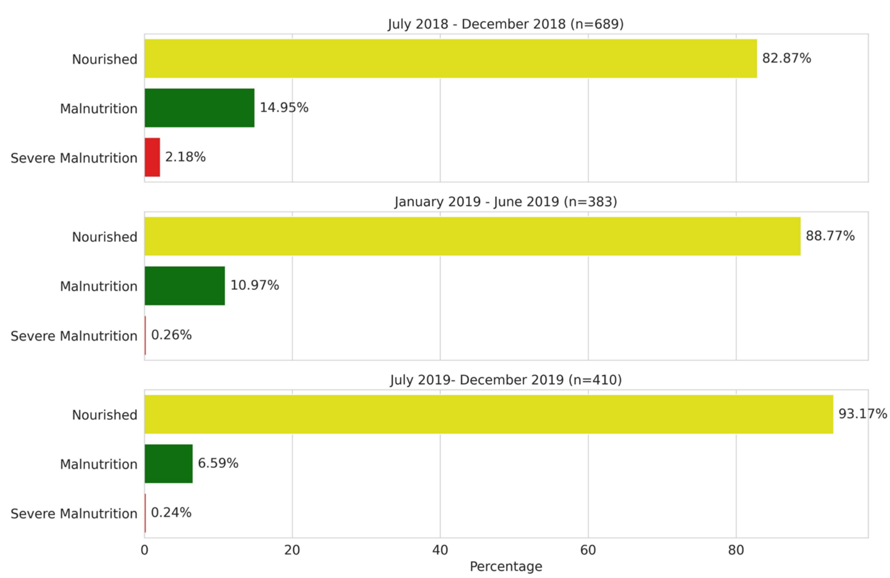

Fig. 6 Nutritional statuses across three periods

respectively [28]. The national prevalence of hypertension rose from 25.70% to 39.40% between 2011 to 2017 [29]. Thus, it was essential to monitor blood pressure regularly and take preventive action to prevent hypertension. Findings from blood pressure measurements show that 9.13% people had prehypertension and 8% had mild high blood pressure initially. They account for more than 17% people at risk of developing hypertension. At the end of the program period, we found a significant reduction in these percentages, indicating that regular blood pressure monitoring resulted in a decrease in their progression rate toward hypertension. For blood glucose measurements, it has to be noted that our system could not afford blood glucose tests free of cost. Therefore, we charged a small fee for conducting the test, and we noticed a reluctance among the patients to perform it. This suggests the general tendency of people toward paid medical tests. Among 1775 patients who took the test, 16.45% had high blood glucose, similar to the national finding of 7.8% pre-diabetes and 10.10% diabetes patients [30]. However, regular screening helps to identify people at risk and these people were provided medical consultation services and referrals to diagnostic centers for confirmatory tests.

We calculated odds ratios (ORs) using a multivariate logistic regression model to find the risk factors of different NCDs. Sex, older age, and obesity were considered for analysis as they were reported to be the risk factors associated with NCDs in Bangladesh [31]. Our study also showed similar results. Hypertension and diabetes were found to have a strong association with age over 40 years. Diabetes and hypertension were associated with each other. Hypertension and CVD were highly correlated with each other, and stroke was associated with CVD. These diseases significantly reduce the quality of life for patients. In 2017, Ischaemic heart disease, which is a form of CVD, ranked 1 st and stroke ranked 3rd in terms of the number of years of life lost (YLL) [6]. Thus, people with these risk factors should be provided special care and consultation.

We visualized the impact of the services on improving health outcomes. To assess the intervention's result, we compared the percentages of different health vitals during different periods. We divided the data obtained from 18 months of services into three periods, six months per period. Then, we took the latest measurement instances from each period and compared the percentage of different vital health results. Our analysis shows our model positively impacted BMI, BP, and MUAC measurements. BMI measurements showed that the proportion of normal BMI levels increased over time while the proportion of underweight people decreased, suggesting that it had a positive impact on people's overall health. Blood pressure measurements showed that the proportion of prehypertension decreased over time, and normal BP increased significantly. The people who were found to be in the prehypertension stage were given consultation and required medication. This helped the population prevent the progression toward hypertension within the served population. Blood glucose measurements did not impact health outcomes as intended. As stated before, most people did not want to perform the paid blood glucose test for diabetes, and those who opted to test initially were uninterested in continuing with follow-up assessments. The contrast of health-seeking behaviour of diabetic and non-diabetic people affected this result. Most diabetic patients continued to take the services, but most non-diabetic people did not in the later periods. Since diabetic patients had uncontrolled blood glucose levels, the high blood glucose levels seemed to have increased, and normal blood glucose decreased in the later periods. MUAC measurements were only taken for children aged less than seven. Data showed that the percentage of nourished children gradually increased while the rate of malnourished children gradually decreased. The reason was that when the family found their children were malnourished, they started giving more attention to their children's nourishment. Qualitative findings from Focus Group Discussions (FGDs) further support this, as beneficiaries reported taking corrective actions after receiving health information [24].

To the best of our knowledge, the CMED digital health intervention model is a unique approach to provide easy access to healthcare in rural regions. The findings of this study show the potential of digital health interventions for primary healthcare in rural Bangladesh. In current practice, many health workers-especially doctors and other allied healthcare providers-are reluctant to work in rural areas, resulting in a significant accountability gap in service delivery. By integrating AI-driven decision support systems and CHW-led health screenings into national healthcare policies, the system not only enhances early detection and management of non-communicable diseases but also ensures quality, accessible care by instilling greater accountability and improving service delivery. In this study, the service was provided free of cost, except for diabetes checkups, which required a small fee. However, to ensure long-term sustainability, this model would require one dollar per month per family, making it a self-sustaining approach. Scaling up these models through public-private partnerships offers a cost-effective strategy to bridge healthcare gaps and promote universal health coverage. Ultimately, this approach demonstrates that technology can enable high-quality, accessible healthcare and should be adopted by the government in primary healthcare service delivery and future policy development, with policymakers also considering subsidies for digital health programs and investments in CHW-based initiatives to ensure long-term sustainability.

Strengths and limitations

This study presents a comprehensive evaluation of a digital health intervention model implemented in rural Bangladesh, offering valuable insights into its effectiveness, challenges, and areas for improvement. Although the research highlights promising outcomes in improving healthcare access and managing non-communicable diseases (NCDs), it also acknowledges several limitations that must be considered when interpreting the findings.

This is the first time at the primary healthcare level that individual and household-level data is being captured using digital tools, integrating IoT and AI for health education, risk screening, and risk assessment at the household level. This approach reassures the success of vaccination and family planning at the domiciliary level in Bangladesh. The best practices established through this initiative have successfully provided access to preventive and primary healthcare, strengthening the system to ensure accessible, quality healthcare at the community level. A key aspect of this success is the empowerment of community health workers through the utilization of technology. This concession provides them with instant information to beneficiaries, enabling need-based referrals and follow-ups. The captured data helps us understand public health needs in real time, allowing health managers to plan resources and public health interventions more effectively for better health outcomes. Additionally, it ensures continuity of care by making healthcare services available in the community, serving more than 30,000 people with empathy and care which entitles patients in their health education and enables them to take control of their own health. The study's focus on real-world application provides actionable insights that can inform the scaling-up of similar interventions at a national level.

Despite these strengths, the system has several limitations and operating challenges. One key limitation is the geographic scope, as the intervention was conducted in only one rural union. While the findings are relevant for similar rural settings, they may not be generalizable to urban populations or areas with different healthcare infrastructures. Additionally, gender imbalance was observed, as most data collection occurred during the daytime when males were at work. This issue could be mitigated by scheduling multiple visits at different hours to ensure more balanced participation. All disease-related data such as diabetes, hypertension, stroke, and CVD were collected using an "Evidence of Acceptability and Clinical Management" approach; however, some information remains self-reported and should be interpreted with caution. We have found that people were impassive about their diabetes checkups because they require tests. As a result, effective management of diabetes remains unachieved. However, if the government or public health sector introduces interventions to improve access to medication for diabetic patients, the situation can be significantly enhanced through these platforms. Moreover, preventive healthcare is not a priority at the population level, so continuous education is necessary in the long term to drive behavioral change. One notable methodological limitation is related to the dataset's repeated measurements. We acknowledge that our dataset includes repeated measurements; however, to evaluate the progressive impact of the digital intervention model, we selected the latest measurement every six months. While this approach may introduce some selection bias, it was a cautious methodological choice to capture the end-of-period outcomes. Many people did not follow up on referrals. A lower retention rate is a big challenge in providing long-term services. The referral rate to secondary or tertiary facilities could not be retrieved because of server issues, which is a limitation of this paper.

Future work

Number of additional features will be added to enhance the "Enriched Sastho" app for more user engagement and better usability. We plan to expand our current services, including early risk prediction for diseases like heart attacks. It is also for empowering users and providing information through Bangla medical-GPT for writing and extracting information and making it available, as well as a symptom checker for any-time risk assessment and referrals. To ensure the accountability of the providers, we plan to integrate face recognition of the user account opening to ensure we create accountable service delivery and capture the user's satisfaction. This will allow us to show better transparency and responsibility. Sociodemographic data will be used to design AI-based personalized health insurance for the people. This will help people who cannot afford quality medical services and ensure health equity. It will also allow the government to aid certain families in need and move one step forward to achieving universal health coverage (UHC) and Sustainable development goals (SDGs).

Conclusion

A modern healthcare system relies on the effectiveness of primary healthcare infrastructure. However, rural Bangladeshis often lack proper primary healthcare due to limited access, low health awareness, and an ineffective referral system. This study implemented and evaluated a digital health intervention model in one union to address these gaps. The model, which was facilitated by community health workers (CHWs), provided doorstep health screenings, consultations, and digital referrals. These CHWs, equipped with smart health kits and mobile applications, played a crucial role in bridging the gap between the rural population and healthcare services.

Over 18 months, the model successfully provided digital health services to over 32,000 individuals in rural Bangladesh, identifying key health concerns such as overweight, prehypertension, high blood glucose, and child malnutrition. Risk analysis highlighted that older adults were at greater risk for hypertension, diabetes, and cardiovascular diseases, emphasizing the need for early detection and intervention.

A comparative analysis across three periods showed a statistically significant improvement in BMI, blood pressure, and mid-upper arm circumference (MUAC) measurements, highlighting the model's positive impact on health outcomes. Specifically, the proportion of underweight individuals decreased, normal BMI levels increased, and prehypertension rates declined. However, blood glucose levels did not consistently improve due to the individuals' lack of interest in paid tests. This highlights the importance of understanding and addressing cultural and economic barriers in the implementation of digital health interventions.

The study demonstrates the feasibility and effectiveness of digital health interventions in improving primary healthcare in rural settings. The potential of integrating AI-driven decision support with CHW-led health screenings is immense, as it can enhance early detection and management of non-communicable diseases (NCDs). Scaling up this model through public-private partnerships could provide cost-effective solutions to bridge healthcare gaps and promote universal health coverage. Future efforts should focus on expanding the model, increasing follow-up compliance, and integrating additional digital features to enhance patient engagement and health outcomes.

Abbreviations

CVD	Cardiovascular Disease
CI	Confidence Interval
CDSS	Clinical Decision Support System
NCD	Non-communicable disease
BMI	Body mass index
BP	Blood pressure
MUAC	Mid upper arm circumference
LMIC	Low middle income country
PKSF	Palli Karma Shahayak Foundation
SpO_2	Oxygen saturation
ECG	Electrocardiogram
OTC	Over the counter
GP	General practitioner
CHW	Community health worker
YLL	Years of life lost
OR	Odds ratio
UHC	Universal Health Coverage
SDG	Sustainable development goals
GPS	Global Positioning System

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

MZ: Conceptualization, Methodology, Writing- Review; RAR: Data analysis, Writing: Original draft and editing; RAB: Data analysis, Writing- Review and Editing; CAG: Investigation, Methodology, Writing- Review; MMR: Conceptualization, Investigation, Methodology; SMSI: Investigation, Writing- Review and Editing; FS: Conceptualization, Investigation, Methodology, Review and Editing; KAM: Conceptualization, Design, Investigation, Methodology, Data Analysis, Writing- Original draft, review and editing, Supervision and Implementation.

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Data availability

The datasets and the analysis are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

All methods were carried out in accordance with the Declaration of Helsinki. The Institutional Research Ethics Board approved all experimental protocols (IREB) (ref no. IREB/2023/008) of the United International University (UIU), Dhaka, Bangladesh. Informed consent was obtained from all subjects (or their parents or legal guardians in the case of children under 16).

Competing interests

The authors declare no competing interests.

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