MEDINFO 2023 — The Future Is Accessible
J. Bichel-Findlay et al. (Eds.)

doi:10.3233/SHTI230966

Patient-Specific Mobile Phone-Generated Reminders and Quality of Hypertension Care in Western Kenya

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Abstract. To evaluate the impact of clinician-targeted mHealth-generated care suggestions on compliance with hypertension care guidelines in a resource-limited setting. This study was conducted in 10 rural health clinics in Western Kenya that offered hypertension care through nurses and clinical officers. Sites were grouped into intervention and control groups. Intervention group clinicians had patient-specific care suggestions triggered and displayed on a mobile application, *mUzima*, for their action. Care suggestions were also triggered in the mHealth application for control arm clinicians but were not displayed. Differences in compliance with hypertension care guidelines were evaluated. The study involved 378 patients with hypertension who had care suggestions generated during visits (217 in intervention group and 161 in control group). There was a higher proportion of adherence to hypertension care guidelines in the intervention group compared to the control group (91.1% vs. 85.7%, p=0.014). The random effects model showed significant variability in compliance rates among study clinicians (variance of 0.44, 95% CI: 0.12 -1.62). When displayed care suggestions were rejected by intervention providers, the most common reason given was 'Previously ordered' (58.8%). Clinicians felt that care suggestions improved awareness of hypertension care guidelines. The successful scaled implementation of *mUzima* with patient specific care suggestions led to higher adherence to hypertension care guidelines and improved quality of hypertension care. Tailormade m-Health applications in resource constrained settings for hypertension care and other chronic non-communicable diseases has the potential to lead to better adherence to care guidelines and quality of care.

Keywords. Clinical decision support, chronic disease, mHealth, low- and middle-income countries

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1. Introduction

Hypertension is the leading risk factor for cardiovascular disease and of premature death globally [1]. The World Health Organization estimates that 1.28 billion adults between 30 and 79 years of age have hypertension, with two thirds of them residing in low- and middle-income countries (LMICs) [2]. Successful management of hypertension requires health systems that offer high-quality, effective, and accessible services to diagnose and treat these conditions. Care systems in Sub-Saharan Africa (SSA) are unable to meet these challenges given human, financial and infrastructure constraints [3].

Mobile health technologies (mHealth) offer one key strategy to better manage hypertension in LMICs [4]. In SSA, mHealth innovations have the potential to strengthen health systems and to improve quality of care through improving compliance with care guidelines, supporting health workers and performance monitoring [5]. One of the powerful tools offered by mHealth solutions is their ability to deliver computerized clinical decision support (CDS) [6]. CDS within mHealth solutions are relevant for LMICs, where hypertension care is often task-shifted to lower-cadre personnel [7].

This was a comparative pilot study set in the resource-limited setting of Western Kenya. The objective of this study was to evaluate the impact of mHealth-generated, patient-specific care suggestions availed to clinicians on compliance with hypertension care and treatment guidelines.

2. Method

2.1. Study Setting

The prevalence of hypertension in Kenya has been estimated at about 24.5% [8]. This study was conducted in Ministry of Health dispensaries and health centers in two rural sub-counties in western Kenya where provision of hypertension care was offered [9]. A conveniently-selected sample of 10 facilities in these rural sub-counties were involved in the study.

2.2. mHealth, EHR System and mHealth-generated Clinical Care suggestions

mUzima is a secure open-source smartphone-based Android application that allows clinicians to collect new data through programmed forms and review a patient's historical clinic data [10]. *mUzima* was customized to interoperate with the OpenMRS electronic record system [11].

Care guidelines for hypertension were developed through a collaboration between the department of NCDs within Kenya's Ministry of Health, Moi University College of Health Sciences, and Moi Teaching and Referral Hospital. These care guidelines provided the foundation for the care suggestions implemented within the *mUzima* mHealth application. Care suggestions focused on three categories: initiation of specific hypertension medication, titration of hypertension medication, and monitoring for potential medication side effects.

2.3. Study procedure and Study Population

All healthcare providers in the 10 primary care facilities in the study were randomly assigned into either the control or intervention group. Patients seen by health care providers in the intervention group had patient-specific mobile phone–generated care suggestions triggered and displayed within the *mUzima* application when the

clinical criteria were met. Patients seen in the control group had patient specific care suggestions triggered, but the care suggestions were *not displayed* to the provider in *mUzima.* Triggered care suggestions were all saved as logs that were transmitted to a secure server. The transmitted logs were downloaded in an Excel spreadsheet and enhanced with clinical-level data abstracted from the AMRS EHR system. The study was approved by the Institutional Review and Ethics Committee at Moi University, Kenya. The study was conducted between 1st November 2018 to 28th February 2020.

2.4. Statistical Methods

The unit of analysis in this study was each unique care reminder that triggered during the patient-provider visit. Descriptive statistics, including frequencies and the corresponding percentages, as well as the median and the corresponding inter-quartile range (IQR) were used to summarize categorical variables, and continuous and discrete variables respectively. Continuous variables were assessed for Gaussian assumptions using histograms. Data analyses were done using STATA version 13 SE (College Station, 77845 Texas USA).

3. Results

3.1. Adherence to hypertension care suggestions

The crude estimates demonstrated evidence of significantly higher adherence to hypertension care suggestions by clinicians in the intervention arm compared to the control arm (91.1% versus 85.7%, p=0.014). However, on adjusting for the effect of the different clinician types (clinical officers and nurses) through random effects model with robust standard errors, the effect of hypertension care suggestions did not change but became statistically non-significant (Adjusted Odds Ratio: 1.78 (95% CI: 0.83, 3.80).

3.2. Reasons for non-adherence to care suggestions

Reasons provided by clinicians for non-compliance with care suggestions included: previously ordered (58.8%); do not agree with reminder (27.7%); not applicable (11.8%) and patient declined (1.7%). 'Previously ordered' featured prominently as a reason to reject care suggestions because the triggered care suggestions did not use historical data stored in the EHRs.

3.3. Patient Characteristics

There were 378 patients seen during the study period for whom a clinical reminder was triggered for hypertension care. Participants were similar by age and gender with a median age of 60 years and 73% being female (P>0.05). (Table 1).

Table 1. Patient characteristics.

	N	Control (n = 161)	Intervention (n = 217)	P – value
Age, Years (Median, IQR)	354	60.0 (24.5, 73.5)	60.0 (38.0, 70.0)	0.987[w]
Age Distribution	354			
18 – 29		49 (32.2%)	47 (23.3%)	0.030[c]
30 – 49		7 (4.6%)	20 (9.9%)	
50 – 59		17 (11.2%)	32 (15.8%)	
60 – 69		28 (18.4%)	51 (25.3%)	
≥ 70		51 (33.6%)	52 (25.7%)	
Gender, n (%)	378			
Female		118 (73.3%)	159 (73.3%)	0.997[c]
Male		43 (26.7%)	58 (26.7%)	

N – Represents the number of participants who responded or who had data for the characteristic, [c] Pearson's Chi-Square test for comparison of proportions, [w] Two-sample Wilcoxon rank-sum test for comparison of median estimates

Mean SBP and DBP were not significantly different between the two groups, with proportion of patients with SBP ≥ 140 mm Hg and DBP ≥ 90 mm Hg being similar 67.4% and 61.0% respectively (p = 0.198) (Table 2).

Table 2. Patient blood pressure distribution.

Characteristic	N	Control (n = 161)	Intervention (n = 217)	P-value
SBP (mmHg), Median (IQR)	374	142.0 (127.0 – 151.0)	143.0 (129.0 – 156.0)	0.129[w]
Range (Min. – Max.)		104.0 – 198.0	102.0 – 208.0	
< 120		16 (10.1%)	23 (10.7%)	0.219[f]
120 – 139		57 (35.9%)	57 (26.5%)	
140 – 159		67 (42.1%)	97 (45.1%)	
160 – 179		18 (11.3%)	32 (14.9%)	
≥ 180		(0.6%)	6 (2.8%)	
DBP (mmHg), Median (IQR)	374	81.0 (72.0 – 919.0)	80.0 (74.0 – 92.0)	0.577[w]
Range (Min. – Max.)		58.0 – 117.0	59.0 – 114.0	
< 80		73 (45.9%)	102 (47.4%)	0.041[f]
80 – 89		46 (28.9%)	42 (19.5%)	
90 – 99		29 (18.2%)	62 (28.8%)	
100 – 109		10 (6.3%)	8 (3.7%)	
≥ 110		1 (0.6%)	1 (0.5%)	

SBP – Systolic blood pressure, DBP – Diastolic blood pressure, N – Represents the number of participants who responded or who had data for the characteristic, [f] Fisher's Exact text for comparison of proportions when Chi Square assumptions are violated, [w] Two-sample Wilcoxon rank-sum test for comparison of median estimates

4. Discussion

mUzima is an m-Health extension of OpenMRS which is the most deployed EHR system in LMICs [10]. This study of *mUzima*-generated care suggestions demonstrated a modest increase in compliance with hypertension care guidelines among HCPs. Even with the high baseline compliance rates to guidelines, phone-generated care suggestions still increased compliance rates. Care suggestions for CDS are in high need areas of care with complex care algorithms and low compliance rates with room for improvement [12].

The leading reason of rejection of care suggestions was the generated care suggestions did not leverage on historical data stored in the EHRs. CDS with resultant patient-specific care suggestions are most effective when based on real-time data in combination with historical electronic health data. Siloed mHealth applications that do not use historical data are unlikely to fully leverage the power of CDS. When inappropriate care suggestions are generated, alert fatigue increases [13]. The providers also mistrust and ignore the alerts [14].

The providers in this study were all able to use the *mUzima* application, with most agreeing that the care suggestions made them more aware of care guidelines. This demonstrates the potential of CDS. Improving performance of CDS requires appropriate stewardship, continuous monitoring and timely improvements based on inputs by end-users [15]. In settings with inadequate human resources to monitor and maintain CDS, solutions that leverage data analytics and machine learning could be employed to identify and respond to patterns of CDS use.

This study had a few limitations. It was a pilot study that involved a few care guidelines for one disease. The care suggestions were implemented in a few facilities, with a few providers, in only one region, and did not integrate historical data. This study demonstrates the potential for use of *mUzima* with CDS in low resource settings with limited healthcare providers to provide ideal care for NCDs. Next steps for this work involve improving the system to incorporate historical data and integrating automated monitoring mechanisms to enable rapid improvement of deployed care suggestions.

5. Conclusions

This study shows the evaluation of patient specific reminders within *mUzima* which is a tailormade m-Health application for resource constrained settings. *mUzima* improved compliance to hypertension care guidelines when used by HCPs in a resource-limited LMIC rural setting.

Funding

This work was supported through the NORHED program (Norad: Project QZA-0484) and USAID (Grant #: 7200AA18CA00019). The contents are solely the responsibility of the authors and do not necessarily represent the official views of NORHED, USAID or the United States Government.

Contributorship Statement

NK: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing - original draft, Writing - review & editing. JH: Supervision, Data Analysis, Writing - review & editing. SS: System development, data curation, Writing - review & editing. LM: Data collection, data curation, Writing – review & editing. SR: Data collection, data curation, Writing – review & editing. MC: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing.

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