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Research and Applications

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Analysis of user interactions with a digital health wallet for enabling care continuity in the context of an ongoing pandemic

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ABSTRACT

Background: The onset of COVID-19 and related policy responses made it difficult to study interactive health informatics solutions in clinical study settings. Instrumented log and event data from interactive systems capture temporal details that can be used to generate insights about care continuity during ongoing pandemics.
Objective: To investigate user interactions with a digital health wallet (DHW) system for addressing care continuity challenges in chronic disease management in the context of an ongoing pandemic.
Materials and methods: We analyzed user interaction log data generated by clinicians, nurses, and patients from the deployment of a DHW in a feasibility study conducted during the COVID-19 pandemic in Kenya. We used the Hamming distance from Information Theory to quantify deviations of usage patterns extracted from the events data from predetermined workflow sequences supported by the platform.
Results: Nurses interacted with all the user interface elements relevant to triage. Clinicians interacted with only 43% of elements relevant to consultation, while patients interacted with 67% of the relevant user interface elements. Nurses and clinicians deviated from the predetermined workflow sequences by 42% and 36%, respectively. Most deviations pertained to users going back to previous steps in their usage workflow.
Conclusions: User interaction log analysis is a valuable alternative method for generating and quantifying user experiences in the context of ongoing pandemics. However, researchers should mitigate the potential disruptions of the actual use of the studied technologies as well as use multiple approaches to investigate user experiences of health technology during pandemics.

Key words: log analysis, user interactions, pandemics, digital health wallet, care continuity

INTRODUCTION

Health care systems in resource-constrained settings are often fragmented and faced with limited capacity to manage the increasing number of individuals with chronic diseases and multiple morbidities. Fortunately, advancements in health information technologies along with their increased adoption promise to improve data collection and analysis in resource-constrained settings. To this end, we developed the digital health wallet (DHW) platform to ensure continuity of care as patients visit different facilities.[1] The DHW platform is a multi-component blockchain-based care-management system for enabling the patient-controlled exchange of health information and coordinated care. The goal of this system is to strengthen patient referral and coordination services in under-resourced and medically underserved communities.

Systems such as the DHW platform may easily fail to meet their goals if they do not have a good user experience or support the functional needs of their users at the right time and sequence. The successful implementation of such systems is highly dependent on a proper understanding of how doctors, nurses, patients, and other end users perceive their ease of use and usefulness.[2,3] Consequently, it is critical to evaluate the usability and usefulness of systems such as the DHW at different stages of their development and implementation. Unfortunately, despite the increase in the health applications of systems such as the DHW, there have been limited usability assessments to capture user behavior and identify potential areas of improvement.[4] Additionally, fewer usability assessments have been published for mobile platforms compared with web-based technology due to the ubiquitous characteristic of mobile platforms.[5]

While there are several methods for conducting usability testing, analyzing user activities and state transitions of a system is useful for studying the quality of interaction between users and interactive systems.[6,7] In contexts such as ongoing pandemics where direct observation of human behavior may not be feasible, log analysis can be informative and complementary to traditional methods of usability testing including surveys, focus group discussions, and in-depth interviews. Unfortunately, however, there is a general dearth of literature on how highly interactive systems have been evaluated in the context of the ongoing pandemics. Furthermore, the majority of log analysis tools tend to treat log event data as a "bag of events" rather than as part of a larger sequence.[8]

This study investigated the interaction between clinician, nurse, and patient end users and the DHW. Specifically, we describe the usage patterns of DHW and identify the challenges and bottlenecks that the end users might have experienced. We present the analysis of user behavior using event log data captured by the DHW platform. Logging user interactions proved to be a valuable complementary way of evaluating the feasibility of DHW during the COVID-19 pandemic that limited physical human interactions. This article reports our findings.

MATERIALS AND METHODS

Study design

This study is a part of the larger feasibility investigation conducted between October 2019 and February 2021 to determine if the DHW platform[1] is technically viable for the management of HIV and comorbid diabetes and/or hypertension in Kenya. In this study, we applied the user interaction log analysis design from the usability testing literature.[6,7] Specifically, we captured and analyzed the interaction between clinicians, nurses, and patients and the DHW in the process of conducting the feasibility investigation.

Study setting

The study was conducted at the Kitengela Sub-County Hospital, a public primary care facility located in Kajiado County, Kenya. This hospital is regulated by the Kenya's Ministry of Health and provides both inpatient and ambulatory services to a catchment population of over 200 000 persons. Although the hospital has several clinics, this study targeted the Comprehensive Care Center (CCC) for the management of persons living with HIV/AIDS and the Medical Outpatient Clinic (MOPC) for ambulatory care of chronic ailments.

The DHW

The DHW was created by IBM Research Africa in collaboration with Lwala Community Alliance to enable care continuity and quality in fragmented resource-constrained settings by supporting documentation and data sharing in the management of chronic illnesses.[1,9,10] The care-management and coordination components of the DHW include a clinical encounters application, a digital patient-care wallet, and a consent platform. The clinical encounters application is used by care providers including nurses, clinicians, lab technicians, and pharmacists to document and share routine healthcare data in outpatient settings using the fast healthcare interoperability resources v3.0 standard. The digital patient-care wallet is a mobile application that enables patients to view their health records such as medications and vital signs. It also allows patients to authorize the sharing of their health records. The consent platform uses blockchain technology to manage and control the sharing of health data through an explicit consenting process. Figure 1 describes the key workflows of interest to this study.

Deployment and feasibility testing of the DHW

We recruited a purposive sample of 17 patients and 8 care providers. The targeted patients were clients of the CCC. The patient participants were expected to have multiple routine visits to the CCC during the feasibility testing period, with some being referred to the MOPC for diabetes and/or hypertensive care when necessary. As illustrated in Figure 2, we specifically focused on the clinic management and referral workflow between the CCC and MOPC. The targeted care providers in this workflow included 1 administrator, 1 nurse, and 1 clinician at the CCC clinic, as well as 1 administrator, 1 nurse, and 1 specialist at the MOPC clinic. The care providers also included 1 laboratory technician and 1 pharmacist who served both clinics. All participants were identified by representatives from the hospital management team.

Before the deployment of DHW, participants were provided with individual handheld devices including tablets for care providers and smartphones for patients. They were trained on the features and functionalities of the DHW application and were subsequently onboarded onto the platform. Up to 90% of the patients were not conversant with smartphone use and required significant assistance to familiarize themselves with technological terms and the use of smartphones. We took the participants through the end-to-end clinic visit process while using the DHW platform. The aim was to help patients understand the workflow from the first stage to the last stage while using the DHW platform. The providers were also shown how the system can support their workflows.

The COVID-19 pandemic interrupted patient visits to the hospitals. The government imposed nonpharmaceutical interventions including cessations of movements that discouraged patients from attending hospital clinics. Consequently, there were limited activities in the hospital at the onset of the COVID-19 epidemic in Kenya in March 2020. Most of the patients received long-term prescription pills. The first major physical return visit batch comprising 11 patients occurred in May 2020.

Data collection

In the process of designing the DHW system, we instrumented the collection of different types of logs and event data including user interaction events and patient tracking logs. Here, instrumentation refers to adding software code to automatically capture and monitor user-generated events in the DHW applications for subsequent analyses.

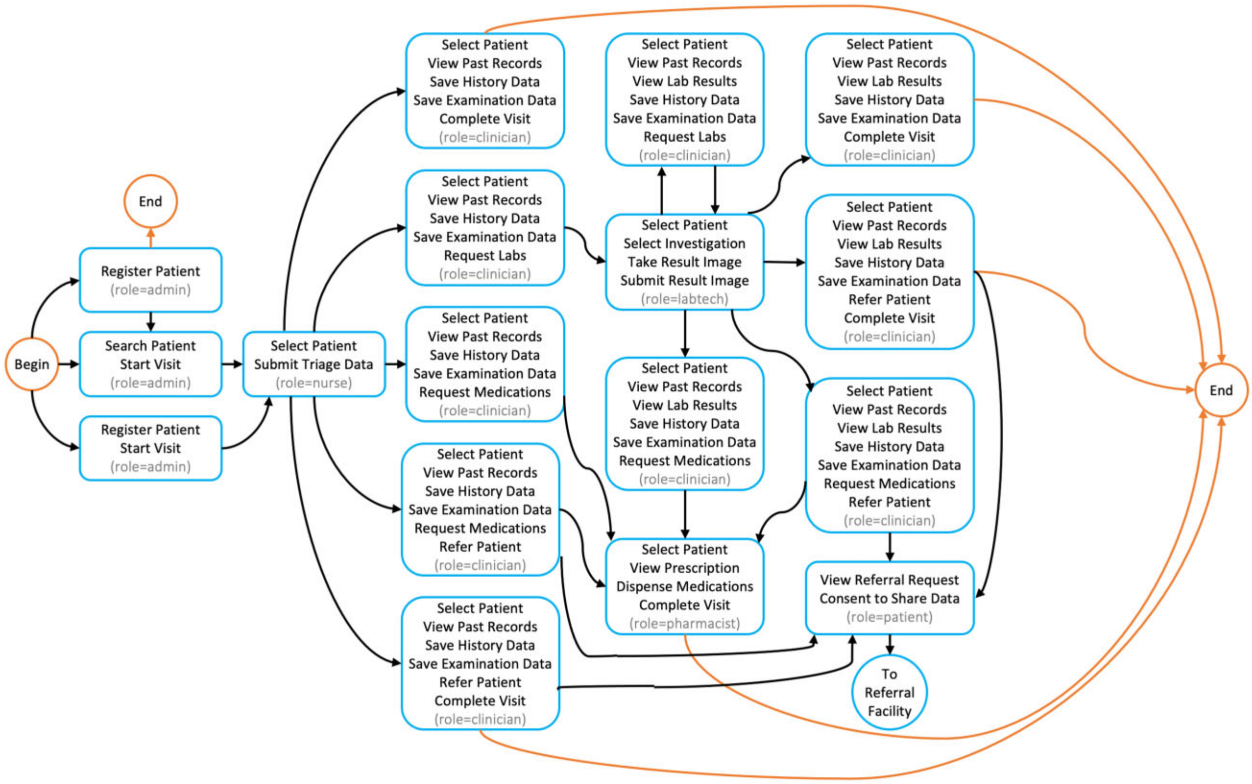

Figure 1. DHW key workflows.

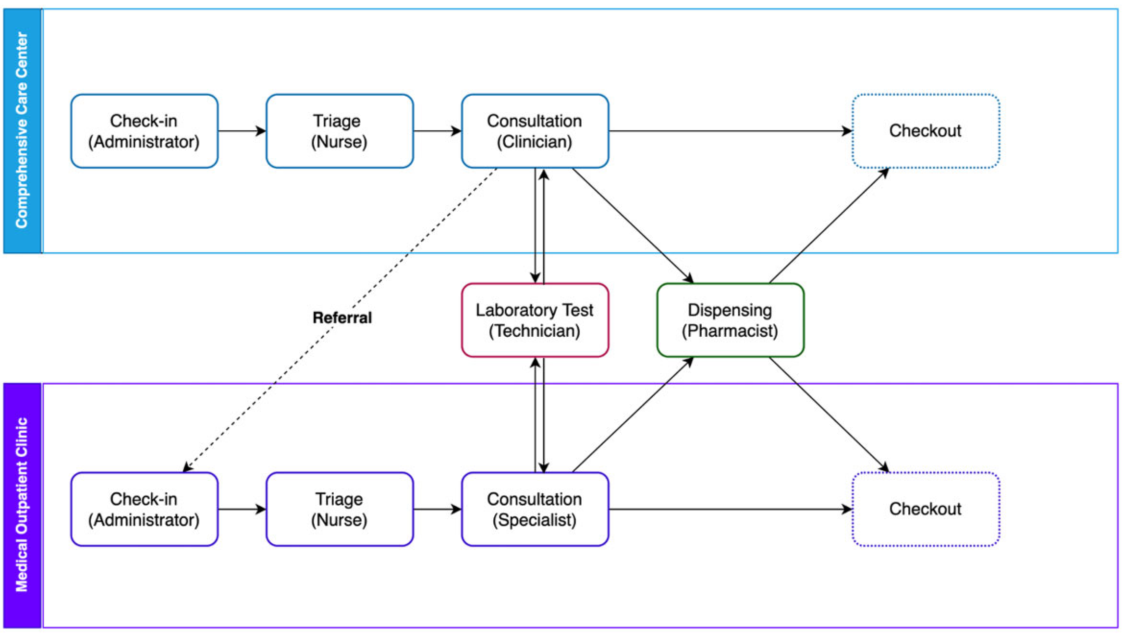

Figure 2. The clinic management and referral workflow between the CCC and MOPC.

The data for the user interaction log analysis were collected between February 2020 and December 2020.

User interaction events

These events capture the user interactions with different interface elements, for example, clicking a button. They were collected by adding "listeners" to each of the interface elements that the users were directly or indirectly using. Whenever an interaction was detected, an event object was generated and stored in a remote database. The event object stored deidentified information about the interaction with interface elements. We categorized the user interaction events into 2 event types: user action and state transitions.

The *user action* event type was assigned to events involving users directly performing actions by interacting with the user interface elements. Examples of such actions include clicking the search patient button, starting a clinic visit, and submitting triage data. The *state transition* event type involved transition of different user interface pages resulting from user actions. Examples of such state transitions include loading the patient queue, loading the vital signs page, and loading the referral page.

Patient tracking logs

These logs capture the different provider encounters that a patient goes through in each visit, for example, nurse to doctor to pharmacist. For each encounter, we instrumented the collection of this data in our system and log the time taken to complete the encounter. To allow for easy computation of the time users wait in the queue, we added the wait as a different encounter. The following encounters were considered: starting a clinic visit, waiting for nurse triage, triage, waiting for consultation, consultation, waiting for lab investigation, and lab investigation.

User interaction log analysis

We guided our analysis with 3 analytic questions: (1) What is the frequency of interactions with user interface components? (2) What are the common sequences of steps the users took to complete tasks? (3) What proportion of observed event sequences deviated from expected event sequences? To answer these questions, we conducted descriptive analysis in Python. Specifically, we employed frequency distributions using histograms to describe elements such as the frequency of user interaction with interfaces and the distribution of steps in a clinic visit. We categorized the logs in to user journeys. We define each journey as a sequence of events, where the interval between subsequent pairs of events in the journey is less than 5 min and the interval between subsequent journeys is 5 min or more. We employed Sankey diagram analysis[11] to identify the most dominant user journey flows. Sankey diagrams allow visual representation of complex processes. They show the flow of events with the width representing the proportion to the total number of events and the color represents transition of an event to another.

Lastly, to estimate deviations from the norm, we computed the Hamming distance between the observed (user-generated) sequences of events and expected sequences of events (base paths). We defined the Hamming distance between 2 sequences of events of equal length as the number of positions at which the corresponding events are different.[12,13] We defined the Hamming distance ratio (normalized Hamming distance) as the ratio of the Hamming distance to the length of the sequence of events.[13] We used the Hamming distance ratio to compute the proportion of user interaction event sequences that deviated from the base path. Of note is that each role may have multiple possible base path sequences. The base paths were identified from expert consultations with care providers including nurses, clinicians, lab technicians, and pharmacists. This was done when designing the system and based on a pre-pilot study conducted on a separate but similar setting.[9,14] For each role, base path sequences were compared with the alternate path sequence of events from the identified paths. The Hamming distance ratio ranges between 0 and 1, where 0 represents an alternate path being 100% similar to the base path and 1 represents an alternate path being 100% different from the base path. Lower Hamming distance ratios represent better compliance to the expert-defined base paths.

Ethical considerations

Institutional review board approval to conduct the feasibility study of the DHW was acquired from the Kenya Medical Research Institute's Scientific and Ethics Review Unit. Additional research permits were acquired from the Kenya National Council of Science, Technology, and Innovation, and the Kajiado County administration. Study participants were considered eligible if they met the study requirement and if they expressed willingness and consented to participate in the study, and all user interaction log data were computationally deidentified.

RESULTS

User interaction events

A total of 9972 unique user event logs were collected from 20 unique users. These included event logs from 13 of 17 recruited patients and 7 of 8 recruited care providers. The distribution of log events across roles is shown in Table 1. We focused on events generated from the user types of nurses, clinicians, and patients. Most of the logs (86%) were generated by the patients. The nurses generated logs for all the unique instrumented nurse events in the application. Clinicians generated logs from 43% of the unique instrumented clinician events, while patients generated logs from 67% of the unique instrumented patient events.

Figure 3 shows the frequency of interactions with interfaces among nurses. In this figure, the blue and purple bars show the user action and state transition event types, respectively. The patients' queue page has the highest number of recorded events. Of note is that 21 events involved selecting a patient from this queue, yet 24 events involved submitting triage data. This shows that in some cases, the submit triage button was clicked more than once in a single triage encounter with the patient. This identifies a bottleneck in the flow as the button was designed to be clicked only once to submit triage results and exit from the triage page. However, when an

Table 1. Distribution of log events across roles

	Events (%)			Proportion (%) of instrumented events		
	CCC	MOPC	Total	CCC	MOPC	Total
Admin	230 (2.3)	167 (1.7)	397 (4.0)	8/10 (80)	13/15 (86.7)	13/15 (86.7)
Nurse	176 (1.8)	104 (1.0)	280 (2.8)	7/7 (100)	7/7 (100)	7/7 (100)
Clinician	453 (4.5)	138 (1.4)	591 (5.9)	17/39 (43.6)	17/39 (43.6)	17/39 (43.6)
Lab tech	71 (0.7)		71 (0.7)	3/13 (23.1)		3/13 (23.1)
Pharmacist	0 (0)		0 (0)	0 (0)		0 (0)
Patient	8633 (86.6)		8633 (86.6)	22/33 (66.7)		22/33 (66.7)
Total			9972 (100)			62/107 (57.9)

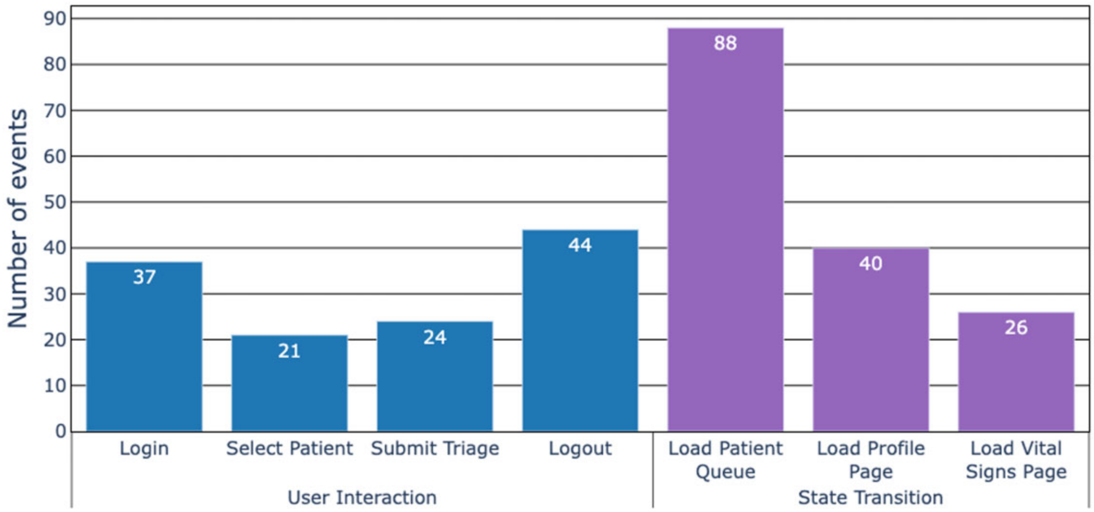

Figure 3. The nurses' frequency of interactions with interfaces, with the left blue colored bar graphs showing the user action event types and the right purple colored bar graphs showing the state transition event types.

error in the submission of the triage data occurs, a user can attempt resubmission multiple times. This is further elaborated in Figure 4, which shows the nurses' Sankey plot. In most instances, the nurses logged in, selected a patient, submitted the patient's triage data, and then logged out or returned to the patient queue. In some instances, the nurses logged in and then logged out without doing anything.

We identified 25 unique observed nurse sequences and compared these with 1 nurse base path (N1) as shown in Table 2. The 25 sequences had a mean Hamming distance ratio of 0.42 and a standard deviation of 0.39. Two sequences had a Hamming distance ratio of 1, 8 had a Hamming distance ratio of 0, and 4 had a Hamming distance ratio of 0.2. The rest of the 11 sequences with Hamming distance ratios ranging from 0.4 to 0.8 were incomplete and the user did not continue.

Figure 5 shows the common user action event sequences generated by the clinicians. After logging in, the users selected a patient from the queue in most instances. From here, most of the instances involved ordering medications or requesting a laboratory test. In a few instances, the clinicians saved their patient's history before ordering medications or requesting a laboratory test. In all instances where medications were ordered, the treatment information was saved. This was followed by, in most cases, sharing encounter resources and referring the patient before logging out of the system or returning to the patient queue.

We identified 27 unique clinician sequences and compared these with 3 clinician base paths as shown in Table 2. The mean of the Hamming distance ratio associated with deviating from any of the 3 base paths (C1, C2, or C3) was 0.36 with a standard deviation of 0.24. The first base path (C1) does not involve a clinician requesting laboratory investigations and ordering medication. Nine observed paths were categorized to match this base path with a mean Hamming distance ratio of 0.36 and a standard deviation of 0.28. The deviations happened after selecting patient where the users proceeded to save examination data.

The second base path (C2) terminated when the clinician referred the patient to the laboratory for investigations. Thirteen observed paths with a mean Hamming distance ratio of 0.32 and a standard deviation of 0.16 matched this base path. The deviations happened after selecting patient where the users proceeded to saving examination data instead of saving history data.

The last base path (C3) involved the clinician not requesting laboratory investigations but ordering medications and referring the patient. Five observed paths matched this base path with a mean Hamming distance ratio of 0.35 and a standard deviation of 0.24. The deviations happened after selecting patients where the users proceeded to save examination data or request medications.

Figure 6 shows the user journey flow of the recorded patient events. The entry point here was login. We can see that all login sequences were followed by the loading of the home page as expected. Unlike the providers' application which had a defined workflow(s) from the user interface, the patient app allowed the users to navigate randomly to any page from the base path using navigation bars. In this regard, we did not compute the Hamming distance ratio for this user type as we do not have a predefined base path(s). However, of interest is the patient consent workflow which we can follow from the home page to the consent page and the user scrolling the consent page before either terminating there or loading the history page or home page. From the home page, most users loaded the profile page, scrolled the homepage, or did nothing.

Patient tracking logs

From the patient tracking logs, a total of 40 clinic visits in both CCC and MOPC were recorded, 34 of which were completed. Six incomplete visits remained at different steps of the workflow as shown in Table 3. Of note is that some of the intermediate steps such as "waiting for consultation" and "consultation" had higher frequencies than the total number of unique clinic visits, and there was a huge difference between the logged total number of encounters and the number of unique user sequences for the nurse and clinician users. This can be explained by the fact that some users would begin encounters such as triage and consultation but fail to complete them, for example by going back to the queue, logging out, or timing out. In such cases, the system was designed to automatically return the patients to the waiting queue. In some instances, it is also possible that the clinicians and the nurses were browsing the application, without the patient being physically present. The assumption made when deriving the user journeys of only including interaction

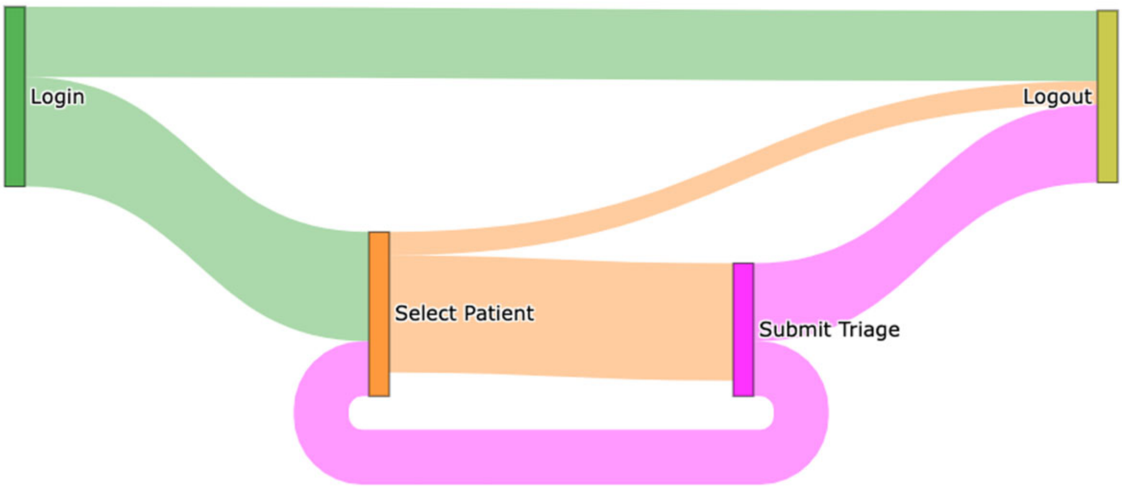

Figure 4. Sankey diagram showing the nurse user journey with user actions. In most instances, the nurses logged in, selected a patient from the queue, submitted triage, and logged out.

Table 2. Hamming distance ratios for nurses and clinicians' events

	Base path	Sequence of steps in base path	Number of unique user sequences	Hamming distance ratio mean (SD)
Nurses	N1	1. Select patient 2. Submit triage	25	0.42 (0.39)
Clinicians	C1	1. Select patient 2. Save history data 3. Save examination data 4. Refer patient 5. Complete encounter	9	0.36 (0.28)
	C2	1. Select patient 2. Save history data 3. Save examination data 4. Request labs	13	0.32 (0.16)
	C3	1. Select patient 2. Save history data 3. Save examination data 4. Request medications 5. Refer patient 6. Complete encounter	5	0.35 (0.24)
	C1, C2, or C3	–	27	0.36 (0.24)

events for a user done within 5 min of each other in a single unique journey would result in some journeys being merged as they would happen within a small span of time. In addition, the design of the user interaction logs lacked reference to the patient who was being attended by a provider, and this affected how the user journeys were derived. It was possible to derive a journey that overlapped across patients.

DISCUSSION

Key findings

This study investigated the user interactions with the DHW, an application developed for documentation and data sharing of health information by care providers and patients within fragmented health systems. We found that the nurses interacted with all the user interface elements of the application that involves their triage workflow. Clinicians interacted with less than half of the user interface elements for their consultation workflow, while the patients interacted with two-thirds of the user interface elements at their disposal.

Interestingly, we observed significant deviations in how the nurses and clinicians used their DHW applications compared with how the application was intended to be used in their optimal documentation workflows. In most cases, users either jumped a step or went back to previous steps perhaps to clarify, confirm, or update documented information. Such deviations from the optimal workflows are sometimes unavoidable but may also compromise user experiences.[15] Furthermore, when entering the patient history, clinicians consistently failed to click an explicit "save history button," perhaps because they assumed that the entered patient history data would be saved automatically. This suggests the need for auto-save functionalities as previously described in the literature.[16]

Our analysis also revealed potentially significant bottlenecks in using the DHW applications. For example, some nurses clicked the "submit button" more than once before successfully submitting their

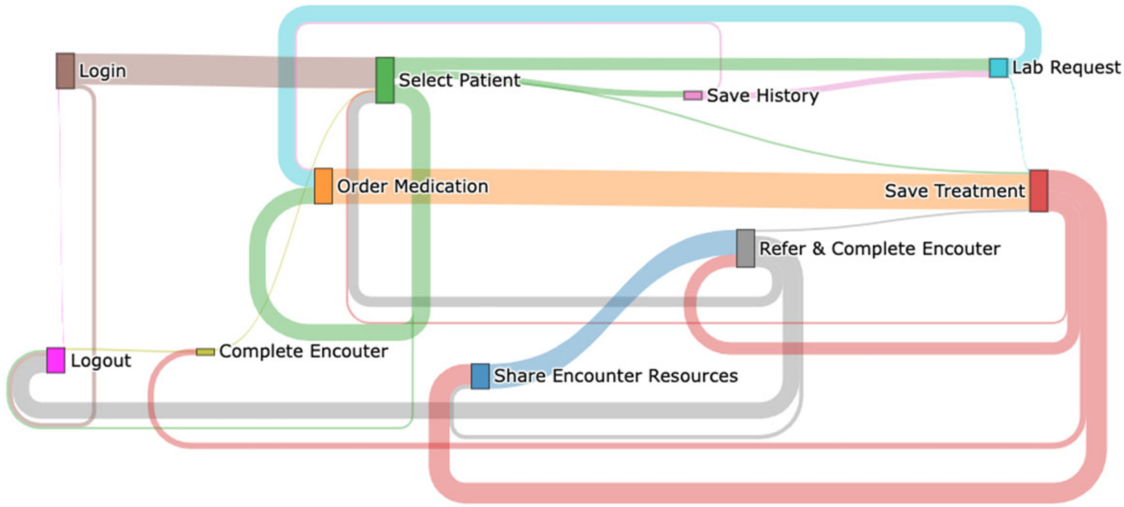

Figure 5. Common sequences of state transition events involving the clinician pages that were loaded. In most instances, the clinicians selected a patient from the queue after login, and proceeded to ordering medication, saving treatment notes, identifying encounter resources to share, referring the patient before logging out.

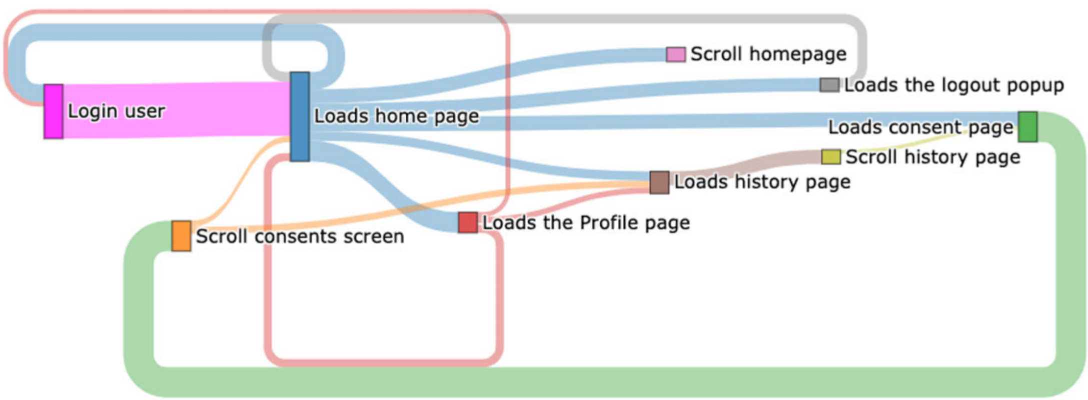

Figure 6. The user journey flow of the recorded patients' events. One forthcoming observation is that patients did spend some time scrolling the consent page, where they were presented with list of encounter resources that clinicians are requesting to share.

documented triage data. We pinpointed these bottlenecks to network connectivity issues. Redesigning the system to cache the data in case of network challenges should alleviate this challenge. Also, in the patient tracking events, we observed that some nurse and clinician users selected patients from their queues but terminated the encounter without documenting any information. This could have resulted from the users just wanting to view patient profiles without necessarily documenting anything. This could also be attributed to users testing the app in the absence of patients or experiencing challenges in completing encounters and having to try again. Importantly, the observation suggests the need for a new functionality in DHW that supports record viewership without necessarily having actual system encounters with patients. Finally, our analysis noted a difference between the logged total number of encounters and the number of unique user sequences for the nurse and clinician users. One of the reasons for this disparity was on the design of the user interaction logs for the providers. Designing the logs to include some reference to the patient being attended to would improve the accuracy of extracting the user journeys.

Comparison with related work

There are several ways in which usability testing can be conducted. These techniques can be classified into 3 categories namely lab studies, field studies, and log studies. Lab studies are conducted in a laboratory setting where participants are asked to perform certain tasks. The challenge with lab studies is that they do not capture activities in a natural setting and may not portray what happens on the ground.[17] Field studies are conducted in the participant's natural environment with the presence of an observer. The presence of an observer may interfere with the natural flow of events.[18] Log studies, which capture users' interactions with software applications in their natural setting, tend to be more objective and are uninfluenced by external observers.[19]

There are existing works in the analysis of user interaction logs, especially using the process mining technique. Gunther et al[20] developed Disco, a commercial software for automatically discovering process models by interpreting sequences of activities in log data. Another approach called Fuzzy Miner[21] visualizes important information in less structured event logs by adopting the concept of

Table 3. Distribution of patient tracking events across clinics

Encounter	Number of encounters in CCC	Number of encounters in MOPC	Total number of encounters	Number of unique user sequences from Table 2
Start visit	33	7	40	–
Waiting for triage	45	9	54	–
Triage	44	8	52	25
Waiting for consultation	107	6	113	–
Waiting for laboratory	4	0	4	–
Consultation	103	6	109	27
Waiting for dispensing	18	3	21	–
Complete visit	29	5	34	–

aggregation, abstraction, emphasis, and customization used in roadmaps. The Fuzzy Miner shows the connection between various activities; however, it does not consider the duration spent on activities which makes it unsuitable for usability testing. Thaler et al[22] use process mining to automatically derive process models that are subsequently analyzed to give concrete hints concerning the process and usability improvement and the further development of the system according to the real customer needs. In addition, they enhance the log data using data from other sources including external sensors. They apply this technique to business information systems whereas our methods target health information systems.

User interaction logging could be a valuable secondary method for collecting useful data about the use of health information technologies by care providers and patients in the context of ongoing pandemics. However, ongoing pandemics may also significantly impact the frequency of use of such technologies. We believe that the feasibility study of the DHW generated less than the expected number of user interaction logs. This is because of the fewer than anticipated number of patient–provider interactions over the study period which coincided with the first wave of the COVID-19 pandemic in Kenya when most patients with chronic illnesses were encouraged to stay home and discouraged from visiting health facilities.[23] Furthermore, without in-person interactions, it was sometimes not possible to quickly identify and address technical and nontechnical challenges experienced by end users, resulting in decreased usage. Accordingly, the findings of our study must be interpreted with caution and future work should focus on how to quantify the true effect of the pandemic on usability and ease of use of technologies such as DHW.

Study limitations

This study has several limitations. First, in response to the onset of the COVID-19 pandemic in Kenya, it was necessary to introduce new modifications and software patch fixes once the feasibility study had started. For example, we added a new automated messaging capability in the applications to allow patients and care providers to interact more frequently even if remote. It is not clear from our log analysis how such modifications influenced user experiences. Second, we could not readily differentiate the events generated by the users who were just browsing the applications as opposed to using them for documenting and sharing patient information. Third, the number of events per user type was relatively low and the number of users especially the providers was low. Finally, assumptions made in deriving sequences from the raw logs could have introduced errors. These assumptions include events for a user done within 5 min of each other were regarded to happen within a single journey.

CONCLUSION

Our findings demonstrate that user interaction log analysis including the analysis of deviations from expected application workflows could be used to identify potential bottlenecks in patient- and provider-facing documentation and data sharing applications such as the DHW. The identified nuances can be used to generate candidate recommendations for the future redesign of this system and any other medication management system. This study also highlights the potential challenges associated with the collection of data for user interaction log analysis in the context of ongoing pandemics. In such scenarios, we recommend robust approaches for limiting disruptions of actual use of the technologies as well as methodological triangulation to evaluate the true effect of pandemics and other unplanned events on user experiences. The DHW asset is still under evaluation and as part of our future work, we will triangulate the findings of this study with the findings of focus group discussions and in-depth interviews designed to evaluate the feasibility of the DHW. We also intend to make the resource open-source.

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AUTHOR CONTRIBUTIONS

C.W., W.O., S.L.R., and A.W.-B. proposed the use of descriptive statistics methods and Hamming Distance for analyzing event logs. C.W. performed the analysis. All the co-authors discussed the results, and their feedback was used to improve the results. All the co-authors contributed to the manuscript. All the co-authors discussed the reviewers' comments and C.W., W.O., S.O., S.L.R., M.K.N., and A.W.-B. updated the manuscript.

CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare.

DATA AVAILABILITY

The user interaction log data used in this study are fully deidentified. The data can be shared on reasonable request to the corresponding author.

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