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Evaluation of mHealth Usage Logs for Health Provider Performance in HIV Care in Zambézia Province, Mozambique

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Abstract. Community health workers (CHWs) offer essential services for people living with HIV (PLHIV) in low-resource settings. However, understanding and optimizing CHW performance is challenging as CHWs work remotely and over large geographical areas. A mobile health (mHealth) application, *mUzima*, was introduced in one district in Mozambique to support CHWs during patient visits. Usefulness of *mUzima*-derived logs to inform CHW performance and work patterns was evaluated. Derived from 113,893 cleaned log records, the 29 CHWs who used *mUzima* for 8,896 distinct encounters worked an average 2.65 days per week, with encounter documentation length within *mUzima* taking 3.6 minutes (SD 5.8). Mean length of *mUzima* usage was 2.7 hours per day (SD 4.0), with 30.7% of encounter data entered outside of regular work hours. Roughly 83% of CHWs entered visit data into *mUzima* on weekends. mHealth-usage logs offer novel insights into work patterns by CHWs, informing approaches to best support them.

Keywords. mHealth; work performance; HIV; low-resource countries

1. Introduction

Data from the INSIDA 2021 report indicate that the prevalence of HIV in Mozambique is 12.4% among adults aged 15 to 49 years, with Zambézia Province having the highest HIV seroprevalence rate at 17.1% [1]. In 2019, the national rate of retention on antiretroviral therapy (ART) at 12 months was estimated to be 67% [2], and in 2021 early retention on ART at 99 days post-initiation was estimated between 82-90% [3]. High attrition rates lead to the emergence of drug resistance and eventual loss of immune function resulting in disease progression and potentially death [4]. Patient tracing and preventive visits are important for tracking patients who have missed scheduled clinic visits and/or who have experienced an interruption in treatment (IIT), as well as supporting those newly initiated on antiretroviral treatment. These activities are often conducted by Community Health Workers (CHWs), who play a critical role in supporting care and treatment programs.

When equipped with mobile devices, CHWs can collect high quality and timely data from the field, with fewer errors and less data losses as compared to paper-based data collection systems [5]. The digital data collected as part of the mHealth applications use provide an opportunity to evaluate performance of outreach workers distributed over large geographical areas. We hypothesized that mHealth-derived log data, collected while the CHWs used the mobile application, could provide key insights (beyond typical clinic visit data) into the work performance of CHWs working remotely.

2. Methods

Study Setting: CHWs and case managers (supervisors) working within an HIV care and treatment program in Namacurra district in Zambézia Province were trained on the *mUzima* smartphone-based mHealth application for use during preventive and tracing (i.e., finding/reconnecting) home visits for adult persons living with HIV (PLHIV), where CHWs performed assessments and adherence counseling for patients. The *mUzima* application is a secure open-source smartphone app on the Android platform that allowed CHWs to collect data and to review historical patient data retrieved from a connected electronic record system, *Sistema Eletrónico de Seguimento dos Pacientes* (SESP), that is based on OpenMRS™. *mUzima* has been used to support HIV testing and chronic disease management in Kenya and has been deployed in 15 districts in Rwanda [6].

mUzima use workflow: Case managers equipped with *mUzima* could see the list of patients identified as potentially defaulting, experiencing care interruption, or those requiring adherence support and follow-up during the critical post-ART initiation period. The case managers conducted data triangulation and updated the status of each patient. They also assigned a volunteer CHW to trace patients identified as needing follow-up. The assigned list of patients was automatically updated in the SESP and on the mobile devices possessed by CHWs. The CHWs could then visit the patients, entering the relevant encounter information within the *mUzima* application, which was then transmitted back to the SESP. Usage of the application were captured using event-log functionality and transmitted securely to the server. The detailed application usage-log data could be analyzed in a de-identified manner, to preserve privacy for PLHIV data and for staff.

Data cleaning: This secondary data analysis study was covered under the approved blanket protocol, titled "*Quality Improvement for HIV Care and Treatment in Zambézia province of the Republic of Mozambique under the President's Emergency Plan for AIDS Relief (PEPFAR)*" (Cooperative Agreements #GGH001943 and #GGH002367). The data use and evaluation plan was approved by the VUMC Institutional Review Board (IRB) (#201887) and the Institutional Research Ethics Committee for Health of Zambézia Province (*Comité Institucional de Bioética para Saúde – Zambézia [CIBS-Z]*; 01/CIBS-Z/22). Data cleaning procedures for the collected log data included: (a) data de-identification by removing all personally identifiable information for patients and providers, (b) exclusion of records that were outside the selected period of interest (January 1 – March 15, 2020), resulting in 115,186 *mUzima* log records in the period of interest; (b) exclusion of 3,122 (2.7% of logs) whose event time stamps were very old (mostly 2012) – these were from devices that had been reset to dates of manufacture for some reasons, e.g., through removal of device batteries, and (c) imputation of the correct timestamps (using geolocation timestamps) for 4,491 records from devices that had the wrong time set on the device, with an additional level of manual check for verification.

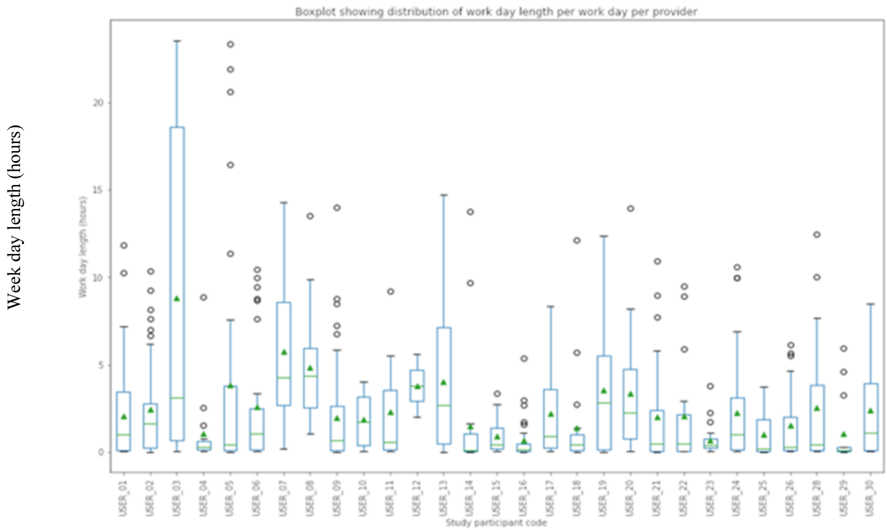
The cleaned logs resulted in a total of 113,893 records (of which 4,491 [3.94%] were imputed) that were transformed to generate encounter records for analyses – an encounter simply signified a series of related data collection events (such as filling a form) by a CHWs on the same patient during a particular day. In total, 18,623 'encounters' were identified, including both complete and incomplete forms, as well as demographic updates captured. From these, a total 2,818 encounter sessions with a usage duration of 'zero' were removed, retaining 15,805 encounters. An additional 6,881 encounters were subsequently removed as they reflected incomplete encounters that were captured later when the full record was saved. This left 8,896 encounters for analyses.

For each derived encounter, a *start time and end time* that defined the *usage session duration* was generated. *Usage duration preceding gap* was also identified as time difference between the end time of the previous session and start time of the new session. Other parameters obtained included: *user-id, device_id, patient_id, encounter_date* and *tags.* The cleaned data from event logs were used to derive pre-defined work performance indicators. Descriptive statistics (frequencies, means and standard deviation [SD]) were calculated and used in evaluating the following work performance metrics of CHWs, namely: (a) *Encounter length; (b) Number of days worked* (mean, SD, range); (c) *Number of completed patient encounters* (mean, SD, range); (d) *Length of workdays* (mean, SD, range); and (e) *Duration of each patient encounter* (mean, SD, range).

3. Results

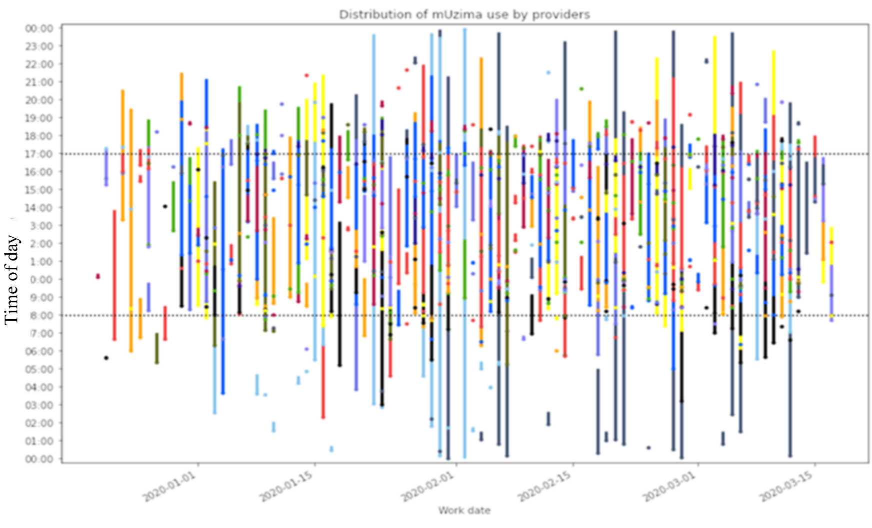
After data cleaning, a total of 8,896 distinct patient encounters were available for analyses to evaluate work performance of CHWs who were using *mUzima*. The records represented 29 unique CHWs over the study period. CHWs worked an average 2.65 days per week (SD 1.36), which also incorporated the times when they entered patient data into *mUzima*. 83% of CHWs (24 of 29) entered visit data into *mUzima* on weekend days. Based on log data, the total number of PLHIV seen by each CHW varied widely, ranging from 1 to 409 (mean 10, SD 30) over the study period. Two users were outliers (User 7 and 8) in seeing many more patients that the other CHWs.

On average, CHWs used 3.5 minutes (SD 5.8 min) to enter each patient encounter into *mUzima*. This calculated encounter length was the duration from the time the first data element was recorded about a particular patient visit to the time that the CHW confirmed that all visit data had been entered and the visit completed for that visit – as such, if data were being entered during the actual patient visit, calculated encounter length would have incorporated time taken to conduct all activities such as patient counseling when CHWs might not actively be entering patient data. Mean length of *mUzima* application usage was 2.7 hours per day (SD 4.0) (**Fig. 1**), with 30.7% of encounter data (2,732/8,896 encounters) entered outside 8 am or after 5 pm (**Fig 2).**



Study participant code

Figure 1. Average encounter length in minutes per provider



Work date per provider (each provider represented by a different color)

Figure 2. Work hours per provider for the various dates during study pe-

4. Discussion and Conclusions

Privacy-preserving approaches leveraging mHealth-derived usage logs provide detailed insights into CHW work patterns beyond what can be derived from regular clinical encounter data collected within electronic records. The additional information from logs include: (a) length of recording of each patient encounter, (b) estimated start and end times of a CHW's workday, (c) how often CHWs conduct partial encounters requiring subsequent completion, and (d) use of application outside of work hours. Use of logs can automate observational-based time-motion approaches to track activities, as well as provide insights into CHW engagement mHealth applications.

The results from log data in Mozambique highlight several things about work patterns by the CHWs. The CHWs in the study site often used the application outside regular work hours and on weekends. In addition, if data were being entered at the time of the patient encounter, encounter length may have incorporated time taken to conduct activities such as patient counseling when CHWs might not actively be entering patient data. These all suggest that a good amount of the data was entered retrospectively, as opposed to recommended *mUzima* use at point-of care for real-time data entry during visits. These findings could mean that the CHWs likely need continuous and targeted training to become comfortable with real-time data entry, as this takes advantage of data validation and any relevant decision support features incorporated into the application. An obvious concern is of providers working outside of their regular work hours and on weekends – adding an extra dimension to use of the mobile application that need to be further understood and addressed. The low number of days and hours worked, short work-day lengths and differences observed between providers offer further opportunities for individualized approaches to improve work-performance for each CHW.

This study was conducted in one setting, limiting generalizability. Log-based analytics can be used in decision support features to alert CHWs about likely retrospective entry of data and in providing recommendations on avoiding work outside of the official hours and days. Approaches for supportive supervision and application redesign can also be implemented using the knowledge derived from log data analyses. In addition, reevaluation of changes to CHW performance after interventions and over time are needed.

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