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Barriers to using eHealth data for clinical performance feedback in Malawi: A case study

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ABSTRACT

Introduction: Sub-optimal performance of healthcare providers in low-income countries is a critical and persistent global problem. The use of electronic health information technology (eHealth) in these settings is creating large-scale opportunities to automate performance measurement and provision of feedback to individual healthcare providers, to support clinical learning and behavior change. An electronic medical record system (EMR) deployed in 66 antiretroviral therapy clinics in Malawi collects data that supervisors use to provide quarterly, clinic-level performance feedback. Understanding barriers to provision of eHealth-based performance feedback for individual healthcare providers in this setting could present a relatively low-cost opportunity to significantly improve the quality of care.
Objective: The aims of this study were to identify and describe barriers to using EMR data for individualized audit and feedback for healthcare providers in Malawi and to consider how to design technology to overcome these barriers.
Methods: We conducted a qualitative study using interviews, observations, and informant feedback in eight public hospitals in Malawi where an EMR system is used. We interviewed 32 healthcare providers and conducted seven hours of observation of system use.
Results: We identified four key barriers to the use of EMR data for clinical performance feedback: provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicator lifespan. Each of these factors varied across sites and affected the quality of EMR data that could be used for the purpose of generating performance feedback for individual healthcare providers.
Conclusion: Using routinely collected eHealth data to generate individualized performance feedback shows potential at large-scale for improving clinical performance in low-resource settings. However, technology used for this purpose must accommodate ongoing changes in barriers to eHealth data use. Understanding the clinical setting as a complex adaptive system (CAS) may enable designers of technology to effectively model change processes to mitigate these barriers.

1. Introduction

Low quality of health services and sub-optimal performance of healthcare providers in low-income countries is a persistent and critical global problem [1,2]. A review of 900 studies on interventions to improve prescribing in low- and middle-income countries (LMICs) found little improvement over a 20-year interval, with an average of only 50% of prescriptions being in compliance with standard treatment guidelines at the conclusion of the review period in 2009 [2]. A lack of individualized performance feedback could be an important factor constraining performance improvement, especially in district hospital settings in Malawi and other African countries where feedback is often not provided [3–5].

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The provision of individualized performance feedback is made more feasible by growing opportunities to automate the measurement of clinical performance, brought about by the rapid growth of electronic health information technology (eHealth) in LMICs [6–8]. We use the term eHealth to refer to any electronic health information technology, such as electronic medical record (EMR) systems, laboratory information systems, and pharmaceutical information systems used to support the delivery of healthcare [9]. Although the routine use of eHealth promises opportunities to support performance measurement and quality improvement, these opportunities are constrained by complex factors that lead to poor data quality [10,11]. Poor data quality is a primary confounder of the use of electronic data in low-income countries [8,12].

Data quality is widely understood as a multidimensional construct, addressing such features as the accuracy, timeliness, and completeness of data, and is increasingly recognized as a “fit-for-use” construct [13,14]. Data quality is “fit-for-use” in that its determinants are dependent on the data consumer’s expectations, in the context of a specific purpose for data use. For example, the quality of clinical data that can be used for the purpose of providing clinic-level performance feedback may be significantly different from the quality of the same data for the purpose of providing individualized performance feedback. By extension, data quality as a “fit-for-use” construct concerns more than just the degree to which the data are free of errors or internally consistent, and concerns how adequately the design of an information system that contains the data represents a real-world system [15]. Data quality in this sense is a design tradeoff involving the representation of a real-world system and the complexity of the information system. For example, an EMR that captures a limited dataset may make data easier to “clean” and use for secondary purposes, at the expense of providing a less complete representation of a patient’s clinical state.

Beyond the challenge of achieving adequate data quality, evidence indicates that performance feedback cannot be expected to reliably lead to performance improvement. Audit and feedback (AF), defined as the provision of performance summaries to healthcare providers, is a commonly used intervention that can contribute significantly to clinical performance improvement [16]. Evidence from the 2012 Cochrane systematic review of AF shows that it has small, positive effects on performance, with a median absolute increase in performance of 4.3% found for studies having dichotomous outcomes, such as adherence to a clinical guideline. But for the 140 studies included in the review, a wide range of effects was revealed. This pattern has been found in other reviews of feedback interventions in organizations [17,18]. Although the effect of feedback involves uncertainty, AF may have larger effects under specific conditions, including when baseline performance is low, when feedback is provided by a supervisor or peer, when feedback is provided for more than one performance interval, and when it is provided both verbally and in writing [16]. AF is frequently used as a complement to other interventions, such as educational outreach and clinical reminders [16]. Multifaceted interventions using AF have been demonstrated to improve care in low-resource settings [1,19].

Inadequate data quality and limited understanding of when feedback is effective are likely to be key barriers to using eHealth for performance feedback. As innovations in the analysis of clinical data are introduced [20] and with increased understanding of when clinical AF is effective for changing behavior, [21] these barriers may begin to be overcome. Furthermore, there may already be limited opportunities to use eHealth data to generate individualized feedback in specific situations. In an effort to understand these barriers in a setting where a software-based tool for generating feedback could have a national-level impact on clinical performance, we designed a qualitative study of the use of routinely collected eHealth data in antiretroviral therapy clinics.

1.1. Antiretroviral Therapy and EMR implementation in Malawi

Since 2004, the Malawi Ministry of Health has developed and implemented a national antiretroviral therapy (ART) program using a public health approach that standardizes and simplifies the clinical management of the Human Immunodeficiency Virus (HIV). The Ministry of Health supervises and coordinates free ART services through drug procurement using a formulary, standardized treatment guidelines, provider training, monitoring tools, and clinical mentoring among other activities, all of which supported the rapid national scale-up of ART in Malawi [22–24]. National supervision efforts in Malawi involve a quarterly, comprehensive review of treatment and treatment documentation practices for each site where ART is provided [25]. Supervision for the quarter ending in December, 2014 required a total of 95 supervisors to spend a combined 2042 working hours, visiting 719 public and private healthcare facilities. This shared effort of Malawi’s health workforce, key donors, and many other stakeholders has resulted in treatment for more than a half million patients, representing coverage of an estimated 67% of Malawi’s population of people living with HIV and who are in need of ART.

The Malawi Ministry of Health partnered with Baobab Health Trust, a Malawian non-governmental organization (NGO), to support monitoring and evaluation of ART using an EMR system [26]. The EMR was endorsed by the Ministry of Health for national scale-up in high-burden ART clinics, defined as clinics having more than 2000 patients on treatment. By the end of June, 2015, the National ART EMR was implemented in 66 facilities across all regions of the country.

Baobab Health Trust developed and implemented the National ART EMR with the dual purposes of maintaining clinical documentation and functioning as an electronic patient registry to generate quarterly cohort reports. In contrast to a general-purpose EMR platform such as OpenMRS, or a general-purpose health data collection and analysis system such as DHIS2, the National ART EMR was designed as a custom EMR system for ART in Malawi. This design choice has traded-off the benefits of participating in a larger community of open source software developers for an increased focus on supporting point-of-care clinical documentation in the Malawian context. The EMR software is free and open source, and can be found at http://github.com/BaobabHealthTrust

Using the EMR, health workers document clinical signs, symptoms, diagnoses, and prescriptions in structured formats. The EMR workflow guides health workers through clinical protocols in accordance with Malawi’s national ART guidelines, which are available at http://www.hiv.health.gov.mw. The EMR provides a minimal past medical history, alerts, and reminders that encourage adherence to guideline recommendations, electronic prescribing, and clinical calculations such as body mass index. A typical EMR site has a minimum of four point-of-care clinical workstations connected to a small server on a local area network. The most common EMR site is an ART clinic within a district hospital, staffed by one or two clinical officers (a non-physician clinician), two nurses, and one registration clerk [26].

National ART supervision teams in Malawi use quarterly, clinic-level reports generated from the EMR data to prepare feedback for teams of healthcare providers. The EMR contains a reporting software module that generates quarterly cohort reports designed by Malawi’s Ministry of Health, based on the DOTS model for control of tuberculosis [27]. The quality of the EMR data is evaluated and maintained for the specific purpose of quarterly cohort analysis [28]. Maintaining the quality of longitudinal clinical records in low-income countries is a tremendous challenge due to limited human resource capacity for data management whether the data is collected on paper or using eHealth systems [12,29,30]. Prior to generating a clinic-level report each quarter, support personnel from Baobab Health Trust conduct a data quality assessment to identify errors or missing data for a standardized set of clinical outcomes. The data is then "cleaned" by identifying sources of error and cross-checking with available paper records. After data cleaning has occurred the quarterly cohort report is generated and remains accessible within the EMR. Supervision teams can access the quarterly report to compare clinical outcomes from the current quarter with those from previous quarters. Supervisors also assess the quality of other clinical processes such as pharmaceutical stock management. Together with their assessment and the cohort report generated by the EMR, and national assessment of ART in Malawi from the previous cohort, supervision teams provide feedback in face-to-face meetings at each ART site. Supervisory visits use a supportive supervision approach that involves providing action points for the clinic team to follow [25].

Because the EMR is used at the point of care and clinical documentation is linked to individual healthcare providers, measuring individual-level compliance with recommended practice in Malawi's national ART guideline is possible [31]. Clinic-level performance feedback is important for ART clinic team performance, but it may be less relevant for supporting learning and behavior change than individualized feedback reports. The aim of this study was to identify and describe barriers to using EMR data for individualized AF for healthcare providers in Malawi and to consider how to design technology to overcome these barriers.

2. Methods

2.1. Setting

This study took place in district and central hospitals in Malawi's public healthcare system. Malawi has a population of more than 16 million and is divided into Northern, Central, and Southern administrative regions. A 2008 national census reported that approximately 13% of its population lives in the Northern region, while 42% and 45% live in the Central and Southern regions, respectively [32]. Malawi's Northern region has more pronounced differences in culture and language than the Central and Southern regions, although each region has unique geographic and cultural characteristics. We conducted research activities in this study within the Central and Southern regions of Malawi. Across all regions Malawi has 28 district hospitals that serve as referral hospitals and four central hospitals in the country's largest cities. NGOs administer and provide support for ART services within three of Malawi's four central hospital clinics, and several district hospital clinics. Within each hospital, an ART clinic provides outpatient care for patients with HIV or autoimmune deficiency syndrome (AIDS) on schedules ranging from two to five days per week, depending on the demand for ART services at the hospital. Staff who are trained to initiate and provide ART are mid-level healthcare providers, including clinical officers, nurses, and certified nurse-midwives [33]. In Malawi's district hospitals, like hospitals in many low-income countries, care is routinely provided without physician oversight or on-site consultation services due to critical shortages of healthcare providers [34]. An ART Coordinator is a clinical officer who supervises a district hospital ART clinic and other clinic sites within the district that provide ART.

2.2. Data collection

To collect qualitative data, we selected a convenience sample of eight ART clinics that used the EMR in Malawi's Central and Southern regions. All data were collected by the first and second authors (ZL and RM). Data collection occurred between June 2012 and February 2013. Six of the ART clinics were located in district hospitals, and two clinics were in central hospitals. One of the central hospital ART clinics was operated by an NGO (Dignitas International). We used open-ended interviews, observations, and informant feedback meetings to collect qualitative data about performance measurement and feedback in ART clinics. Participants were recruited using flyers distributed at each clinic. To protect the rights of participants, we kept research data confidential and did not document identifiable information. The study protocol was reviewed and approved by Malawi's National Health Sciences Research Committee (Lilongwe, Malawi, protocol #1019) and the Institutional Review Board at the University of Pittsburgh (Pittsburgh, PA, USA, protocol #PRO11070112).

2.2.1. Interviews

We developed an open-ended interview guide based on our understanding of the clinical setting and on theoretical constructs from two conceptual models. The first model we used was the Consolidated Framework for Implementation Research (CFIR). The CFIR was derived from 19 published frameworks in the field of implementation science, with a goal of unifying what is known about implementation within a single framework [35]. We used the CFIR to inform questions regarding the use of feedback in the context of implementing evidence-based practice in clinical settings. The second conceptual model we used was a cognitive processing model of performance feedback in organizations (Fig. 1) [36]. This model was derived from a review of psychological theories of performance feedback. The model features a sequence of cognitive variables that may mediate the influence of a feedback message on a recipient. For example, the construct *perceived feedback* in Fig. 1 is the first variable in the sequence, which refers to the accuracy with which a recipient perceives the intended meaning of a feedback message. The primary feedback-related theoretical constructs we focused on were feedback quality, credibility of feedback sources, perceived feedback, acceptance of feedback, desire and intent to respond to feedback, and external constraints that prevented behavior change in response to feedback.

We tested the interview guide using two preliminary interviews and revised the interview guide for clarity of language and cultural appropriateness. Interviews were designed to last approximately 30 min and were developed to be feasible to complete during clinic time. All interviews were conducted in English which is a national language in Malawi and is used for medical education. All participants agreed to have the interview audio recorded, except for one participant. For this participant's interview, data were captured in written notes, then typed into an electronic text file for analysis with other interview data. Audio recordings for all other interviews were transcribed verbatim by ZL. We interviewed 32 ART providers, six of whom were clinic supervisors (Table 1). Interview duration ranged from 11 to 39 min, with an average duration of 20 min.

2.2.2. Observations

We conducted 1-hour observations of healthcare providers using the EMR. We observed seven healthcare providers using the EMR for approximately one hour each. We observed providers in the clinic, before or after holding interviews as time allowed for participants who gave consent to be observed. During the observation, we took field notes about factors that we anticipated could impact the data quality for the purpose of generating performance feedback. These factors included the clinic workflow, system workarounds, EMR use behaviors, software versions and configuration differences, and the validity of performance indicators.

Understanding when performance indicators are no longer valid is an important challenge in the maintenance of performance feed-

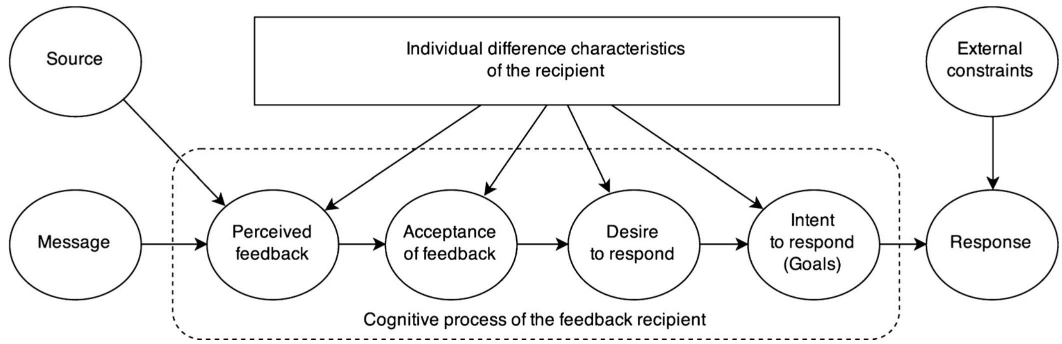

Fig. 1. A cognitive model of feedback processing from Ilgen, Taylor and Fisher, 1979.

Table 1
Characteristics of interview participants ($N = 32$).

Characteristic	N	%[a]
Sex		
Female	20	62.5
Male	12	37.5
Organization		
Ministry of Health	23	71.9
NGO (Dignitas International)	9	28.1
Professional role		
Nurse	12	37.5
Clinical officer	11	34.4
ART Coordinator	3	9.4
Nurse supervisor	3	9.4
Certified nurse-midwife	3	9.4
District Hospitals		
Hospital 1	3	9.4
Hospital 2	4	12.5
Hospital 3	3	9.4
Hospital 4	4	12.5
Hospital 5	3	9.4
Hospital 6	2	6.3
Participant total	19	59.4
Central Hospitals		
Hospital 1	9	28.1
Hospital 2	4	12.5
Participant total	13	40.6
Region		
Central	19	59.4
Southern	13	40.6

[a] Percentage values may not sum to 100 due to rounding.

back interventions [37]. In a prior study we developed a method for creating performance indicators from statements within a clinical practice guideline document for existing EMR data and identified 21 auditable guideline recommendations that could be used as performance indicators in ART clinics in Malawi [31]. For this reason we aimed to observe factors that can directly impact the validity of performance indicators. Malawi published revisions of its national ART guidelines three times over the previous decade, and has implemented other planned transitions in recommended practice between publication of a revised guideline. During these transitions some guideline recommendations have remained valid, such as those recommending the routine collection of patients' height and weight. Other recommendations were removed, such as first-line therapy recommendations that changed as new, more effective and more affordable drug regimens became available.

We also used observations to follow up on what we heard in interviews and reviewed field notes to inform subsequent interviews and the interview guide. Because of logistical challenges to scheduling observations in advance and the routine nature of ART provision, we did not select cases for observation. We collected a convenience sample of cases in observations as participants indicated their availability, with participants handling an average of 13 clinical cases per one-hour observation.

2.2.3. *Informant feedback meetings*

We met with healthcare providers and supervisors to review preliminary findings at multiple stages during data analysis, with the goal of collecting informant feedback that allowed us to refine our interpretation of the interview data. Informant meetings were held in three district hospitals and at one central hospital. We held three meetings initially after approximately 40% of the interviews had been analyzed, and one meeting after 70% of the interviews had been analyzed. Meetings lasted approximately 30 min, with attendance ranging from four to seven participants per site. Additionally, we routinely met and followed up with healthcare provider informants and with representatives from the Department of HIV and AIDS in the Ministry of Health to discuss our findings. Informant feedback meetings were held between December, 2012 and July, 2013. In meetings with informants, we collected field notes that we later used to refine our interpretation of the interview data. We also relied on informant feedback to interpret changes we observed in the EMR software and clinical guidelines over time.

2.3. *Data analysis*

All interview transcripts were imported into NVivo10 (QSR International Py Ltd, Doncaster, Victoria, Australia); ZL and RM analyzed the interview data. We constructed a codebook using the editing method described by Crabtree and Miller [38]. All codes emerged from the data in an open, iterative process. We also looked at constructs from our two conceptual models and the way they were reinforced by our emerging codes. We maintained an audit trail to document the creation and refinement of all codes. In addition, each code was clearly defined and inclusion/exclusion criteria were provided that helped differentiate one code from others. As part of the coding process, ZL and RM independently coded interviews using the codebook and then met to process any differences in the assessment of codes for each case until agreement was achieved. The codes determined through this adjudication process were then recorded in a master file, which was used for the final analysis.

3. Results

Based on our analysis of the interview data, which was informed by field notes from observations and informant feedback, we identified four key barriers to implementing EMR-based AF for individual healthcare providers in ART clinics in Malawi: provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicator lifespan.

3.1. Provider rotations

Provider rotations refer to clinic staff schedules that determine how long a healthcare provider works in a clinic. Provider rotations reduce the effect of individualized feedback on performance when a healthcare provider does not stay long enough in a clinic to receive feedback. District hospital clinic participants reported the use of scheduled staff rotations that varied in length from three months to one year.

District hospital providers frequently mentioned rotation schedules:

"I think because we just come here for a few months, ... then you can't have much experience." (District hospital nurse-midwife)

"We have adjusted the rotation because in the past we used to have just a week, the other team... now we have said that each individual should be in the ART at least for three months." (District hospital clinical officer)

A secondary issue related to provider rotations is an indirect influence on EMR user training. When user training is not provided frequently enough or in coordination with staff rotations, providers who did not receive EMR user training could potentially create lower-quality data. Several providers raised the issue of not receiving training for the use of the EMR:

"When you come again... you will not find me here. I will be in another place... If the training is only done, not quite often, that's the problem." (District hospital nurse supervisor)

Although staff rotations were common in district hospital settings, at least one district hospital supervisor reported having permanent staff who did not rotate away from the ART clinic. In contrast to district hospital providers, central hospital providers did not mention staff rotations and were more likely to work full time in the clinic.

3.2. Disruptions to care processes

Disruptions to care processes are unexpected events such as basic infrastructure failures, shortages of pharmaceutical resources, and EMR outages that interrupt or temporarily alter delivery of care. Disruptions represent *external constraints* on performance that reduce the potential impact of feedback and may lead individuals to perceive feedback as unhelpful for improving performance. Therefore, disruptions that impact clinical behaviors targeted by feedback can represent a barrier to provision of effective individualized feedback.

Disruptions to care processes were common in ART clinics, according to participants. Resource shortages were mentioned by participants as a disruption that interrupted the delivery of recommended care:

"Like at the moment we are supposed to be giving cotrimoxazole, but we don't have those." (Central hospital nurse)

Participants also described disruptions originating from the EMR in the form of system outages. A central hospital clinic had recently experienced system outages that one provider perceived to prevent the clinic from receiving a quarterly performance award:

"For us, we have been having excellence, excellence, apart from this quarter, where, yeah because of this system, it used to break down, break down, break down, so... they have seen that we haven't done well. They haven't given us the certificate of excellence." (Central hospital nurse)

Providers also characterized EMR-associated disruptions as minimal in other clinics:

"I just feel that, the system to me, it's actually good. It does ease the work, yeah. Apart from the disruptions sometimes that are happening, but they are not so common, but with a very high workload, it makes our work actually a bit easier." (District hospital ART coordinator)

Another type of disruption that we observed when visiting clinics was broken clinic scales that prevented healthcare providers from accurately recording patients' weight. We received a range of comments about disruptions to care, suggesting that the nature of disruptions may vary according to the hospital setting – district vs central hospital clinics – but disruptions to care were nevertheless common throughout all of the clinics.

3.3. User acceptance of eHealth

User acceptance concerns an individual's attitudes and intentions towards a technology and his or her actual use of a technology [39]. User acceptance is a barrier to the use of eHealth data for performance feedback in that an individual's complete or partial rejection of the EMR can reduce the quality of data for measuring the individual's performance. Participants reported a range of attitudes towards the EMR, and variable system usage patterns. The majority of participants described the EMR as useful and easy to use:

"Using the computer machines has made it simple. I can review so many patients in a minute, unlike using the manual [paper-based system]." (Central hospital nurse)

"The system is working quite OK, and it's doing a great job to us, looking at the number of patients we are having. It's easier for us to do the job, rather than to document it... in the files." (Central hospital clinical officer)

In one district hospital clinic, a participant indicated that user acceptance among clinical officers was low:

"To be honest, most [clinical officers] are not using it much, most of the data is entered by the clerks and the nurses." (District hospital ART coordinator)

In this clinic, the clinical officers were reported to use paper records that the nurses entered into the EMR to enable the quarterly clinic-level reports to be generated for national quarterly supervision. As a result the quality of the data entered was suitable for clinic-level reporting but would not be adequate for individual-level performance measurement.

Our observations of EMR use also revealed that variable user acceptance of eHealth led to constraints on the ability to use EMR data for performance feedback. ART providers appeared to avoid using some EMR functionality when the EMR workflow did not support established clinical processes, often related to optimizing provision of care under a heavy workload. For example, referral workflow within the EMR was bypassed routinely in district hospital settings, due to the establishment of a more efficient referral process that had not been accommodated by design of the EMR. In central hospital clinics, the EMR workflow appeared to have been configured to match the optimal workflows more closely.

3.4. Performance indicator lifespan

The lifespan of performance indicators refers to the average length of time that a performance indicator, once created, remains valid for measuring individualized clinical performance. When the lifespan is short, meaning that the indicator is at risk of quickly becoming obsolete, it is a barrier to the provision of individualized performance feedback because of the cost of developing and maintaining indicators. Based on our observations of the clinical setting and during follow-up with informants, we observed changes in EMR software and guideline recommendations that invalidated some performance indicators quickly, while others remained valid.

Performance indicators were impacted by differences in EMR software that we observed in ART clinics in Malawi resulting from ongoing development and implementation of the EMR. In some ART clinics, new versions of the EMR software had not yet been implemented, resulting in differences in the data collected across clinics. We observed that several of the indicators that had previously been useful for referral and the prescribing of specific drug regimens became obsolete due to software changes.

Changes in guideline recommendations occurred as new versions of the guideline were published or new phases of the guideline were implemented nationally in Malawi. We learned that performance indicators that are based on more stable guideline recommendations such as those referring to documentation of care will require less maintenance and will serve as more reliable indicators of performance over time.

4. Discussion

Our goal was to understand barriers to using eHealth data to provide individualized performance feedback in low-resource settings. We identified provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicator lifespan as factors in hospitals in Malawi that could prevent us from generating EMR-based performance feedback. The variability of these factors across hospitals within the same national public healthcare system hold important implications for the design of technology to support the creation and delivery of individualized performance feedback.

As a barrier to providing routine performance feedback, provider rotations in district hospitals resemble the problem of staff turnover caused by other factors such as burnout, which has been identified as a barrier to improving the quality of care in other low-income countries [40]. The provider rotations we encountered in district hospitals in Malawi have been used for "cross-training," within a capacity building effort to increase provider skills in the management of co-infection for diseases like HIV/AIDS and tuberculosis [41]. Considering that the length of staff rotations appeared to be quarterly in several district hospitals, we anticipate that monthly performance feedback would give staff enough time to respond to reports.

Provider rotations in district hospitals also represent a barrier to using eHealth data because shorter rotations can undermine EMR training activities, which in turn can reduce user acceptance of eHealth, compromising the quality of EMR data created by providers. Resources for EMR training are likely to be extremely limited. Therefore, to address the challenge of provider rotations, EMR training should be informed by staff rotation schedules at each hospital. Training interventions delivered via the EMR itself, for example, using interactive tutorials, may successfully address limited training resources in the face of quarterly provider rotations in district hospital settings. Furthermore, feedback messages that are provided only within the ART clinic may not be received by individuals who have rotated to another location. The EMR could potentially be used to disseminate feedback reports to providers who have rotated out of the ART clinic but are using another EMR software module within a hospital.

Our analysis revealed that disruptions to care processes, in the form of resource shortages and EMR technical problems, can reduce the effectiveness of feedback. In situations where EMR data are used to monitor performance and the EMR itself is believed to be a source of disruption to clinical care, it follows that the *source credibility* and *perceived feedback* of such EMR-based performance feedback is likely to be worse than for disruptions that are not EMR-related. To accommodate disruptions to care processes in the clinical setting, technology designed to provide performance feedback should include monitoring tools for indicators such as pharmacy stock levels, server uptime, or system usage patterns that could signal when a disruption is likely compromise the relevance or accuracy of feedback. Disease surveillance approaches may be feasible for use in monitoring eHealth-based disruptions to care processes [42].

We identified performance indicator lifespan as a factor that should be understood within a given context to inform the process of indicator selection and development. Indicators with a shorter lifespan become outdated more quickly and require more frequent maintenance, depending on ongoing changes in clinical guidelines and EMR software. The most stable performance indicators are likely to be those that are widely used for quality improvement for a specific disease or medical domain. For example, several low-income countries have used simple quality measures developed by HEALTHQUAL, an organization focusing on clinical quality improvement in low-income countries, such as the proportion of patients whose weight was recorded within the month of an ART visit [43]. We found that these indicators were supported by recommendations within Malawi's national ART guideline. The HEALTHQUAL indicators commonly used in low-income countries for ART represent reliable measures of performance that are less likely to become obsolete as guideline recommendations and EMR software change.

Drawn together, the four barriers we have identified suggest that the clinical context may be best understood as a complex adaptive system (CAS) [44]. Technology that provides meaningful performance feedback in this context should therefore accommodate CAS characteristics, including ongoing environmental change, nonlinear responses of the system to quality improvement efforts, and emergent patterns of system behavior resulting from complex interactions of lower level system factors. A CAS perspective requires automated performance measurement tools to be adaptive to environmental change in low-resource settings, and especially to be able to fail gracefully (e.g., shutting down when problems occur rather than risk generating further errors) by monitoring the presence of errors that may compromise the integrity of performance reports.

Data quality monitoring is likely to be essential for all performance indicators that are implemented for individualized performance feedback. Data quality measures can be used to estimate the proportion of clinical records that contain errors, and the severity of the errors [13,45]. One effective solution to identifying data quality problems may be the development of a mechanism for healthcare providers to give feedback about performance feedback reports, based on an approach used for improving data quality for clinical decision support in an HIV clinic in Kenya [46]. When data quality is routinely assessed prior to the creation of performance feedback reports, an AF system could deprioritize or withhold feedback reports containing unacceptable levels of errors. Furthermore, data quality assessment could be used as a form of performance feedback for providers, encouraging standardized use of the EMR and thereby improving data quality. When individual performance differences are associated with poor data quality, training could be targeted to address the specific providers who have not received instruction about using the EMR, which appears to be a function of provider rotations in many district hospital settings. Data quality assessment programs at each clinic should account for variability in provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicators.

Understanding the clinical setting as a CAS holds further implications beyond the issue of data quality for using eHealth data for performance feedback. Even when attribution of individual performance and the validity of a performance indicator can be ascertained, providing standardized performance feedback may

Summary points

What was already known on this topic:

- Adoption of eHealth in low-income countries is creating large-scale opportunities to use data for clinical performance feedback.
- Data quality is a significant barrier to the secondary use of clinical data in low-resource settings.

What this study has added to our knowledge:

- Key barriers to using eHealth for individualized performance feedback in Malawi are provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicator lifespan.
- Technology designed for eHealth-based audit and feedback in low-resource settings could accommodate these barriers using routine data quality assessment.
- Understanding low-resource clinical settings as complex adaptive systems (CASs) may enable designers of technology to effectively model change processes for audit and feedback.

not be effective because of lower-level individual and situational differences that could lead feedback to be ineffective. Toward this end we are developing tools for tailoring performance feedback that may be used to mitigate the challenges presented by a CAS [47].

4.1. Limitations

Due to the nature of the qualitative data we collected, the results, while important in terms of the information we can gather, are not generalizable. However, for the purpose of identifying design implications for technology that conducts AF, we believe that our methods yielded a sufficient understanding of the key challenges that system developers must overcome in this setting. To address the limitation of recruiting volunteer participants without a purposive sampling strategy, we recruited participants from a geographically broad area within the country, and we excluded participants who did not work in ART clinics. Another limitation in our approach is that we interviewed ART providers from district hospitals that were located only in Malawi's Central Region, and from central hospitals located only in the Malawi's Southern Region. Therefore, any differences between district and central hospitals may be regionally biased. Nevertheless, we believe it is more likely that the differences noted reflect the resource and contextual differences associated with each type of hospital, rather than regional differences. Finally, we collected data only in public hospital facilities in Malawi; therefore, the findings may be less relevant to private hospital settings and clinics with different systems of care in Malawi.

5. Conclusion

Using eHealth data to generate individualized performance feedback shows potential at large-scale for improving clinical performance in low-resource settings. However, technology used for this purpose must be designed to adapt to variation in provider rotations, disruptions to care processes, user acceptance of eHealth, and performance indicator lifespan. Understanding the clinical setting as a CAS may enable designers of technology to effectively model change processes to overcome barriers to using eHealth data for performance feedback.

Author's contributions

ZL, BNS, SLZ, GPD and RSJ conceived and designed the research. ZL and RM collected and analyzed the data. ZL, RM, OJG, BNS, GPD, MK and FC contributed to the acquisition and interpretation of data. ZL, RM, OJG, MK, SLZ, GPD, and RSJ wrote the paper.

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References

[1] A.K. Rowe, D. de Savigny, C.F. Lanata, C.G. Victora, How can we achieve and maintain high-quality performance of health workers in low-resource settings? Lancet 366 (9490) (2005) 1026–1035.
[2] K.A. Holloway, V. Ivanovska, A.K. Wagner, C. Vialle-Valentin, D. Ross-Degnan, Have we improved use of medicines in developing and transitional countries and do we know how to? Two decades of evidence, Trop. Med. Int. Health: TM&IH 18 (6) (2013) 656–664.
[3] S. Bradley, F. Kamwendo, H. Masanja, R. Pinho Hd Waxman, C. Boostrom, E. McAuliffe, District health managers' perceptions of supervision in Malawi and Tanzania, Hum. Resources Health 11 (2013) 43.
[4] I. Mathauer, I. Imhoff, Health worker motivation in Africa: the role of non-financial incentives and human resource management tools, Hum. Resources Health 4 (2006) 24.
[5] O. Manafa, E. McAuliffe, F. Maseko, C. Bowie, M. MacLachlan, C. Normand, Retention of health workers in Malawi: perspectives of health workers and district management, Hum. Resource Health 7 (2009) 65.
[6] J.D. Piette, K. Lun, L.A. Moura, H.S. Fraser, P.N. Mechael, J. Powell, S.R. Khoja, Impacts of e-health on the outcomes of care in low- and middle-income countries: where do we go from here, Bull. World Health Organ. 90 (5) (2012) 365–372.
[7] T. Lewis, C. Synowiec, G. Lagomarsino, J. Schweitzer, E-health in low- and middle-income countries: findings from the Center for Health Market Innovations, Bull. World Health Organ. 90 (5) (2012) 332–340.
[8] J.A. Blaya, H.S.F. Fraser, B. Holt, E-health technologies show promise in developing countries, Health Aff. (Project Hope) 29 (2) (2010) 244–251.
[9] H. Oh, C. Rizo, M. Enkin, A. Jadad, What is eHealth (3): a systematic review of published definitions, J. Med. Internet Res. 7 (2005), e1.
[10] A. Powell, H. Davies, R. Thomson, Using routine comparative data to assess the quality of health care: understanding and avoiding common pitfalls, Qual. Saf. Health Care 12 (2) (2003) 122–128.
[11] W.R. Hersh, M.G. Weiner, P.J. Embi, J.R. Logan, P.R.O. Payne, E.V. Bernstam, H.P. Lehmann, G. Hripcsak, T.H. Hartzog, J.J. Cimino, J.H. Saltz, Caveats for the use of operational electronic health record data in comparative effectiveness research, Med. Care 51 (8 (Suppl 3)) (2013) S30–S37.
[12] M. Forster, C. Bailey, M.W.G. Brinkhof, C. Graber, A. Boulle, M. Spohr, E. Balestre, M. May, O. Keiser, A. Jahn, M. Egger, Electronic medical record systems, data quality and loss to follow-up: survey of antiretroviral therapy programmes in resource-limited settings, Bull. World Health Organ. 86 (12) (2008) 939–947.
[13] M.G. Kahn, M.A. Raebel, J.M. Glanz, K. Riedlinger, J.F. Steiner, A pragmatic framework for single-site and multisite data quality assessment in electronic health record-based clinical research, Med. Care 50 (2012) S21–S29, Suppl.
[14] R.Y. Wang, D.M. Strong, Beyond accuracy: what data quality means to data consumers, J. Manage. Inf. Syst. 12 (4) (1996) 5, 33.
[15] Y. Wand, R.Y. Wang, Anchoring data quality dimensions in ontological foundations, Commun. ACM 39 (11) (1996) 86–95.
[16] N. Ivers, G. Jamtvedt, S. Flottorp, J.M. Young, J. Odgaard-Jensen, S.D. French, M.A. O'Brien, M. Johansen, J. Grimshaw, A.D. Oxman, Audit and feedback: effects on professional practice and healthcare outcomes, Cochrane Database Syst. Rev. 6 (1996) CD000259, Online.
[17] A.N. Kluger, A. DeNisi, The effects of feedback interventions on performance: a historical review, a meta-analysis, and a preliminary feedback intervention theory, Psychol. Bull. 119 (2) (1996) 254–284, March.
[18] D. Ilgen, C. Davis, Bearing bad news: reactions to negative performance feedback, Appl. Psychol. 49 (3) (2000) 550–565 http://onlinelibrary.wiley.com/doi/10.1111/1464-0597.00031/abstract

[19] J. Nzinga, S. Ntoburi, J. Wagai, P. Mbindyo, L. Mbaabu, S. Migiro, A. Wamae, G. Irimu, M. English, Implementation experience during an eighteen month intervention to improve paediatric and newborn care in Kenyan district hospitals, Implement. Sci.: IS 4 (2009) 45.
[20] G. Hripcsak, D.J. Albers, Next-generation phenotyping of electronic health records, J. Am. Med. Inform. Assoc. (2012), http://dx.doi.org/10.1136/amiajnl-2012-001145
[21] N.M. Ivers, A. Sales, H. Colquhoun, S. Michie, R. Foy, J.J. Francis, J.M. Grimshaw, No more 'business as usual' with audit and feedback interventions: towards an agenda for a reinvigorated intervention, Implement. Sci. 9 (2014) 14.
[22] A.D. Harries, P. Gomani, R. Teck, O.A. de Teck, E. Bakali, R. Zachariah, E. Libamba, A. Mwansambo, F. Salaniponi, R. Mpazanje, Monitoring the response to antiretroviral therapy in resource-poor settings: the Malawi model, Trans. R. Soc. Trop. Med. Hyg. 98 (12) (2004) 695–701.
[23] E. Libamba, S. Makombe, E. Mhango, O. de Ascurra Teck, E. Limbambala, E.J. Schouten, A.D. Harries, Supervision, monitoring and evaluation of nationwide scale-up of antiretroviral therapy in Malawi, Bull. World Health Organ. 84 (4) (2006) 320–326.
[24] E.J. Schouten, A. Jahn, A. Ben-Smith, S.D. Makombe, A.D. Harries, F. Aboagye-Nyame, F. Chimbwandira, Antiretroviral drug supply challenges in the era of scaling up ART in Malawi, J. Int. AIDS Soc. 14 (Suppl 1) (2011) S4.
[25] Malawi Integrated HIV. Program Report, –October –December 2015 [http://www.hiv.health.gov.mw/cha_repository/file.php/92/92.pdf].
[26] G.P. Douglas, O.J. Gadabu, S. Joukes, S. Mumba, M.V. McKay, A. Ben-Smith, A. Jahn, E.J. Schouten, Z. Landis Lewis, J.J. van Oosterhout, T.J. Allain, R. Zachariah, S.D. Berger, A.D. Harries, F. Chimbwandira, Using touchscreen electronic medical record systems to support and monitor national scale-up of antiretroviral therapy in Malawi, PLoS Med. 7 (8) (2010) e1000319.
[27] A.D. Harries, A. Jahn, R. Zachariah, D. Enarson, Adapting the DOTS framework for tuberculosis control to the management of non-communicable diseases in sub-Saharan Africa, PLoS Med. 5 (6) (2008) e124.
[28] O. Gadabu, C. Munthali, R. Zachariah, S. Gudmund-Hinderaker, A. Jahn, H. Twea, A. Gondwe, S. Mumba, M. Lungu, K. Malisita, E. Mhango, S. Makombe, L. Tenthani, L. Mwalwanda, C. Moyo, G. Douglas, Z. Lewis, F. Chimbwandira, Is transcription of data on antiretroviral treatment from electronic to paper-based registers reliable in Malawi? Public Health Action 1 (2011) 10–12.
[29] S.D. Makombe, M. Hochgesang, A. Jahn, H. Tweya, B. Hedt, S. Chuka, J.K.L. Yu, J. Aberle-Grasse, O. Pasulani, C. Bailey, K. Kamoto, E.J. Schouten, A.D. Harries, Assessing the quality of data aggregated by antiretroviral treatment clinics in Malawi, Bull. World Health Organ. 86 (4) (2008) 310–314.
[30] K.S. Mate, B. Bennett, W. Mphatswe, P. Barker, N. Rollins, Challenges for routine health system data management in a large public programme to prevent mother-to-child HIV transmission in South Africa, PloS One 4 (5) (2009), e5483.
[31] Z. Landis Lewis, C. Mello-Thoms, O.J. Gadabu, E.M. Gillespie, G.P. Douglas, R.S. Crowley, The feasibility of automating audit and feedback for ART guideline adherence in Malawi, J. Am. Med. Inform. Assoc.: JAMIA (2011).
[32] 2008 Population and Housing Census: Preliminary Report 2008, [http://www.malawihighcommission.co.uk/MWCensus08.pdf].
[33] M. Bemelmans, T. van den Akker, N. Ford, M. Philips, R. Zachariah, A. Harries, E. Schouten, K. Hermann, B. Mwagomba, M. Massaquoi, Providing universal access to antiretroviral therapy in Thyolo, Malawi through task shifting and decentralization of HIV/AIDS care, Trop. Med. Int. Health 15 (12) (2010) 1413–1420.
[34] The World Health Report, Working together for health, in: Tech. Rep., WHO, 2006 http://www.who.int/whr/2006/en/
[35] L.J. Damschroder, D.C. Aron, R.E. Keith, S.R. Kirsh, J.A. Alexander, J.C. Lowery, Fostering implementation of health services research findings into practice: a consolidated framework for advancing implementation science, Implement. Sci.: IS 4 (2009) 50.
[36] D.R. Ilgen, C.D. Fisher, M.S. Taylor, Consequences of individual feedback on behavior in organizations, J. Appl. Psychol. 64 (4) (1979) 349–371.
[37] D. Reeves, T. Doran, J.M. Valderas, E. Kontopantelis, P. Trueman, M. Sutton, S. Campbell, H. Lester, How to identify when a performance indicator has run its course, BMJ 6 (2010) c1717 (apr06 1).
[38] B.F. Crabtree, W.L. Miller, Doing Qualitative Research in Primary Care: Multiple Strategies, Sage Pubns., 1992.
[39] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. 27 (3) (2003) 425–478.
[40] P. Ayieko, S. Ntoburi, J. Wagai, C. Opondo, N. Opiyo, S. Migiro, A. Wamae, W. Mogoa, F. Were, A. Wasunna, G. Fegan, G. Irimu, M. English, A multifaceted intervention to implement guidelines and improve admission paediatric care in Kenyan district hospitals: a cluster randomised trial, PLoS Med. 8 (4) (2011), e1001018.
[41] G. Friedland, A. Harries, D. Coetzee, Implementation issues in tuberculosis/HIV program collaboration and integration: 3 case studies, J. Infect. Dis. 196 (Suppl 1) (2007) S114–S123.
[42] M.S. Ong, F. Magrabi, E. Coiera, Syndromic surveillance for health information system failures: a feasibility study, J. Am. Med. Inform. Assoc.: JAMIA 20 (3) (2013) 506–512.
[43] HEALTHQUAL Performance Measurement Report 2013, [http://www.healthqual.org/healthqual-performance-measurement-report].
[44] J.P. Sturmberg, C.M. Martin, D.A. Katerndahl, Systems and complexity thinking in the general practice literature: an integrative, historical narrative review, Ann. Fam. Med. 12 (2014) 66–74.
[45] A. Maydanchik, *Data Quality Assessment*, Technics Publications, Bradley Beach, N.J, 2007.
[46] S.F. Noormohammad, B.W. Mamlin, P.G. Biondich, B. McKown, S.N. Kimaiyo, M.C. Were, Changing course to make clinical decision support work in an HIV clinic in Kenya, Int. J. Med. Inf. 79 (3) (2010) 204–210.
[47] Z. Landis-Lewis, J.C. Brehaut, H. Hochheiser, G.P. Douglas, R.S. Jacobson, Computer-supported feedback message tailoring: theory-informed adaptation of clinical audit and feedback for learning and behavior change, Implement. Sci. 10 (2015) 12.