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Original Research Article

Evaluating the Impact of a Digital Hospital Information Management System on the Operational and Financial Performance of Health Facilities in Kenya

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ABSTRACT

Background: In Sub-Saharan Africa, hospital information management systems (HIMS) are predominantly paper based. Countries like Kenya are adopting digital HIMS. However, there is limited evidence about their impact. This study aimed to evaluate the impact of a digital HIMS on the operational and financial performance of Kenyan health facilities.
Methods: A retrospective analysis was done using longitudinal data collected at 21 health facilities in Kenya that had actively used the outpatient and/or billing modules of the Elephant HIMS (EHIMS) for at least 9 months. Trends of operational and financial performance indicators across months 3,6,9 after EHIMS adoption were compared to pre-adoption baseline values. The Wilcoxon test was performed to determine the statistical significance of the difference between baseline and 9 months post-adoption.
Results: The EHIMS had positive impact on operational performance evidenced by statistically significant reduction, between baseline and 9 months after adoption, in monthly waiting (43.55 vs 35.79 minutes) and journey times (59.90 vs 60.34 minutes). Positive impact was also observed on financial performance as shown by an increase in recorded monthly revenue (100000 vs 210000 KES) and improved tracking of unpaid revenue (0.57 vs 1.19). The above changes were associated with and not directly caused by the EHIMS.
Conclusion: The EHIMS was found to have a positive impact on the performance of health facilities at the time points analysed in this study. To demonstrate the full impact of digital HIMS and for clearer attribution, further research should be done to analyse the confounding factors that affect health facility performance.

Keywords: *digital health, electronic health records, operational, financial, performance*

INTRODUCTION

Reliable health information delivered by Health Information Systems (HIS) forms the bedrock for decision-making across all the six building blocks that constitute the health system strengthening framework (1). The performance of a country's health system is heavily dependent on the functionality and efficiency of its HIS (2). Therefore, health systems globally are strengthening their HIS to produce credible information for sound decision-making (3). A HIS is particularly important for monitoring and measuring service delivery (4). At every point of service delivery, data is generated and inputted into the HIS for analysis, visualization, and reporting of information (2).

The strengthening of HIS is particularly needed in Sub-Saharan Africa (SSA) where HIS are uncoordinated and fragmented (5). Multiple health interventions and disease-specific programs are being implemented in parallel by the public sector, private players, donors, and international organisations (2). These stakeholders have different data collection and information systems ranging from paper-based to digital applications. These disaggregated systems result in an overall weak HIS. This leads to poor decision-making which contributes to weak health systems incapable of meeting population health needs (6).

To improve the quality of data management for health systems strengthening, 45 countries in SSA have adopted the free, web-based District Health Information System version 2 (DHIS2) (4). The DHIS2 has improved the performance of health systems and led to better health outcomes in SSA. An example of this was seen in Uganda where the reporting on the immunisation of one-year-old children increased by 52.6% in one year (2012 – 2013) after adoption of DHIS2 (7). The completeness of outpatient reporting also increased by 135% in the same year. In Kenya, the timeliness of reporting antenatal clinic (ANC) visits and facility delivery rates increased (8).

Health facilities generate over 75% of the data for DHIS2 because they deliver most of the health services (9). Hence, health facilities employ Hospital Information Management Systems (HIMS) to collect routine data for input into DHIS2(1). Just as HIS impact the performance of health systems, HIMS also affect the performance of health facilities. HIMS facilitate data sharing between functioning parts of a health facility and generate information for decision-making by hospital administrators (10).

In SSA, most of the HIMS records are paper based which poses several problems (11). The manual recording and analysis of the data are time-consuming. Storing high volumes of paper requires a large amount of space, as was seen in Malawi where a whole floor was dedicated to paper records (12). Furthermore, continuity is often disrupted, as records can be lost or damaged and are not easily transferable between facilities. Therefore, paper-based systems hinder health facilities' ability to provide timely, complete, and reliable information for disease trend monitoring, quality assessment, resource distribution and performance improvement (13).

Relying on paper particularly hampers the operational and financial performance (OFP) of health facilities, thereby affecting service quality and clinical outcomes (14). Operational performance refers to the processes and steps involved in providing quality and prompt health services to patients. It includes patient access and experience, resource utilisation, staff productivity and admission/discharge procedures (15). Financial performance is the balance between the costs and revenues of a health facility.

Digital HIMS have been widely adopted in high-income countries (HIC) countries and resulted in a positive impact on OFP of health facilities. In a meta-analysis, Paolo et al noted that EHR reduced documentation time by 22%, thereby increasing time and process efficiency (16). They also reported increased adherence to guidelines and reduced medication errors by healthcare providers. They argued that the time saved from manual documentation was used for direct patient contact, thus improving service quality, productivity, and patient satisfaction. Increased patient satisfaction with EHR was also demonstrated by Liu et al in a systematic review (17). Patient satisfaction defined as the extent to which patients feel their needs are being met by the provided services was linked to features of the digital HIMS such as ease of use, interoperability, speed, and response time.

Digital HIMS can also improve financial performance, not only by increasing revenue due to better operations and improved financial recording, but also by reducing costs due to less wastage of resources and overprescription (18). Howley et al noted increased revenues after digital HIMS implementation in an ambulatory practice despite a reduction in patient visits because of improved efficiency in office procedures (19). In Hawaii, digital HIMS were shown to decrease practice costs in the long run regardless of the initial heavy investment in infrastructure and training of the workforce (20). Overall, digital HIMS has enabled better communication and care coordination between departments and hospitals due to ease of data-sharing and integration of datasets, faster decision-making during service delivery, greater convenience of data access and optimal utilisation of resources (16,19,21).

In SSA where health systems are under-resourced, the impact of digital HIMS on hospital performance has not been well investigated. SSA has specific contextual and infrastructural challenges which make it difficult to transfer the results from HIC to SSA where digital adoption is still in its infancy. Health workers in these low-resource settings are less familiar with these digital systems and hence, may spend more time entering data digitally than manually on paper records (22). In addition, digital HIMS may increase the cost of training and even necessitate the employment of additional staff to help practitioners input data. Also, a lack of reliable electricity and internet can result in high maintenance costs and decreased profit margins (23). All the above challenges may negatively impact performance, but insufficient research has been done in SSA to either confirm or refute this. Further studies are needed to investigate whether digital HIMS have a similarly positive impact on performance in SSA.

Kenya is one of the SSA countries that have overcome some of the challenges to deploy digital HIMS. This country, therefore, offers an opportunity to explore whether digital HIMS benefits outweigh the investment costs and ongoing operating costs. Kenya’s health system provides services ranging from preventive and promotive care to curative and rehabilitative care. These services are delivered in communities and health facilities by public and private systems. The latter include private for-profit, faith-based organisations, and non-governmental providers (24). The public system accounts for 51% of facilities (25). The health system is jointly managed by the 47 counties and the national Ministry of Health (MoH).

Kenyan health facilities are divided into 6 levels as seen in figure 1 below: Level 1 comprises community facilities managed by certified clinical officers. Level 2 consists of health dispensaries with no in-patient facilities. Level 3 facilities are health centres run by at least one doctor, nurses, and clinical officers. They offer in-patient services and a more diverse set of services than level 2. Level 4 consists of county hospitals that offer more specialised services like surgery. Level 5 are county referral hospitals also known as provincial hospitals with over 100-bed capacity. Level 6 facilities are the national referral hospitals that also receive patients from other countries in East and Central Africa (26). Counties control level 1-5 facilities while the MoH controls level 6 facilities.

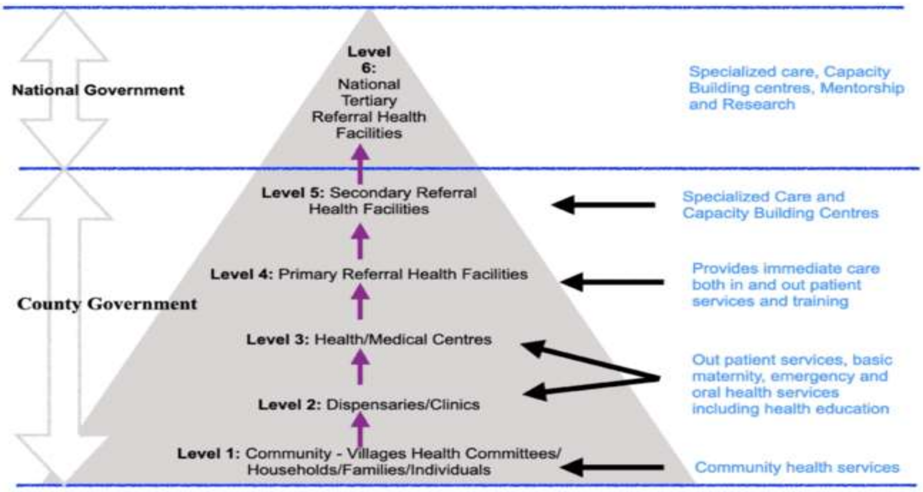

Figure 1: Classification of health facilities in Kenya

Kenya is currently leading the information and communication technologies (ICT) growth in East Africa and its capital city Nairobi has been described as Silicon Savannah because of its technological hub (27). As a result of the technological advancements, the adoption of digital HMIS has increased over the years in line with Kenya's national eHealth strategy first published in 2011. The latest version of this strategy (2018-2023) highlights investment in digital HIMS as key to achieving its strategic health goals (28). For this purpose, the Kenyan government has created an enabling environment and launched initiatives to support adoption of digital health information management. An example is the development of electronic health record (EHR) standards and guidelines. This initiative of the MoH helps developers to align EHR systems with global standards but tailor them to the Kenya context so that, they sync with the national DHIS2 and meet patients' needs (29).

Kenya is investing in digital HIMS to optimise the OFP of health facilities so that they deliver quality health services. A mixed-methods study in a level 4 Kenyan facility highlighted financial accountability and management of outpatient clinical service delivery as the two main reasons for purchasing EHR (30). Because up to 40% of health expenditure is lost to inefficiencies and corruption, policymakers are introducing digital tools to close gaps in operations and finances as well as optimise resource utilisation (31,32). There are several private providers of digital HIMS in Kenya, but few studies have explored their effect on OFP in Kenyan health facilities. Marete et al showed an increase in the number of patients served, reduced waiting time and cost savings in a level 3 facility where digital HIMS was being used (22). Also, Waithera et al demonstrated that an EHR system used in a level 5 referral hospital increased staff productivity, improved clinical decisions, and enhanced accountability for funds and resources (33). Despite these benefits, a focus group discussion done by Ngugi et al with digital HIMS users in a health facility pointed out that infrastructural and technical issues posed an important barrier (34).

Elephant Healthcare (EH) is a UK-based health technology company that has developed a digital HIMS and is currently being deployed in SSA and Asia (35). Kenya is one of the SSA countries where this software is being widely adopted. The Elephant HIMS (EHIMS) currently consists of 17 interconnected modules that perform one or multiple functions from organising medical records to capturing financial, stock, and clinical data from different services of the health facility (36). Specific modules are accessible to patients and healthcare providers in the various health facility departments. For example, the outpatient module registers patients, manages queues, and tracks patient journey times through different services such as laboratory and pharmacy. The electronic medical records module stores information on patient medical history and can be accessed by patients. These data collected by these modules are stored in the Elephant database. Upon registration, patients are given an electronic health (EH) card carrying a unique code which is used to retrieve their records. This EHIMS has been deployed to 127 public, faith-based and private health facilities ranging from level 2 to level 5 facilities in Kenya since 2019(37).

A previous internal evaluation study in Kenya, conducted shortly after launching revealed that, the adoption of this software improved operational performance by reducing admission length and patient waiting times, and also increased productivity of staff and patient turnover (38). As demonstrated in HICs, it has been shown that better operational performance can lead to improved financial performance by increasing insurance reimbursements, decreasing operating costs and reducing the waste of resources (39,40). However, this study used considerably fewer data. This present study aims to summarise some key performance indicators using a longitudinal dataset collected across multiple hospitals.

Research gap and significance of the study

Despite the growing evidence of the positive effects of digital HIMS on OFP in HICs, these effects have not been well-researched in low-resource settings. Although some digital HIMS have been evaluated in Kenya, they offer limited supporting evidence about the effect on the OFP of health facilities. This is particularly important given the rapid expansion of digital HIMS across Kenya.

Without careful evaluation of the impact of digital HIMS, policymakers may be investing scarce resources in systems that are not able to deliver the expected objectives of operational and financial improvements. Also, the lack of evidence about the impact of digital HIMS makes the stated benefits contestable and subject to scrutiny by policymakers and hospital administrators. To guide IT investment and increase the adoption of digital HIMS, Kenyan decision-makers need more evidence of the impact of digital HIMS on the OFP of health facilities.

To address the above research gap, this study aims to study the impact of EHIMS on the OFP of several health facilities in Kenya. Previous studies examining the impact of digital HIMS in Kenya have each focused on one facility but this study involving multiple facilities across different levels and sectors will increase the credibility of the evidence.

MATERIALS & METHODS

This study is a retrospective analysis of a longitudinal dataset collected since the launch of Elephant Health in Kenya. This research was carried out over five months (March – July 2022) with onsite facility visits lasting two months (May and June 2022). The study population included all health facilities in Kenya that adopted the EHIMS since 2019 when it was first launched.

We included all health facilities that have actively used the outpatient and/or billing modules of the Elephant HIMS for at least 9 months and had available data at four-time points; before adoption, and at months 3, 6, and 9 after adoption were selected.

We excluded facilities that dropped out or did not use the software consistently for 9 months, facilities not using the relevant modules under study and facilities that did not consent to share their financial or operational data.

Data Sources

The data used for the present study were initially entered into the outpatient and billing modules of the EHIMS by its users, employees of partner health facilities. Aggregated data summarised in averages were extracted from the EH database. No primary data were collected. The outpatient module is integrated with patient registration, medical records, and patient triage modules. This module can provide information on the number of registrations, waiting time, patient journey time, medical history, patient visits and method of triage. It links with other modules that capture clinical consultations, laboratory testing, radiology, pharmacy dispensation and queuing. The billing module tracks the invoices and payments of patients and thus, collects data about collected revenue, income owed to the facility, and income written-off (waivers, exemptions, and refunds).

Statistical Methodology

Key performance indicators for health facility OFP were obtained from the literature and the WHO handbook of indicators for monitoring HIS (1,41). These indicators were compared to the ones highlighted in the Kenya MoH framework for health sector monitoring and evaluation (42). Indicators relevant to Kenya were selected. The final indicators used were those that could be measured with the available data in the EH database. Some locally relevant indicators were left out because corresponding data could not be obtained in the short time frame dedicated to the study. An example of this is the financial indicator of operating costs, which could not be measured because no EHIMS module captures overall facility costs.

The final operational performance indicators for which data were provided included:

- Average monthly waiting time (AMWT) in minutes calculated as the average of time spent from registration to consultation for patients registering in a facility, for each month used as a timepoint in this study.
- Average monthly journey time (AMJT) in minutes calculated as the average of patients' total time spent in the facility

from the first recorded event to the last, for each month used as a timepoint in this study.

- Total monthly visits (TMV) per facility measured as the total number of patients accessing a facility for any of the health services offered, for each month used as a timepoint in this study.

The financial performance indicators for which data were provided included:

- Total monthly revenue (TMR) calculated as the total value of all paid patient invoices created for each month used as a timepoint in this study.
- Monthly proportion of unpaid revenue (MPUR) calculated as the percentage of the unpaid revenue compared to the total revenue collected, adding all unpaid patient invoices registered for each month used as a timepoint in this study.

Data Collection and Management

Aggregated data for the above indicators from the sample group of Kenyan health facilities were extracted and saved in a password-protected google sheet with the name of each facility concealed for privacy reasons. The indicators were measured for each facility at a three-month interval after the adoption of EHIMS, from the date the first patient was registered until nine months post-adoption. The 3-month interval was chosen because a health facility takes approximately 90 days to adapt and get acquainted with new technology for efficient use (43). Also, the total median duration of use of the EHIMS was 8-9 months. Hence, 9 months was chosen as a duration adequately long for the analysis of performance trends for several facilities. This means that post-adoption data for respective indicators were harvested at 3 time points for each facility: months 3, 6, and 9.

To ensure that any changes detected in the OFP indicators are associated with the adoption of the EHIMS, we compared each indicator after EHIMS adoption to baseline data obtained from facilities before the introduction of EHIMS. For TMR and TMV, baseline data were also extracted for this study. However, for MPUR, AMWT and AMJT, no such information was accessible. To overcome this impediment, post-adoption month 1 data were extracted as a proxy for pre-elephant data. Hence each facility had four time-points of data for each indicator: baseline data (exact or proxy), post-elephant months 3,6,9.

STATISTICAL ANALYSIS

Statistical analysis was done using R software version 4.1.1. After data cleaning, the analysis was approached in three steps. First, we carried out general descriptive statistics. Health facilities were stratified by sector and level. Health facilities were broadly divided into public and non-public sectors. The non-public sector comprised private and faith-based facilities. For each sector, facilities were divided into their designated levels according to the Kenya classification of health facilities, as previously shown.

Then we calculated the median values for the indicators with interquartile ranges. The Shapiro test for normality indicated that data for all indicators were not normally distributed. For this reason, the median was used to explore the trends in OFP across sectors and levels. The median was calculated for each indicator in the respective sectors and levels, then compared across the different time points.

Finally, we performed a paired Wilcoxon test (44). We employed this non-parametric t-test to test the statistical significance of the difference between the baseline data and the post-adoption data for each indicator. For each indicator, we calculated the median difference between values at baseline and month 9 after adoption.

RESULT

A total of 127 facilities had used the EHIMS since its launch in Kenya as at the time of this study and 35 of them had used the software for at least 9 months. However, 14 were excluded because of inconsistent use. Hence, 21 facilities were selected. The data of 21 facilities were analysed for operational indicators and 11 for financial indicators because of differences in the use of modules by the various facilities. Public health facilities made up 81% of all included facilities. Facilities were of levels 2, 3 and 4 with Level 4 facilities representing 52.4% of all health facilities. Most of the public facilities were of a higher level (level 4) than the non-public facilities which were mostly level 3 facilities as seen in figure 2.

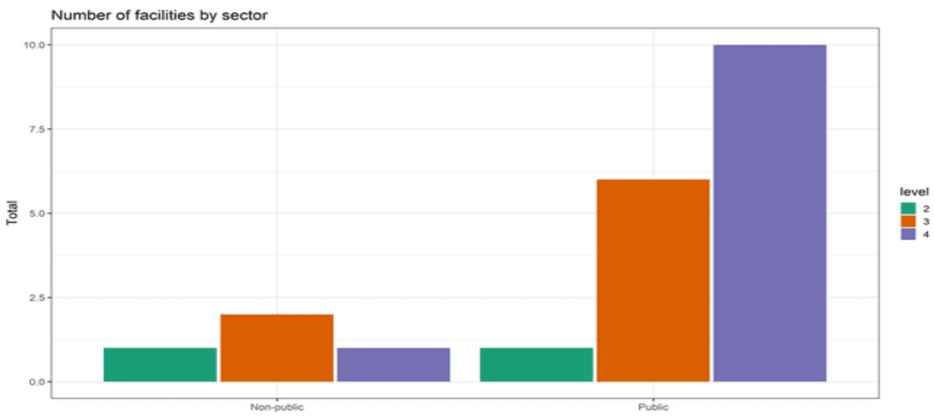

Figure 2: Bar chart showing the distribution of facilities by sector and level

Trend of operational performance indicators

The table 1 below summarises the median values with interquartile ranges of all operational indicators for facilities in the respective sectors and levels, across the different time points of interest in this study. The overall percentage difference between baseline and month 9 was calculated for each indicator.

Operational KPIs	Months		Baseline	Month 3	Month 6	Month 9
Average TMV (n=21 facilities)	By levels	Level 2 (n=2)	645.00 (427.50 -862.50)	1,365.00 (734.50 - 1,995.50)	595.00 (350.00 - 840.00)	830.50 (511.25- 1,149.75)
		Level 3 (n=8)	555.00 (417.00 - 757.50)	1,026.50 (720.50 - 1,404.25)	926.50 (572.50 - 1,287.25)	1,053.50 (714.25- 1,211.50)
		Level 4 (n=11)	960.00 (720.00 - 2,605.00)	1,277.00 (976.50 - 1,977.50)	1,039.00 (880.50 - 1,749.50)	1,004.00 (551.00- 1,315.50)
	By sector	Public (n=17)	720.00 (540.00 - 1,170.00)	1,319.00 (915.00 - 2,184.00)	1,088.00 (865.00 - 1,358.00)	1,103.00 (566.00- 1,467.00)
		Non-public (n=4)	489.00 (223.50 -825.00)	653.50 (304.25 - 961.50)	611.00 (369.00 - 833.50)	705.50 (564.00-833.25)
	Overall, for TMV	% diff = 28.28%[a]	720.00 (480.00 - 1,080.00)	1,254.00 (837.00 - 1,771.00)	1,039.00 (697.00 - 1,324.00)	1,004.00 (566.00- 1,351.00)

Table 1 To Be Continued…						
AMWT in minutes (n=21 facilities)	By levels	Level 2 (n=2)	25.58 (15.5 - 35.60)	16.92 (11.45 -22.39)	7.55 (6.43 - 8.67)	14.92 (10.52 - 19.32)
		Level 3 (n=8)	43.93 (32.19 - 58.49)	33.12 (26.25 - 40.32)	29.58 (21.34 - 45.13)	23.97 (17.87 - 30.48)
		Level 4 (n=11)	43.55 (40.43 - 57.55)	37.35 (32.54 - 50.16)	41.02 (28.51 - 52.39)	40.31 (36.26 - 51.26)
	By sector	Public (n=17)	45.62 (41.89 - 62.82)	37.35 (29.78 - 49.30)	41.02 (26.43 - 48.43)	36.93 (28.35 - 50.69)
		Non-public (n=4)	29.81 (20.18 - 35.67)	24.01 (14.85 - 31.60)	18.48 (14.39 - 21.81)	18.38 (13.94 - 22.43)
	Overall for AMWT	%diff = -21.68%[a]	43.55 (37.15 - 55.81)	35.75 (27.85 - 40.43)	32.74 (25.24 - 47.12)	35.79 (23.72 - 44.81)
AMJT in minutes (n=21 facilities)	By levels	Level 2 (n=2)	43.26 (34.36 - 52.15)	32.20 (28.81 - 35.58)	18.04 (15.52 - 20.55)	28.02 (26.00 - 30.05)
		Level 3 (n=8)	66.63 (55.80 - 75.91)	44.91 (40.75 - 53.08)	45.72 (34.37 - 56.45)	40.48 (32.37 - 52.48)
		Level 4 (n=11)	80.50 (69.62 - 85.32)	71.29 (65.35 - 78.18)	68.08 (61.59 - 78.95)	72.48 (62.01 - 76.28)
	By sector	Public (n=17)	75.18 (61.09 - 80.54	65.20 (43.16 - 73.92)	59.27 (47.82 - 72.93)	63.68 (36.20 - 75.04)
		Non-public (n=4)	59.90 (42.10 - 77.88)	49.32 (36.00 - 63.58)	39.43 (32.20 - 49.73)	44.85 (39.56 - 51.52)
	Overall for AMJT	%diff = -22.24%[a]	73.76 (61.04 - 80.54)	59.12 (41.16 - 73.92)	59.02 (37.63 - 68.08)	60.34 (36.20 - 74.02)

[a] *This represents the percentage difference between baseline measurements and subsequent measurement taken at 9 months*

Table 1: Median values (interquartile range) for operational indicators across timepoints

Indicator 1: Total monthly visits (TMV)

Overall, the TMV showed an upward trend in all facilities. The upward trend was highest in level 3 facilities. Overall, the percentage difference between baseline and month 9 after adoption was 28.28%. The median TMV in public facilities were higher than in non-public facilities. The highest increase occurred in the first 3 months of adoption. Before adoption, level 3 facilities had the lowest median TMV but after 9 months, they had the highest.

Indicator 2: Average monthly waiting time (AMWT) in minutes from registration to consultation

Overall, all facilities had a downward trend in AMWT with an overall reduction by 21.68% between baseline and month 9 after adoption (baseline = 43.55 vs Month 9 =35.79 minutes). Most of the reduction in AMWT took place within the first 3 months, continued through 6 months, and stabilised between 6 and 9 months at a level lower than the baseline. Median AMWT showed a downward trend in both non-public and public facilities. Public facilities had a higher median AMWT than non-public facilities. All levels experienced a downward trend with level 2 facilities having the lowest median AMWT.

Indicator 3: Average monthly journey time (AMJT) in minutes from registration to pharmacy

All health facilities had a general downward trend in AMJT with overall reduction by 22.24% between baseline and month 9 after adoption. Median AMJT showed a downward trend across non-public and public facilities, but public facilities had a higher median AMJT than non-public facilities. All levels experienced a downward trend with level 2 facilities having the lowest median AMJT.

After noting the changes above, the Wilcoxon test was performed to test the statistical significance of the observed differences. The difference (indicated as delta) between month 9 (M9) and baseline (M0) values was calculated for all indicators of operational performance. For median TMV, Null hypothesis = M9 – M0 ≤ 0 while for median AMJT and AMWT, Null hypothesis = M9 – M0 ≥ 0

There was a statistically significant negative difference in AMWT and AMJT between post-elephant month 9 and baseline data. There was a positive difference in total monthly visits between post-elephant month 9 and baseline data. However, this difference was not statistically significant as seen in Table 1.

Indicators	Delta (M9 – M0)	p-value
Median TMV	284	0.1078
Median AMWT	-7.76	0.0003
Median AMJT	-13.42	0.0019

Table 2: Table showing operational performance indicators, differences, and p-values obtained from paired Wilcoxon rank-sum test.

Trend of financial performance indicators

A total of 11 facilities using the billing module were included in the analysis of the financial indicators. Of the 11 facilities, there were 9 public facilities with 7 being level 4 and 2 being level 3 facilities. Of the 2 non-public facilities, 1 was a level 4 and 1 was a level 3 non-public facility. All facilities except one public level 3 facility had baseline data which were compared with post-adoption values and p-values derived. The table 3 below summarises the median values of all financial indicators for facilities in the respective sectors and levels, across the different time points of interest in this study. Also, the percentage difference between baseline and month 9 was calculated for each indicator.

Financial KPIs	Months		Baseline	Month 3	Month 6	Month 9
TMR in 10000KES (n=11 facilities)	By levels	Level 3 (n=3)	15.00 (12.50 - 17.50)	24.77 (24.56 - 38.39	27.68 (25.43 - 50.95)	21.76 (19.46 - 50.07)
		Level 4 (n=8)	9.36 (5.24 - 30.47)	23.96 (17.48 - 72.21)	16.07 (9.66 - 62.29)	38.20 (5.81 - 61.67)
	By sector	Public (n=9)	7.31 (5.22 - 10.31)	23.34 (17.48 - 40.23)	16.07 (9.66 -37.90)	21.05 (5.81 - 60.40)
		Non-public (n=2)	20.00 (15.00 - 35.15)	52.01 (38.18 - 60.32)	55.69 (41.68 - 64.95)	57.75 (37.45 - 68.06)
	Overall	% diff. = 54. 00%[a]	10.00 (5.27 - 20.00)	24.77 (20.68 - 60.32)	23.17 (11.83 - 64.95)	21.76 (11.52 - 65.59)
MPUR (n=11 facilities)	By levels	Level 3 (n=3)	0.15 (0.14 - 3.18)	0.05 (0.03 - 6.91)	0.56 (0.28 - 6.95)	0.21 (0.10 - 7.53)
		Level 4 (n=8)	1.07 (0.49 - 2.17)	0.41 (0.13 - 0.95)	0.43 (0.28 - 1.29)	1.38 (0.67 - 2.02)
	By sector	Public (n=9)	1.07 (0.41 - 2.17)	0.41 (0.10 - 0.95)	0.53 (0.28 - 1.29)	0.95 (0.55 - 1.63)
		Non-public (n=2)	0.43 (0.29 - 3.33)	0.13 (0.07 - 6.95)	0.36 (0.16 - 6.85)	3.70 (1.85 - 9.28)
	Overall	% difference = 52.10%[a]	0.57 (0.29 – 2.23)	0.21 (0.08 - 1.04)	0.50 (0.22 - 1.72)	1.19 (0.53 - 2.19)

[a] *This represents the percentage difference between baseline measurements and subsequent measurement taken at 9 months*

Table 3: Median values (interquartile range) for financial indicators across timepoints

Indicator one: Total monthly revenue (TMR) in 10000KES

All facilities experienced an upward trend in total monthly revenue with overall increase by 54.00%. This upward trend was observed in level 2, 3 and 4 health facilities and in the public and non-public sectors. Most of this increase took place in the first 6 months.

Indicator 2 – Monthly proportion of unpaid revenue (MPUR)

All facilities except public facilities showed an upward trend in median MPUR with an overall increase of 52.10%. Both public and non-public facilities had a downward trend in MPUR within the first 3 months of adoption but after the 6th month, the non-public facilities displayed a sharp increase. This resulted in an overall upward trend for non-public facilities in contrast to public facilities with a downward trend.

Comparison between baseline and post-adoption financial performance

The difference (indicated as delta) between M9 and M0 was calculated for both indicators of financial performance. To test if the difference was statistically significant, the Wilcoxon test was also performed. For median TMR, Null hypothesis = M9 – M0 ≤ 0 while for median MPUR, Null hypothesis = M9 – M0 ≥ 0. There was a statistically significant positive difference in median TMR after 9 months of adoption. There was also a positive difference in median MPUR, but this was not statistically significant.

Indicator	Delta (M9 - M0)	P-value
Median TMR	117639	0.0098
Median MPUR	0.62	0.6812

Table 4: Financial indicators, difference, and p-values from a paired Wilcoxon rank-sum test

DISCUSSION

Public facilities accounted for 80% of all included facilities, indicating that they were the earliest adopters of the EHIMS. The included facilities displayed continued use of the EHIMS for at least 9 months and were mostly level 3 and 4 facilities. This may be linked to the comparatively higher allocation of resources for digital HIMS in these higher-level facilities (26). In addition, the staff in these facilities are more familiar with sophisticated equipment and hence will be more likely to accept new technologies such as digital HIMS as demonstrated by Philomena et al (34). Level 2 facilities were the least represented and this may be linked to fewer resources for IT infrastructure making it difficult to afford or sustain these systems.

While acknowledging that the changes observed in this study may not be entirely due to the adoption of the EHIMS, this discussion will focus on examining the role that the EHIMS could have played in the performance trends of partner facilities.

Objective 1: Trends in operational performance after the adoption of EHIMS

The majority of facilities experienced an upward trend in TMV between baseline and 9 months after adoption data (720 vs 1004 visits) though the difference was not statistically significant. Many factors influence the number of visits to a health facility. EHIMS may have contributed to the increase in visits in two ways: by improving the recording of patients and by attracting more patients due to higher patient satisfaction. One problem with paper-based records is the issue of missing entries whereby patients visit the facility and services are offered but they are not recorded (45). The digital system may have ensured correct recording of every patient who visited the facility. In addition, the reduced average waiting time noted in this study may have increased patient satisfaction and word-of-mouth marketing which could have attracted more patients to the facilities

Looking at changes over time, the highest increase was observed in the first three months. During this period, users were getting acquainted with the digital systems and received extensive onsite training from EH staff. The intense support in the first few months after adoption could explain why health providers could enter data correctly thereby increasing the number of recorded patient visits. When support was reduced after 3 months, there was a downward trend until month 6 before the number of recorded visits started picking up again. Probably, after month 6, the users would have been better acquainted with the software.

Average monthly waiting time (AMWT) witnessed a statistically significant (p-value = 0.0003) decrease. This drop could be related to the quick registration process facilitated by the electronic health card. The AMWT stabilised after 6 months when users were supposed to be well-acquainted with the system. This is in line with several studies that have demonstrated lower waiting time with EHR (21,46) but in contrast to the study by Mohan et al showing an increase in waiting time. It is worth mentioning that the results in Mohan's study were linked to a specific system which had a sophisticated interface and was difficult to operate.

A statistically significant drop was also found for AMJT (p-value = 0.0019). Unsurprisingly, a reduction in average waiting time also leads to a reduction in overall average journey time from registration to the last point of contact which is usually the pharmacy where patients collect their drugs.

Overall, there was a positive trend in operational performance after the adoption of EHIMS. The AMWT and AMJT decreased significantly while TMV increased hence, reflecting an improvement in operations and possibly, patient satisfaction. A similar trend is also observed in a number of HIC studies (39,40,47,48). This positive trend could also be linked to the functionality, user interface and operability of the EHIMS which was designed to suit low-resource settings and primary facilities (levels 2 and 3).

Objective 2: Trends in financial performance post-adoption of EHIMS

The majority of individual facilities using the billing module experienced a statistically significant increase in total monthly revenue (TMR). Similar to other indicators, many factors contribute to the revenue collected by a health facility. EHIMS may have contributed to this increased TMR in two ways; by improving willingness to pay because of patient satisfaction and by better tracking of invoices/unpaid revenue. Though the public facilities had more visits and were more represented in the sample, they had a lower TMR than non-public facilities. This could be explained by lower prices. However, the EH Kenya team noted that public facilities did not input all financial data into the software and therefore, the financial data analysed could be just a fraction of their actual income. This could also suggest a lack of accountability in public facilities (49). Financial accountability is one of the main reasons why public facilities in Kenya adopt digital HIMS. However, with incomplete or corrupt input by users, tracking becomes unreliable, and this defeats the purpose. Hence, additional measures must be put in place to motivate hospital users to use digital HIMS for all financial recording.

All facilities except public facilities had an upward trend in MPUR, however this was not statistically significant (p-value = 0.6812). The MPUR was higher in non-public facilities and this could be related to better use of EHIMS and as a consequence, better financial tracking by these facilities. Because non-public facilities need to be self-sustainable, they are more likely to enforce EHIMS usage by staff than public facilities (50). It is also possible that non-public facilities treat more privately insured patients and insurance claims may take time to process. The EHIMS does not yet have electronic insurance forms that can be completed and processed easily, necessitating manual handling of insurance forms. It is also worth noting that the recorded unpaid revenue was higher than recorded collected revenue for some facilities reason why their MPUR is greater than 1. This reiterates the importance of invoice tracking offered by the EHIMS and the need to motivate users to enter all revenue collected so that more accurate analytics can be performed.

Limitations and Weaknesses of the study

The most important limitation of this study was the lack of reliable baseline data. Without these, it was difficult to make assertions about the role played by the adoption of EHIMS in partner facilities. For this reason, we used data from the first month after adoption as a proxy for several indicators which is unlikely to be an accurate representation of actual facility performance before the adoption of EHIMS.

Secondly, we did not perform adjustments for confounding factors such as health provider density, seasonality, and patient income levels, among many others that may have also influenced the indicators. For this reason, the identified changes are only correlated with the introduction of the EHIMS, and no causal relationship can be established. The results and discussion in this study can however, be used as hypotheses for future studies.

Not all performance indicators of interest to the Kenyan MoH, as part of their health strategy, could be analysed because data were not available. Hence, this study delivers only part of the picture of health facility OFP.

Clinical significance

This study contributes to a growing field of research attempting to evaluate the impact of digital HIMS on the OFP of health facilities in SSA. The impact of digital HIMS has been widely studied in HICs but there is limited evidence from SSA where health systems suffer from infrastructural and technical constraints. Hence, the results of this study could guide policymakers in Kenya and SSA to make evidence-based decisions before the adoption of IT systems in health facilities

In our discussion, we presented several possible explanations for the observed trends in OFP. This information can be used by stakeholders (users, providers, administrators, and patients) to improve the adoption, usage, and sustainability of digital HIMS. Some of the suggested factors responsible for the trends have been researched while others need further exploration. This study thus opens areas for further research about the complex and nuanced impact of digital HIMS in SSA.

CONCLUSION

This study demonstrates that digital HIMS can have a positive impact on OFP of health facilities in Kenya when contextualised, simplified, and implemented with close engagement of users. Further research is needed to determine the direct impact of digital HIMS by comparing it with either facilities not using digital HIMS or with more baseline data. Also, confounding factors of OFP should be studied, so that causality can be established between digital HIMS and facility performance. Lastly, further study about the impact of digital HIMS on other parts of the health system is needed to get a full picture.

Declaration by Authors

Ethical Approval: Ethical approval by a regulatory board was not needed for this study because there was neither direct contact with nor primary data collection from human participants. This study was a secondary data analysis of aggregated facility data which was not traceable to any individual. Consent was sought from partner facilities by EH to use their data for research, marketing, and evaluation purposes. Patient consent is always collected at the point of registration and the patient is notified that their data will be processed within or out of the country following the company privacy policy. Patients and users could request to opt-out of the consent at any time by reaching out to any EH team member through a designated email.

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Conflict of Interest: The data that was analysed in this study was extracted by the Elephant Health data team. Vera Oliviera is an employee of Elephant health and has provided input in the data analysis and interpretation.

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